Stochastic Check-in Employee Scheduling Problem

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ABSTRACT This work addresses the problem of assigning airline check-in employees to tasks related to departing flights under uncertain circumstance at an international terminal of a large airport. The uncertainty of flight departing time mainly stems from delays and traffic control. Airlines specifics the minimum and target number of staff for each flight task in each time period. Taking uncertain tasks starting time into account and introducing risk measure (e.g., conditional value-at-risk) into optimization objective function, we present a risk-averse two-stage stochastic model with the mixed-integer recourse that minimizes both staffing costs and risk measurement to respond the time uncertainty. The first-stage decision is to make personal-area allocation plan; and the particular personnel-task scheduling decisions are determined in the second stage as the actual flight departing times are realized. To solve the NP-hard problem, a progressive hedging algorithm is proposed. Numerical experiments are carried out to demonstrate the efficiency and effectiveness of the proposed approach as compared with a sample average approximation method. Finally, we utilize a real-world case to illustrate how the proposed method can be used to obtain a near-optimal solution for practical problem.

INDEX TERMS Employee scheduling, stochastic programming, airport ground optimization, risk measure, progressive hedging algorithm.

I. INTRODUCTION

Cost-effective staff scheduling is one of the key issues attracting the attention of management in service-oriented airline industry. This work we study is motivated by the major airline’s problem of scheduling check-in staff to support passenger boarding service with uncertain flight departing time. A number of airports in the China, such as Beijing, Guangzhou and two international airports in Shanghai, have different levels of delay. When the status of planned departing time changes, it is difficult for schedulers to reschedule the employee and flight tasks. In addition, terminal consisting of many check-in areas is large, it is undesirable for check-in staffs to move between different areas within a work shift. Therefore, it is necessary to take into account both random tasks starting time and personnel to area assignment when designing employee scheduling plans.

Figure 1 gives an illustration of check-in activities at an airport terminal. Depending on destinations, the terminal consists of four areas: A, B, C, and D. 30-60 minutes before the departure of each flight, check-in personnel would be arranged at the boarding gate to take charge of check-in services (such as ticket check-in, collecting board cards, etc.). The duration of the check-in task depends on the size of the aircraft. The shift plan of check-in personnel is provided by airlines, which can be divided into two shifts or three shifts according to the number of shifts per day. Check-in staffs complete a series of check-in services and rest/meal breaks during working hours within a shift. Check-in staffs try to avoid cross-regional tasks, as this not only takes a lot of walking time but also increases the burden on employees. Specifically, it is not advisable that employees are arranged to area B to perform the task at 10:15 after completing the check-in task of area A at 09:15. On the contrary, a reasonable arrangement is to let the staffs in charge of area B complete all check-in tasks located at that area. When designing the personnel schedules, planners also need to consider the
The purpose of this article is to propose a stochastic check-in personnel scheduling model that takes into account the uncertain starting times of flight tasks, so that the right personnel are correctly arranged in the right position at the right time. This paper proposes a scenario-based two-stage stochastic check-in staff scheduling model, where the first stage makes staff allocation to avoid employees cross-region activities, while the second stage, as the time closing to the actual period of tasks starting time realization, assigns specific staffs to tasks in accordance with the staff-area decisions. The stochastic model guarantees employee’s rest breaks and meal break requirements by minimizing weighting (1) short-falls of total staff from the target demand, (2) assignment of partially skilled staff, and (3) undesirable starting times for meal break.

Furthermore, there has a potential risk that the solution based on generic two-stage stochastic programming with expected objective function may perform poorly in extreme cases. To reduce the risk of huge losses while the actual realization is the extreme scenario, the interest of risk measure should be incorporated into the optimization objective function. In this work, conditional value-at-risk (CVaR), a coherent risk measurement method, is applied in our optimization problem.

The remainder of this article is organized as follows. In Section II, a brief literature review is introduced. The mathematical formulation of stochastic check-in employee scheduling is given in Section III. In Section IV, we detail our solution method. In Section V, we carry out a lot of numerical experiments to demonstrate the performance of the proposed model and algorithm. Section VI gives a case study that provides insights into the implementation of our procedure to realistic problem. Finally, Section VII concludes this work.

II. LITERATURE REVIEW

The literature on personnel scheduling is immense. Here, we focus on articles that address problems that are most similar to ours. We refer interested readers to recent surveys [8]–[11] for more details of the state-of-art works. Many articles address one or both of the following problems: (i) determining a finite-horizon (perhaps cyclic) work schedule, and (ii) assigning staff to shifts within such a schedule, usually considering factors such as days-off and shift-change constraints.
The articles that are closely related to ours are some literature on applications of personnel scheduling in airports and at airlines, such as ground crew scheduling [12]–[14], airline crew scheduling [5]–[7]. These works are mainly designed to device a roster at the granularity of days or shifts, and the microcosmic rest and meal breaks assignment decisions is not incorporated in a shift. Scheduling of meal and rest breaks is not often tackled in the airline crew scheduling literature. Recently, Hur et al. [15], [16] investigate a daily shift scheduling problem with flexible breaks under stochastic demand that allows for break adjustments on the day of operation. Kiermaier et al. [17] studies the problem of assigning multiple breaks to shifts in the context of large-scale tour scheduling. They firstly determine the shift and day-off scheduling, and then the breaks is placed optimally in accordance with the results of former shift and day-off scheduling.

While a large amount of mathematical models and methods have been established in the literature for finding optimized schedules, only few propose methods for practically relevant problem settings including uncertainty, which is an important aspect of employee scheduling in the service industry. In deterministic situation, hourly staff requirements are predicted based on historic data, or generated by using some sales response model [18]. These known demand are then used as the input parameters of a mixed integer optimization model, which finds an optimum assignment of the staff to daily shifts. In reality, uncertain events, such as short demand perturbations arising from staff absenteeism or customer surge, would cause original employee schedules perform poorly. Motivated by the uncertain factors, there are a growing attentions on accounting for random employee demand in the scheduling models [15], [19]–[23], especially in the context of employee plans in retail stores [10], [24], [25]. In particular, Bürgy et al. [25] studies the employee scheduling problem considering uncertain demand arising in retail stores, and their strategy to cope with uncertain demand is assigning overtime work by extending shifts to cope with a lack of employees in real-time. Similar to the proposed methodology used in our work, Kim and Mihrotra [21] addresses the problem of integrated nurse staffing and scheduling under demand uncertainty in a two-stage stochastic modeling fashion. In [21], the first-stage decision is to find initial staffing levels and schedules, and the second-stage decision is to adjust these schedules at a time closer to the actual date of demand realization. For more details regarding employee scheduling with uncertain demand, we refer readers to Defraeye and Van Nieuwenhuysye [10] for a recent survey.

For many situations studied previously, random demand is the main uncertain factor and few cases account for the fluctuation of tasks starting time. Very few articles take into account the uncertainty of tasks starting time among employee scheduling problems. However, in the context of other fields, such as machine scheduling problem, stochastic release time of job task is captured for a roust scheduling [26], [27]. In the airport terminal, ground operations are dynamic and uncertain, and departure delays of 15 to 30 minutes are common [28]. It is necessary, therefore, that takes into account the uncertain starting times of check-in tasks when airlines make employee schedule to support traveler service.

