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Robust Maintenance Scheduling of Aircraft Fleet: A Hybrid Simulation-Optimization Approach

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ABSTRACT We study the maintenance task scheduling problem for an aircraft fleet in an uncertain environment from the viewpoint of robust optimization. Given a daily horizon, the maintenance tasks delegated to a shop should be scheduled in such a way that sufficient aircrafts are available on time to meet the demand of planned missions. The tasks are either scheduled maintenance activities or unexpected repair jobs when a major fault is detected during pre- or after-flight check of each mission. The availability of skilled labour in the shop is the main constraint. We propose a robust formulation so that the maintenance tasks duration is subject to unstructured uncertainty due to the environmental and human factors. As a result of the specific structure of the primary model and non-convexity of the feasible space, the classical robust optimization methods cannot be applied. Thus, we propose an ϵ-Conservative model in tandem with Monte-Carlo sampling to extract the set of all feasible solutions corresponding to various disturbance vectors. Since the one-way sampling-then-optimization approach does not guarantee the probabilistic feasibility, we employ a hybrid simulation-optimization approach to ensure that the solutions provided by the ϵ-Conservative model are robust to all uncertainty scenarios. The experimental results confirm the scalability of the proposed methodology by generating the robust optimal solutions, satisfying all conservatism levels and uncertainty scenarios irrespective of the problem size.

INDEX TERMS Robust optimization, simulation-optimization, maintenance scheduling, aircraft fleet.

NOMENCLATURE

SETS

- W Scheduled missions, where w $\in W$.
- M Tasks, where m $\in M$.
- R Workforce skills, where $r \in R$.
- K Aircraft, where k $\in K$.
- T Time period, where $t \in T$.

PARAMETERS

- A Number of fighters available in the hangar at the beginning of the horizon.
- ST_w Start time of mission w $\in W$.
- CT_w End time of mission w $\in W$.
- a_w Number of required aircrafts
- e_{mk} A binary parameter which equals 1 if task m $\in M$ is associated with kth aircraft; Otherwise, it equals 0.
- λ_{rm} Number technicians of skill r are required to rectify task m $\in M$.
- p_{mr} Processing time of task m $\in M$ by skilled workforce $r \in R$.
- ζ^1 Probability that a major fault is detected during the pre-flight check.
- ζ^2 Probability that a major fault is detected during the after-flight check.

VARIABLES

- C_m Completion time of task m $\in M$.
- c_{mr} Completion time of task m $\in M$ by skill $r \in R$.
- δ Minimum fleet availability of missions.
- z_w Number of fighters assigned to mission w $\in W$.
- E_w Expected number of fighters available for mission w $\in W$.
- U_w Number of fighters released from the shop before time ST_w

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u_{mw} A binary variable which equals 1 if task m $\in M$ is completed before the start time of mission w $\in W$. Otherwise, it equals 0.

Q_w Number of aircraft which are ready for pre-flight check of mission w $\in W$.

y_{mrt} A binary variable which equals 1 if task m is started by skill $r \in R$ in time slot $t \in T$; Otherwise, it equals 0.

λ_r^{max} Required number of workforce with skill $r \in R$

I. INTRODUCTION

The maintenance task scheduling problem (MTSP) is an essential challenge at the operational level for many industries. The scheduled maintenance tasks and unscheduled repair jobs must be done in an efficient manner, given a short planning horizon, to increase the equipment uptime and asset availability [1]. The air transportation industry has a unique condition that is not comparable to any other transportation industry. Flight management is more than just take-off and landing schedules. Many procedures, authority, and maintenance requirements have to be taken into account. Maintenance tasks not only have to