Stochastic programming is the prevailing modeling method to account for uncertainty with the specific probability distribution. However, the traditional stochastic programming model is based on minimizing (maximizing) optimization objective function in an expected way, and the risk of extreme scenarios occurring is ignored. For the sake of avoiding the potential risk of solutions in extreme situations, some mean-risk stochastic programming models are developed by weighting risk measures in the objective function. Common risk measures include conditional value-at-risk (CVaR), value-at-risk (VaR) and mean absolute semi-deviation (MASD). Specifically, CVaR is specified as the risk measure in humanitarian relief network design [29], system design and preventive maintenance planning [30] and stochastic fixed-charge transportation [31], and the supply chain replenishment problem with MASD as a risk measure.

Interestingly, although there are a vast of literature on personnel scheduling, we were unable to find work that tackle the characteristics of our problem: (i) random starting times of check-in tasks, (ii) risk measure under stochastic situation. To the best of our knowledge, none considers (i) and (ii) in the personnel scheduling of airport ground activities. In the next section, we formulate mathematical models that adequately capture these features of our problem.

### III. PROBLEM FORMULATION

In order to make the stochastic model to reflect the risk preferences of decision makers, we adopt the risk measure into the objective function. This section firstly introduces the general stochastic check-in personnel scheduling model. Then, the definition of conditional value-at-risk (CVaR) used to measure risk is briefly introduced. Finally, the risk-averse version of stochastic check-in personnel scheduling problem is presented.

To improve the accuracy of the model, the following assumptions need to be made before the mathematical model of the problem is formulated.

1) The check-in schedule for the day is known. The number of shifts and employees, and the category of employees in each shift are given.
2) The terminal is divided into multiple check-in areas based on flight destinations, and check-in personnel cannot undertake check-in activities across regions within work shift.

#### A. TWO-STAGE STOCHASTIC MODEL BASED ON EXPECTATION

We use $\omega$ to represent random event, and $\Omega$ to represent a set of finite discrete random events. A scenario-based two-stage modeling method is adopted. The sets, parameters and variables used in our model are defined as follows.
Set and input parameters:
I: set of staffs, indexed by $i$.
J: set of tasks, indexed by $j$.
L: set of areas, indexed by $l$.
T: set of time periods, indexed by $t$.
d$_i$: the target staff number for task $i$.
d$^\omega_i$: the minimum staff number for task $i$.
p$^\omega$: probability of scenario $\omega$ occurrence.
s$^\omega_j$: the starting time of task $j$ in scenario $\omega$.
e$^\omega_j$: the ending time of task $j$ in scenario $\omega$.
l$: the area of task $j$.
J$: set of tasks in area $l$, $J_l = \{ j \in J : l_j = l \}$.
J$: set of tasks at time period $t$ in scenario $\omega$, $J^\omega_t = \{ j \in J : t \in [s^\omega_j, e^\omega_j] \}$.
a$_{ij}$: = 1 if staff $i$ can fully skilled to fulfill task $j$; = 0, otherwise.
$\beta_{ij}$: = 1 if staff $i$ can partially skilled to fulfill task $j$; = 0, otherwise.
off$^\omega_i$: = 1 if staff $i$ is unavailable in time period $t$; = 0, otherwise.
t$^0$: the earliest possible time period for the start of the meal break for employee $i$.
t$^1$: the latest possible time period for the start of the meal break for employee $i$.
q: minimum number of time periods between rest break and meal break.
H$: duration of meal break.
w$^d_j$: the cost penalty per staff shortage for task $j$.
w$^p_j$: the cost penalty per partially skilled staff $i$ assigned to task $j$.
w$^h_l$: the cost penalty for employee $i$ to start meal break in time period $t$.

Decision variables:
x$_{il}$: = 1 if employee $i$ is assigned to area $l$; = 0, otherwise.
y$_{ij}^\omega$: = 1 if employee $i$ is assigned to task $j$ in scenario $\omega$; = 0, otherwise.
h$^\omega_l$: = 1 if the meal break starting time period of employee $i$ in scenario $\omega$ is $t$; = 0, otherwise.
r$^k_{ij}$: if employee’s $k$-th rest break in scenario $\omega$ is in period $t$; = 0, otherwise.
$\zeta$$_j^\omega$: staff shortage of task $j$ in scenario $\omega$.

According to the above notations, the equivalent deterministic mathematical model of stochastic check-in employee scheduling problem can be written as:

$$\begin{align*}
\text{(M1) } \min f_1 &= \sum_{\omega \in \Omega} p^\omega \left( \sum_{j \in J} w^d_j \zeta_j^\omega + \sum_{i \in I} \sum_{j \in J} w^p_{ij} \beta_{ij} y_{ij}^\omega \\
&\quad + \sum_{i \in I} \sum_{l \in L} w^h_{il} h_{il}^\omega \right) \\
\text{s.t. } &\sum_{i \in I} x_{il} = 1, \quad \forall i \in I \quad (2) \\
&y_{ij}^\omega \leq x_{il}, \quad \forall i \in I, j \in J_l, l \in L, \omega \in \Omega \quad (3) \\
&\sum_{i \in I} a_{ij} y_{ij}^\omega \geq d_j, \quad \forall j \in J, \omega \in \Omega \quad (4)
\end{align*}$$

The objective function (1) is to minimize the weighted sum of the shortfalls of total staff (whether fully or partially skilled) from the target demand (first term), the cost of assigning partially skilled employees (middle term), and the undesirable starting times for meal breaks (last term). Constraint (2) guarantees that each employee is allocated to only a check-in area. Constraint (3) determines the tasks that employees can perform at area $l$ in scenario $\omega$. The minimum staffing levels of $d_j$ for language requirement must be satisfied by constraint (4). Constraint (5) requires that the target number of staffs for each task in scenario $\omega$ is met to the greatest extent, though the shortfalls of employees is allowed. Constraint (6) guarantees that each worker in scenario $\omega$ will only be assigned check-in tasks during the available time periods. Constraint (7) ensures that the starting time of meal breaks assigned to each employee in scenario $\omega$ is an allowable time period. Constraint (8) guarantees that each employee in scenario $\omega$ has two rest breaks. Constraint (9) requires that each employee in the scenario $\omega$ completes the first break at least $q$ unit time periods before the meal break begins. Constraint (10) requires that each employee in scenario $\omega$ completes the second break at least $q$ unit time periods after the meal break. Constraints (11)-(12) provide the domains of variables.

Formulation (1)-(12) is a so-called risk-neutral stochastic model in which the optimization objective function is based on the expectation recourse cost of all possible scenarios. The obtained solution by risk-neutral model is a compromise result accepted by considered scenarios. There are possibilities that the risk-neutral solution would perform poorly in some extreme scenarios for lack of robustness. Hence, it is important to consider the potential risk values of candidate solutions in the objective function, as the optimality and the robustness should be weighted.
B. RISK-AVERSE MODEL

In this section, the basic concept of CVaR and the linear programming expressions of CVaR are briefly introduced. Finally, we end this section with the mathematical model of check-in employee with CVaR as risk measurement.

In risk-neutral two-stage stochastic models in which the objective function is regarded as a generic expectation function, the sample space \( \Omega \) is treated as a finite probability distribution \( \Omega = \{ \omega^1, ..., \omega^|\Omega| \} \). Then, the commonly used expression based on the expected stochastic linear programming problem can be written as

\[
\min_{x \in X} E_{\omega \in \Omega} [f(x, \omega)] = \min_{x \in X} c^T x + E_{\omega \in \Omega} [Q(x, \omega)] \tag{13}
\]

where \( f(x, \omega) = c^T x + Q(x, \omega) \) represents the total cost function in the first stage, \( Q(x, \omega) \) represents the recourse function value of the second stage, and its generic expression is given as follows.

\[
Q(x, \omega) = \min_{y(\omega)} \{ q^T(\omega)y(\omega) : T(\omega)x + W(\omega)y(\omega) = h(\omega), y(\omega) \geq 0 \} \tag{14}
\]

In the above equation, “\( x \)” is the vector of the first-stage decision variables, such as the assignment decision of employee to area in this work, which is determined one or two days before the actual tasks begin; “\( y(\omega) \)” is the second-stage decision variables vector, in this article, that is employee-task scheduling decision which is determined after the random event \( \omega \) realized. The above formulation (14) only considers the recourse function of \( E_{\omega \in \Omega} [Q(x, \omega)] \) based on the expectation, and does not consider the potential risk that the large costs resulting by extreme scenario occurrence. The risk-neutral two-stage stochastic optimization can be extended to the risk-averse version by using the following equation (15):

\[
\min_{x \in X} (1 - \lambda)E_{\omega \in \Omega} [f(x, \omega)] + \lambda CVaR_\alpha (E_{\omega \in \Omega} [f(x, \omega)]) \tag{15}
\]

where \( \lambda \in [0, 1) \) is a trade-off coefficient, which represents the exchange rate between the expected cost and risk, and is called the risk coefficient or risk level. In particular, when \( \lambda = 0 \), the objective function (15) is risk-neutral. For the random variable \( f((x, \omega), CVaR_\alpha \) represents the conditional value-at-risk of \( f((x, \omega) \) with given confidence level \( \alpha \). The mean-risk model minimizes both the expected cost \( E_{\omega} [\cdot] \) and the risk measurement function \( CVaR_\alpha(\cdot) \). The related definition of the linearized risk measure \( CVaR_\alpha \) is as follows:

**Definition 1:** Conditional value-at-risk of random variable \( Z \) at confidence level \( \alpha \) \[32\]

\[
CVaR_\alpha(Z) = \inf_{\eta \in \mathbb{R}} \left\{ \eta + \frac{1}{1 - \alpha} E_{\eta} [Z - \eta]_+ \right\} \tag{16}
\]

where \( [Z - \eta]_+ := \max(0, Z - \eta) \) for \( \alpha \in (0, 1] \). With the term \( ([Z - \eta]_+) \) in the linearization formulation (16) and the assumption that the probability distribution space is discrete finite, the conditional value-at-risk of the random variable \( Z \) at the confidence level \( \alpha \) can be rewritten as:

\[
CVaR_\alpha(Z) = \inf_{\eta \in \mathbb{R}} \left\{ \eta + \frac{1}{1 - \alpha} E_{\eta} [u^\omega] \right\} \tag{17}
\]

\[
= \min \left\{ \eta + \frac{1}{1 - \alpha} \sum_{\omega \in \Omega} p^\omega u^\omega \right\} \tag{18}
\]

s.t. \( \varepsilon^\omega - \eta \leq u^\omega, \ \forall \omega \in \Omega \) \tag{19}

\[
0 \leq u^\omega, \ \forall \omega \in \Omega \tag{20}
\]

\[
\eta \in \mathbb{R} \tag{21}
\]

Given the definition of risk measurement, the mathematical formulation of risk-averse stochastic model is clearly. The model is based on the model M1 and the equations (15), (17)-(21). Its equivalent deterministic mathematical formulation is as follows:

\[
(M2) \min (1 - \lambda) f_1 + \lambda \left( \eta + \frac{1}{1 - \alpha} \sum_{\omega \in \Omega} p^\omega u^\omega \right) \tag{22}
\]

s.t. \( \text{constraints (2)-(12)} \)

\[
\sum_{j \in J} w^j_1 y^\omega_1 + \sum_{i \in I} \sum_{j \in J} w^j_2 \beta_i y^\omega_2 + \sum_{i \in I} \sum_{i \in T} w^i_3 h^\omega_i - \eta \leq u^\omega, \ \forall \omega \in \Omega \tag{23}
\]

\[
0 \leq u^\omega, \ \forall \omega \in \Omega \tag{24}
\]

\[
\eta \in \mathbb{R} \tag{25}
\]

Note that the deterministic check-in personnel scheduling problem with single scenario is NP-hard [28], solving the risk-averse stochastic model is more challenging in that the proposed model incorporates multiple scenarios. In the following section, we present the solution methods for the complicated problem.

IV. SOLUTION APPROACH

In this section, we introduce sample average approximation (SAA) method and progressive hedging algorithm (PHA), respectively. Both SAA and PHA are two mainstream heuristic solution approaches to address stochastic programming problems. When the considered scenario set is large, the stochastic problem formulated as a large-scale deterministic model can not be directly solved by using commercial solvers in an acceptable time. Therefore, scenarios decomposition strategies, such as PHA, are developed to obtained feasible solutions according to the considered scenarios. Scenarios decomposition is obtained by applying Lagrangian relaxation to the non-anticipativity constraints (i.e., the constraints (3) ensuring that a single staff-area allocation used under all considered scenarios). The original problem stochastic problem is decomposed per scenario. The resulting scenario subproblem can be used to obtain a general lower bound of original problem objective value.

Common decomposition algorithms estimate the separability of objective functions formulated in terms of expected costs, however, the expected objective values is not the only goals of interest in our work. Minimization of risk measure
A. SAMPLE AVERAGE APPROXIMATION METHOD

SAA is an approach for solving stochastic optimization problems by deterministic optimization techniques using Monte Carlo simulation. In SAA, the expected objective of the original stochastic problem is approximated by a sample average estimate derived from a set of samples \[33\]. In the SAA strategy, a set of random samples \(s^j, \ldots, s^N\) of \(N, N \leq |\Omega|\) realizations of the random variable \(s^j\) are generated, and the expected recourse value is approximated by the sample average function. The SAA approach approximates problem M2 by the following problem M3:

\[
\begin{align*}
\text{M3:} & \quad \min_{x, y, u} \frac{1 - \lambda}{N} \sum_{n=1}^{N} \left[ \sum_{j \in J} w^d_{ij} z^n_{ij} + \sum_{i \in I} \sum_{j \in J} w^b_{ij} B_j y^n_j \right] \\
& \quad + \sum_{i \in I} \sum_{t \in T} \sum_{k \in K} w^h_{ik} h^n_{ik}^t + \frac{\lambda}{N} \left[ \eta + \frac{1}{1 - \alpha} \sum_{n=1}^{N} u^n \right] \\
& \quad \text{s.t. constraints (2)-(12), (23)-(25)} \quad (26)
\end{align*}
\]

Formulation M3 can be solved by calling commercial solvers, such as CPLEX, with small-scale problem. This method converges to a near-optimal solution of a mixed-integer two-stage stochastic optimization problem provided that the sample size is sufficiently large \[34\].

B. PROGRESSIVE HEDGING ALGORITHM

This section gives the general expression of PHA for generic two-stage stochastic mixed-integer programming (SMIP). The equivalent expression of a general two-stage stochastic mixed-integer programming model is shown as (27)-(31).

\[
\begin{align*}
\text{min} & \quad c^T x + \sum_{\omega \in \Omega} P^\omega g(\omega) y(\omega) \\
\text{s.t.} & \quad Ax \geq b \\
& \quad T(\omega)x + W(\omega)y(\omega) \geq r(\omega), \quad \forall \omega \in \Omega \\
& \quad x \in \mathbb{Z}^{m_1}_+ \times \mathbb{R}^{m_2 - p_1} \\
& \quad y \in \mathbb{Z}^{m_3}_+ \times \mathbb{R}^{m_4 - p_2}, \quad \forall \omega \in \Omega
\end{align*}
\]

where \(x\) and \(y\) denote the first-stage and the second-stage decision variables, respectively. \(A, b, T(\omega), W(\omega), r(\omega)\) are model parameters. In the risk-averse stochastic model of our problem, random event \(\omega\) is uncertain task starting time, \(x\) represents employee-area assignment decision \(x_{ij}\) and additional variable \(\eta\) in risk measure, \(y\) denotes all second-stage decision variables \(y_{ij}, h_{ik}, z_{ij}\), as well as additional decision variable \(u\). \(X(\omega)\) denotes the feasible domain of decision variables in scenarios \(\omega\).

The progressive hedging algorithm for stochastic programming problems is a decomposition method which, in each iteration, solves a separate subproblem with modified costs for each scenario. The pseudo-code of the PHA is shown in Algorithm 1. PHA is first initialized by solving the sub-problems of a single scenario (Step 1); each iteration of the algorithm aggregates the solutions in all scenarios (Step 3); the dual price \(w^\omega(\omega)\) and \(m^\omega(\omega)\) are updated in each iteration (Step 4), the penalty coefficient \(\rho\) is an external input parameter of the algorithm, and its value affects the convergence effect. PHA decomposition step (Step 5) solves the single-scenario subproblem in which the objective function is disturbed by the dual price and the deviation of the aggregate solution. In this sense, PHA uses a by-scenario decomposition approximation scheme to find feasible solutions for the complete problem \[35\]. The algorithm terminates based on whether the solution converges within a given tolerance or exceeds a default maximum number of iterations.

Algorithm 1 Progressive Hedging Algorithm for M2

Input: \(\rho, \nu_{max}, \epsilon\)
Output: \(x\), lower bound value;

1: **Step 1 Initialization:** Let \(v \leftarrow 0\), \(w^\omega(\omega) \leftarrow 0\), \(m^\omega(\omega) \leftarrow 0\), \(\forall \omega \in \Omega\). For each \(\omega \in \Omega\), calculate \((\hat{x}^{\omega + 1}(\omega), \hat{y}^{\omega + 1}(\omega), \hat{u}^{\omega + 1}(\omega))\) \(\in \arg\min_{(x, y, u, \omega) \in \mathbb{X}(\omega)} c^T x + \lambda \eta + (1 - \lambda) g^T y + \lambda \frac{1}{1 - \alpha} u + w^\omega(\omega)x + m^\omega(\omega)y + \frac{\eta}{2}(x - \hat{x}^{\omega + 1}(\omega))^2 + \frac{\lambda}{2}(y - \hat{y}^{\omega + 1}(\omega))^2\).
2: **Step 2 Iterative update:** \(v \leftarrow v + 1\);
3: **Step 3 Aggregation:** \(\hat{x}^{\omega} \leftarrow \sum_{\omega \in \Omega} P^\omega x^{\omega + 1}(\omega), \hat{y}^{\omega} \leftarrow \sum_{\omega \in \Omega} P^\omega y^{\omega + 1}(\omega), \hat{u}^{\omega} \leftarrow \sum_{\omega \in \Omega} P^\omega u^{\omega + 1}(\omega);\)
4: **Step 4 Price update:**

\[
\begin{align*}
& w^\omega(\omega) \leftarrow w^{\omega - 1}(\omega) + \rho(x^{\omega}(\omega) - \hat{x}^{\omega}) \\
& m^\omega(\omega) \leftarrow m^{\omega - 1}(\omega) + \rho(\hat{y}^{\omega}(\omega) - \hat{y}^{\omega})
\end{align*}
\]

5: **Step 5 Decomposition:** For each \(\omega \in \Omega\), calculate \((\hat{x}^{\omega + 1}(\omega), \hat{y}^{\omega + 1}(\omega), \hat{u}^{\omega + 1}(\omega)) \in \arg\min_{(x, y, u, \omega) \in \mathbb{X}(\omega)} c^T x + \lambda \eta + (1 - \lambda) g^T y + \lambda \frac{1}{1 - \alpha} u + w^\omega(\omega)x + m^\omega(\omega)y + \frac{\eta}{2}(x - \hat{x}^{\omega + 1}(\omega))^2 + \frac{\lambda}{2}(y - \hat{y}^{\omega + 1}(\omega))^2\).
6: **Step 6 Stop:** If \(\sum_{\omega \in \Omega} P^\omega ||x^{\omega}(\omega) - \hat{x}^{\omega}||^2 \leq \epsilon\) or maximum iteration number \(\nu_{max}\) reach, algorithm stops; go to **Step 2** otherwise;

We now state our lower bounding result for the PHA. Let \(z^*\) denote the optimal objective function value of the SMIP defined by (27)-(31). In the following, we assume that the SMIP is feasible and has an optimal solution with \(-\infty < z^* < +\infty\), and \(X(\omega) \neq \emptyset\), \(\forall \omega \in \Omega\). The following result shows that the dual prices \(w(\omega), \omega \in \Omega\), define implicit lower bounds on \(z^*\).

Proposition 1: Let \(D_\omega(w(\omega))\) denotes the low bound of objective value determined by dual price \(w(\omega)\) in scenario \(\omega\), for all \(\omega \in \Omega\) where \(w(\omega) \in \mathbb{R}^{n_1}\) satisfy \(\sum_{\omega \in \Omega} P^\omega w(\omega) = 0\). Let

\[
D_\omega(w(\omega)) := \min_{(x, y) \in X(\omega)} \left( c^T x + g^T y + w(\omega)^T x \right)
\]
Algorithm 2 Heuristic Adjustment

Input: $x_{raw}$;
Output: $x_{feasible}$;
1: $workload_l \leftarrow$ number of all flight tasks in area $l$, $l \in L$;
2: $assigned_l \leftarrow$ number of employees assigned in area $l$, $l \in L$;
3: $unassign \leftarrow$ set of employees without assigned areas;
4: while $|unassign| > 0$ do
5: $l_{assign} \leftarrow$ the area with the most tasks $workload_l$, $l \in L$;
6: if $assigned_{l_{assign}} \leq$ number of people assigned based on the number of tasks then
7: $l_{assign} \leftarrow$ an employee from the set $unassign$ (qualification is preferred);
8: $x_{raw}(l_{assign}, l_{assign}) \leftarrow 1$;
9: $assigned_{l_{assign}} \leftarrow assigned_{l_{assign}} + 1$;
10: $unassign = unassign \setminus \{l_{assign}\}$;
else
12: $workload_{l_{assign}} = 0$;
end if
14: end while
15: $x_{feasible} \leftarrow x_{raw}$;

Then $D(w) := \sum_{\omega \in \Omega} p^\omega D_{\omega}(w(\omega)) \leq \varepsilon^*$, the estimated $D(w)$ is the lower bounding result for the PHA.

Proof 1: The proof is same as Gade et al. [36], we omit it here.

For the risk-averse SMIP with additional variable $\eta$ and $u^o$, the variable $\eta$ is interpreted as a first-stage variable. The lower bound of risk-averse version is estimated as follows. For each $\omega \in \Omega$, calculate the objective value of problem (33).

$$\min D_{\omega}(w(\omega), m(\omega)) = c^T x + g^T y + w(\omega)^T x + m(\omega) \eta$$

s.t. constraints (2)-(12), (23)-(25) (33)

The lower low bounding result of PHA to solve risk-averse model is estimated by $D(w) := \sum_{\omega \in \Omega} p^\omega D_{\omega}(w(\omega), m(\omega))$.

It should be noted that as a heuristic method, PHA’s solution is an approximately optimal solution in the case of continuous variables. When the decision variables contain integer variables and the algorithm terminates the iteration within a given convergence error, the original solution obtained by PHA is relaxed. In order to obtain a feasible integer solution, some revisions need to be adopted to adjust the original solution to meet the integer constraint conditions. Algorithm 2 gives a heuristic method to adjust the original solution of the PHA. The heuristic adjustment based on the workloads and staff shortages of check-in areas, for unassigned staffs, we prioritize the assignment of full-skilled personnel to high workload areas with staff shortfall. Once the assigned staff of the area meets the number of personnel required by the proportion of tasks, we delete the area from the collection of underemployed areas. This procedure terminates until there are no unassigned employees.

Table 1. Objective function coefficient and meal rest coefficient.

| $w^o_j$ | $w^o_i$ | $w^o_\alpha$ | $t^0_i$ | $t^1_i$ | $H$ | $q$ |
|--------|--------|-------------|--------|--------|-----|-----|
| 1000   | 100    | ($L_i - T_i$)$^2$ | $T_i$  | $2(T_i - T_f)$  |

V. NUMERICAL EXPERIMENT

To illustrate the computing effect of the PHA, we compare the computational results obtained by the SAA. In addition, as the risk coefficient $\lambda$ of the risk averse objective function and the confidence level $\alpha$ of CVaR are two control parameters, at the end of this section, sensitivity analysis is performed.

The commercial solver CPLEX with version 12.8 is used. The mathematical model is implemented by MATLAB2018b and runs on a HUWEI PC with 4.0GHz 32 RAM. Considering the complexity of the problem, we set time limit is 4800s as an acceptable time.

The convergence effect of PHA is impacted by the penalty coefficient $\rho$. Before starting the formal numerical experiments, a pretest with the parameter $\rho \in \{1, 5, 10, 20, 50, 100, 200, 500\}$ is performed, and $\rho = 20$ is selected as the optimal parameter according to the optimal results of the pretest.

A. DATA DESCRIPTION

In line with Kuo et al. [28], Table 1 gives the cost penalty values of the model objective function $w^o_j$, $w^o_i$, $w^o_\alpha$, meal starting time range $t^0_i$, $t^1_i$ and the meal break duration $H$, and the minimum time period interval $q$ between meal break and rest break. $T_i$ and $T_f$ represents the shift starting time and ending time of employee $i$, respectively. $L_i = T_i + \frac{(T_f - T_i)}{2}$ represents the intermediate time period of the employee $i$’s shift. The base time period is 15 minutes. Each check-in task requires the participation of at least one fully qualified employee. The standard check-in number of ordinary flights is 3 and the standard check-in number of large flights is 4. The number of tasks for the flight is 48, the total number of employees is 60, and the number of check-in areas at the terminal is 4.

In the check-in personnel scheduling problem, the problem size is determined by the length of the scheduling time horizon and considered scenario number $|\Omega|$. The longer the scheduling time horizon, the higher the complexity of the model. Second, the uncertainty of tasks starting time plays an important role in affecting the scheduling plan, as the personnel schedules are different under different delay levels. Finally, the composition of the check-in staff impacts the scheduling cost as well, because each check-in task has the minimum requirements for the number of fully qualified employees. Therefore, the experimental instances need to analyze the combinations of above factors. These influencing factors profile we consider here are listed as follows:

1. Schedule duration:
   ST1: Only consider the personnel allocation and task scheduling within one shift (9 hours), and the scheduled time is $|T| = 36$. 
**TABLE 2.** Weighted objective value and optimality gap of instances.

| Inst.          | Objective value | gap       |       |       |       |       |       |       |
|----------------|-----------------|-----------|-------|-------|-------|-------|-------|-------|
|                | $|\Omega| = 5$ | $|\Omega| = 10$ | $|\Omega| = 20$ | $|\Omega| = 30$ | $|\Omega| = 5$ | $|\Omega| = 10$ | $|\Omega| = 20$ | $|\Omega| = 30$ |
| ST1×FT1×SO1   | 5.634           | 4.370     | 5.677 | 5.668 | 0.000 | 0.000 | 0.000 | 0.000 |
| ST1×FT1×SO2   | 4.834           | 3.570     | 4.734 | 4.843 | 0.000 | 0.000 | 0.000 | 0.000 |
| ST1×FT2×SO1   | 6.368           | 8.922     | 6.069 | 6.636 | 0.048 | 0.000 | 0.000 | 0.048 |
| ST1×FT2×SO2   | 5.348           | 8.167     | 5.108 | 5.904 | 0.022 | 0.017 | 0.017 | 0.016 |
| ST2×FT1×SO1   | 21.754          | 24.108    | -     | -     | 0.011 | 0.488 | -     | -     |
| ST2×FT1×SO2   | 18.648          | 31.822    | -     | -     | 0.000 | 0.650 | -     | -     |
| ST2×FT2×SO1   | 21.284          | 995.973   | -     | -     | 0.005 | 0.984 | -     | -     |
| ST2×FT2×SO2   | 18.748          | 993.718   | -     | -     | 0.029 | 0.987 | -     | -     |

**TABLE 3.** Staff cost of instances by SAA and PHA.

| Inst.          | Staff cost (SAA) | Staff cost (PHA) |
|----------------|------------------|------------------|
|                | $|\Omega| = 5$ | $|\Omega| = 10$ | $|\Omega| = 20$ | $|\Omega| = 30$ | $|\Omega| = 5$ | $|\Omega| = 10$ | $|\Omega| = 20$ | $|\Omega| = 30$ |
| ST1×FT1×SO1   | 4.478            | 3.930            | 4.423 | 4.602 | 4.372 | 3.795 | 4.218 | 3.917 |
| ST1×FT1×SO2   | 3.678            | 3.130            | 3.438 | 3.777 | 3.601 | 3.004 | 3.105 | 3.401 |
| ST1×FT2×SO1   | 5.346            | 6.974            | 5.927 | 6.101 | 4.971 | 6.791 | 4.504 | 5.490 |
| ST1×FT2×SO2   | 4.306            | 6.164            | 4.956 | 5.388 | 4.164 | 5.964 | 3.629 | 4.894 |
| ST2×FT1×SO1   | 20.478           | 21.946           | -     | -     | 18.914 | 16.231 | 17.461 | 15.684 |
| ST2×FT1×SO2   | 17.346           | 25.308           | -     | -     | 14.661 | 12.556 | 13.912 | 14.570 |
| ST2×FT2×SO1   | 20.358           | 189.860          | -     | -     | 18.872 | 24.705 | 18.237 | 23.543 |
| ST2×FT2×SO2   | 17.886           | 180.676          | -     | -     | 16.360 | 20.127 | 15.254 | 19.912 |

**TABLE 4.** Employ cost difference of instances by SAA and PHA.

| Inst.          | Difference |
|----------------|------------|
|                | $|\Omega| = 5$ | $|\Omega| = 10$ | $|\Omega| = 20$ | $|\Omega| = 30$ |
| ST1×FT1×SO1   | 0.024      | 0.034      | 0.046     | 0.149  |
| ST1×FT1×SO2   | 0.021      | 0.040      | 0.097     | 0.100  |
| ST1×FT2×SO1   | 0.070      | 0.026      | 0.240     | 0.100  |
| ST1×FT2×SO2   | 0.033      | 0.032      | 0.268     | 0.092  |

ST2: Consider three shifts (20 hours) for staff assignment and task scheduling. The shift starting times are {06:15, 12:00, 17: 30}, and the scheduled time horizon length is $|T| = 80$.

(2) Flight delay levels: since the flight delay is too long, the flight will be canceled. There is an upper limit on the delay times. Therefore, this work assumes that the flight delay time obeys the uniform distribution of the fixed interval.

FT1: Assume that the delay time of the flight obeys the uniform distribution of the interval [1,2], which means the delay is slight.

FT2: The delay time of the flight obeys the uniform distribution of the interval [1,6], which means the delay is serious.

(3) Staff skill levels:

SO1: Only 50% of employees are fully qualified for check-in work, and the remaining employees are partially qualified.

SO2: Only 70% of employees are fully qualified for check-in work, and the remaining employees are partially qualified.

By considering the different levels of influencing factors, a total of 8 instances can be designed to carry out numerical experiments.

**B. ALGORITHM EFFECT ANALYSIS**

This section assesses the performance of the PHA by comparing it with the SAA method. All experimental instances

in this section take $\lambda = 0.5$, $\alpha = 0.9$, and the sensitivity analysis of the parameters $\lambda$, $\alpha$ is discussed in the following section. The maximum number of iterations of the PHA takes 10 as a trade-off between computing time and algorithm convergence accuracy. Table 2 gives the computational results with different scenario sizes, where the left of Table 2 records the objective function values of model M2, and the symbol ‘-’ indicates that the solutions are not obtained within given time. Table 3 lists the employee costs by using SAA method and the employee costs lower bounds obtained by PHA. Table 4 reports the employee cost’s difference estimated by $\text{cost}_{\text{SAA}} - \text{cost}_{\text{PHA}}$ between the SAA and the PHA for all instances involving ‘ST1’. Table 5 shows the computing times of different methods.

From Table 2, it can be found: (1) When other factors are identical, the higher the ratio of employees who are fully qualified for check-in tasks, the lower the weighted employee
TABLE 5. Computational time of instances by SAA and PHA.

| Inst.       | Computational time (SAA) | Computational time (PHA) |
|-------------|--------------------------|---------------------------|
|             | $|\Omega|=5$             | $|\Omega|=10$             | $|\Omega|=20$             | $|\Omega|=30$             |
|             | $|\Omega|=5$             | $|\Omega|=10$             | $|\Omega|=20$             | $|\Omega|=30$             |
| ST1×FT1×SO1 | 23.76                   | 62.47                     | 186.91                    | 640.02                    |
| ST1×FT1×SO2 | 22.28                   | 63.08                     | 191.54                    | 649.29                    |
| ST1×FT2×SO1 | 23.29                   | 65.17                     | 193.99                    | 653.48                    |
| ST1×FT2×SO2 | 23.30                   | 64.25                     | 194.25                    | 681.08                    |
| ST2×FT1×SO1 | 561.21                  | 2,123.72                  | >4800                     | >4800                     |
| ST2×FT1×SO2 | 562.95                  | 2,138.18                  | >4800                     | >4800                     |
| ST2×FT2×SO1 | 566.98                  | 2,139.11                  | >4800                     | >4800                     |
| ST2×FT2×SO2 | 568.12                  | 2,494.32                  | >4800                     | >4800                     |

cost and risk value. For example, with the same scenarios size $|\Omega|$, the objective values of “ST1 × FT1 × SO2” are less than instances of “ST1 × FT1 × SO1”. In addition, the results on the left of the Table 3 also confirm the conclusion. (2) The higher the delay level of the flight tasks starting time (such as “FT2”), the greater the weighted staff cost and risk value. Specifically, comparing the case of “ST1 × FT1 × SO2” and “ST1 × FT2 × SO2” with $|\Omega|=5$, the weighted total cost with “FT2” is of 5348, yet the weighted total cost with “FT1” is of 4834. (3) In all the instances containing “ST1”, SAA can solve the problem scale with the number of scenarios $|\Omega| \leq 30$, and the optimality gap values of the solutions are all within 0.05. (4) However, turning to the computational results containing “ST2”, SAA method hardly solve the problems while scenarios size is greater than 10. As shown in the “gap” column on the right of the Table 3, when $|\Omega|=10$, the minimum gap value is of 0.488 and the maximum is of 0.987. In addition, when $|\Omega| \geq 20$, the computer runs out of memory. These observations indicate that the SAA method does not perform well in solving large-scale problems.

Table 3 reports the employee costs. According to the SAA results on the left table 3, we can also find the impacts of the proportion of employee’s skill level and the uncertainty of the tasks starting time on the scheduling costs. In addition, comparing the results of SAA, it can be found that the lower bounding values of PHA are all smaller than the exact value of SAA. Table 4 gives the differences between the lower bounding values of the heuristic PHA and the exact values of SAA. Combining the results of table 3 and table 4, what can be found is that, in small-scale problems, the lower bound of the heuristic PHA is very close to the exact value of SAA. In particular, the biggest gap is of 0.268 appearing in the example “ST1 × FT1 × SO2” with $|\Omega|=5$. These results show that the computational effect of heuristic PHA is guaranteed.

Furthermore, to demonstrate the efficiency of PHA, it is also necessary to compare the computing time by different solution methods. The time consumption of the two methods is shown in Table 5, as shown in Table 5, we can observe:

(1) In small-scale problems (such as rows 2-5), SAA method takes less time than PHA. The computing time of SAA increases non-linearly with the increase of the scenario size $|\Omega|$. The relationship between the computing time of PHA and scenario size $|\Omega|$ is linear. As the number of scenarios increases, the ratio of time consumption between the PHA and the SAA decreases. The reason why the PHA takes longer time than SAA in small-scale instances mainly attributes to its continuous iterative process. Each iteration of PHA needs to decompose and calculate all the scenarios. Therefore, the advantage of the PHA is not obvious for small-scale problems. (2) In large-scale problems (such as rows 6-9), the PHA can solve problem size with more than 10 scenarios. In all instances involving “ST2”, as long as the number of scenarios is greater than 10, the memory of the computer is insufficient for the SAA. However, the PHA can achieve the feasibility of solving large-scale problems by resolving a single scenario at a time through decomposition and iteration. In addition, the computing time of the heuristic PHA increases linearly with the number of scenarios, which ensures that only if the problem of single scenario is able to solved, solutions of large-problem can be obtained in polynomial time.

C. CVAR SENSITIVITY ANALYSIS

This section analyzes the impacts of the risk parameter $\lambda$ and the confidence level $\alpha$ on objective values. The instance used relies on “ST1 × FT1 × SO1” with $|\Omega|=20$. The computational results of $\lambda$ in the interval [0.1, 0.9] and $\alpha \in \{0.5, 0.7, 0.9\}$ are listed in Table 6.

As shown in Table 6: (1) Objective value increases with the increase of risk coefficient $\lambda$, and there is a linear relationship between the value of the objective function and the increases of value $\lambda$. The larger the risk coefficient $\lambda$, the more the model emphasizes the performance of employee scheduling decision in the worst scenario of all possible scenarios. Alternatively, the more risk-averse the decision maker is, the more conservative the employee decision making is. (2) Objective value increases with the increase of the confidence $\alpha$, which dose match the definition of CVaR. However, compared with
TABLE 6. Impact of CVaR risk coefficient $\lambda$ and confidence $\alpha$ on results.

| $\lambda$ | Objective value |
|-----------|-----------------|
| $\alpha = 0.5$ | $\lambda = 0.1$ | 4,794 | 4,982 | 5,170 | 5,359 | 5,547 | 5,735 | 5,923 | 6,112 | 6,300 |
| $\alpha = 0.7$ | $\lambda = 0.2$ | 4,796 | 4,986 | 5,176 | 5,366 | 5,556 | 5,747 | 5,937 | 6,127 | 6,317 |
| $\alpha = 0.9$ | $\lambda = 0.3$ | 4,799 | 4,992 | 5,185 | 5,378 | 5,571 | 5,764 | 5,957 | 6,150 | 6,343 |

TABLE 7. China Eastern Airlines departure flight information in Shanghai Hongqiao International Airport.

| Planned time | Flight number | Area | Actual time | Planned time | Flight number | Area | Actual time |
|--------------|---------------|------|-------------|--------------|---------------|------|-------------|
| 7:40         | MU5395        | B    | 7:41        | 13:55        | MU5271        | B    | 13:56       |
| 8:00         | MU5401        | C    | 7:57        | 14:25        | MU2158        | B    | 14:25       |
| 9:00         | MU5103        | C    | 9:04        | 14:30        | MU5307        | C    | 14:35       |
| 9:00         | MU5633        | B    | 9:08        | 15:00        | MU5115        | C    | 15:03       |
| 9:00         | MU5333        | C    | 9:01        | 15:30        | MU5559        | B    | 15:31       |
| 9:05         | MU5529        | B    | 9:16        | 15:55        | MU5543        | B    | 16:07       |
| 9:15         | MU2152        | B    | 9:29        | 16:00        | MU5349        | C    | 16:01       |
| 9:25         | MU7584        | B    | 9:33        | 16:05        | MU2354        | B    | 15:56       |
| 10:00        | MU9977        | B    | 10:06       | 16:50        | MU5445        | B    | 17:00       |
| 10:15        | MU5337        | C    | 10:17       | 17:15        | MU2994        | B    | 17:16       |
| 10:15        | MU5691        | C    | 10:09       | 17:35        | MU5549        | B    | 17:31       |
| 11:30        | MU5305        | C    | 11:29       | 18:00        | MU2128        | B    | 17:56       |
| 11:50        | MU2409        | B    | 11:54       | 18:10        | MU2166        | B    | 18:12       |
| 12:40        | MU5647        | B    | 12:50       | 19:30        | MU5413        | C    | 19:26       |
| 12:45        | MU5375        | B    | 12:54       | 19:35        | MU2168        | B    | 19:28       |
| 13:00        | MU5111        | C    | 13:00       | 20:15        | MU5415        | C    | 20:09       |
| 13:10        | MU2549        | B    | 13:19       | 20:20        | MU2170        | B    | 20:21       |
| 13:20        | MU2156        | B    | 13:24       | 20:25        | MU2407        | B    | 20:19       |
| 13:40        | MU2403        | B    | 13:57       | 21:15        | MU9969        | B    | 21:31       |

the risk coefficient $\lambda$, confidence level $\alpha$ has very little effect on objective function value. The reason for this phenomenon is related to the objective function given in this work. The cost of the first-stage employee allocation is 0; the second-stage cost value depends on the lack of staff and matching, there is not much difference in the second-stage objective values under different scenarios.

VI. CASE STUDY

This section shows how the results of model and algorithm can be applied to practical problems. This case is based on China Eastern Airline’s flight data and check-in area information at Shanghai Hongqiao International Airport.

A. CASE DATA

Table 7 shows the actual flight data of China Eastern Airline at Shanghai Hongqiao International Airport on March 7, 2020. Scheduling time horizon range is 07:40-21:15 with 38 flights. The target number of check-in personnel required for each flight task is 2-3, and at least one English-speaking staff member is required. According to the information in Table 7, flights delay times are about 0-20 minutes, so we set 10 minutes as the base time period. The uncertainty of tasks starting time is in the time period interval $[1, 2]$. The scheduling period of a task starts at 07:00, ends at 22:00, and the total time periods is 90. Time 07:00 is represented by 1, 07:15 is 2, ..., 22:00 is 90. There are two work shifts, the first shift is from 07:00 to 15:00, and the second shift is from 14:00 to 22:00.

Before the case analysis, we need to derive the staffing requirement so that the flight tasks are covered. Because the actual data on staff work schedule is airline’s private information, we are unable to obtain real personnel data for confidentiality reason. Therefore, according to the number of flights and check-in tasks density, we need to design a staffing requirement to meet the check-in task requirements as close to reality as possible. The generation of personal data is as follows. First, the minimum number of personnel must cover all flights. Figure 2 shows the number of tasks in discrete time. The maximum number of tasks in all time periods is 6, so the lower number of personnel is 12 and the upper bound is 18; the number of English-skill staff in the shift must not be less than 6. The actual test results show that 16 staffs per shift is enough as the proportion of English-speaking
employees is of 50%. Therefore, the number of check-in personnel determined in this article is 32. Employees are divided into two shifts, each with 16 employees of whom half are skilled in English. The employee number are # 1, # 2, ..., # 32, where # 1-# 16 are English-Skill employees. Because the tasks of the Figure 2 are evenly distributed, the number of people in the two shifts is identical. We casually select $|\Omega| = 20, \lambda = 0$ for illustration results and solve it with PHA.

### B. COMPUTATIONAL RESULTS AND ANALYSIS

The results of employee-area assignment decision are reported in Table 8. Table 9 and Table 10 respectively gives the employee-task scheduling result and the allocation of two rest breaks for each staff in a random scenario. In this random scenario, the meal break starting time of shift 1 is 23, which translates to a specific time of 10:50 am; the meal starting time of shift 2 is 68, which is 18:20 pm.

Table 8 gives employee-area decision result. As shown in the table, there are 10 English-speaking employees (# 1; # 2; # 5; # 6; # 7; # 11; # 12; # 13; # 14; # 15) assigned to check-in area B, and 6 English-skill employees (# 3; # 4; # 8; # 9; # 10; # 16) assigned to check-in area C. Based on the check-in area distribution of the Table 7, there are more flight tasks in check-in area B than in area C, so more English-skill check-in staffs are required. The model result reflects this feature. Table 9 and Table 10 are specific employee-task scheduling results in a random scenario. These results give a plan regarding when and where tasks are performed by whom, and determine the rest breaks of employees.

#### TABLE 8. Staff-area assignment results.

| Aera B | Aera C |
|---|---|
| #1; #2; #5; #6; #7; #11; #12; #13; #14; #15; #17; #20; #21; #22; #23; #29 | #3; #4; #8; #9; #10; #16; #18; #19; #24; #25; #26; #27; #28; #30; #31; #32 |

#### TABLE 9. Results of personnel scheduling in a random scenario.

| Flight number | Area | Staff | Flight number | Area | Staff |
|---|---|---|---|---|---|
| MU5395 | B | #1, #2, #5, #6, #7 | MU5271 | B | #6, #7 |
| MU5401 | C | #3, #4, #8 | MU2158 | B | #1, #2, #14 |
| MU5103 | C | #4, #18, #24 | MU5307 | C | #8, #16 |
| MU5633 | B | #2, #21 | MU5115 | C | #10, #16 |
| MU5333 | C | #3, #8 | MU5559 | B | #11, #14 |
| MU5529 | B | #7, #23 | MU5543 | B | #13, #15 |
| MU2152 | B | #1, #6 | MU5349 | C | #9, #10, #16 |
| MU7584 | B | #5, #17, #20 | MU2354 | B | #12, #14 |
| MU9977 | B | #1, #2, #6, #7 | MU5445 | B | #11, #12, #15 |
| MU5337 | C | #3, #4 | MU2994 | B | #13, #14 |
| MU5691 | B | #1, #6, #7 | MU5549 | B | #11, #12, #15 |
| MU5305 | C | #3, #4, #8 | MU2128 | B | #11, #13, #14 |
| MU2409 | B | #2, #5 | MU2166 | B | #12, #15 |
| MU5647 | B | #2, #5, #20 | MU5413 | C | #9, #10, #16 |
| MU5375 | C | #1, #7 | MU2168 | B | #11, #12 |
| MU5111 | C | #3, #4, #8 | MU5415 | C | #9, #10, #16 |
| MU2549 | B | #6, #17, #23 | MU2170 | B | #12, #14 |
| MU2156 | B | #7, #21 | MU2407 | B | #11, #13, #15 |
| MU2403 | B | #1, #2, #5 | MU9969 | B | #11, #12, #13, #14, #15 |
In general, by considering various possible random scenarios, the proposed personnel scheduling model can generate employee-area assignment decisions. Compared with the deterministic personnel scheduling model, which directly gives the employee-task assignment decisions, our method has more flexibility for adjustment. Specifically, by assigning employee-areas in advance, check-in activities are the responsibility of designated staffs assigned to this area, which contributes to reduce the decision burden of scheduling planners when tasks starting time is disturbed. For example, if there has a task change in area B within shift 1, the schedule planner only needs to adjust the task assignment among 8 employees in charge of area B (#1, #2, #5, #6, #7, #17, #20, #21), instead of all employees in shift 1.

### VII. CONCLUSION

This article studies the problem of stochastic check-in employee scheduling in airport terminal. The work takes into account the uncertainty in airport check-in activities by considering the starting times of the check-in tasks as uncertain parameters. To account for the randomness in personnel scheduling, a two-stage stochastic personnel scheduling model with risk aversion is established. The first stage of the model aims at allocating terminal activity areas to check-in personnel, and the second-stage responses to personnel-task scheduling. Unlike the risk-neutral stochastic model with expected objective function, our work adopts CVaR as risk measure in objective function to overcome the disadvantage that risk-neutral solutions perform poorly in the worst cases. In order to solve the problem of practical size, we use the SAA method and heuristic PHA as solution approaches. The SAA method is superior to the SAA method. In large-scale problems, the PHA is superior to the SAA method. We also analyze the influences of employee skill levels and the uncertainty levels of tasks starting time on scheduling results. Numerical experimental results show that: (1) the higher the proportion of fully skilled employees, the lower the total employee cost; (2) the more uncertainty the tasks starting time, the higher the total staff cost. Sensitivity analysis of the risk parameter \( \lambda \) and confidence \( \alpha \) of CVaR is given as well. Finally, taking the realistic flight data of China Eastern Airlines in Hongqiao Terminal 2 as an input data, we illustrate how the output of the proposed approach can be applied to practical problem.

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### TABLE 10. Allocation of rest time for people in a random scenario.

| Staff | Break time | Staff | Break time | Staff | Break time | Staff | Break time |
|-------|------------|-------|------------|-------|------------|-------|------------|
| #1    | [9:48]     | #9    | [56:89]    | #17   | [8:48]     | #25   | [43:89]    |
| #2    | [10:43]    | #10   | [56:84]    | #18   | [1:43]     | #26   | [43:90]    |
| #3    | [8:48]     | #11   | [56:89]    | #19   | [1:43]     | #27   | [43:84]    |
| #4    | [1:43]     | #12   | [43:84]    | #20   | [9:43]     | #28   | [43:90]    |
| #5    | [8:48]     | #13   | [43:84]    | #21   | [1:43]     | #29   | [56:84]    |
| #6    | [10:43]    | #14   | [56:90]    | #22   | [9:43]     | #30   | [56:89]    |
| #7    | [10:48]    | #15   | [43:90]    | #23   | [10:48]    | #31   | [57:89]    |
| #8    | [10:43]    | #16   | [56:90]    | #24   | [10:48]    | #32   | [57:90]    |
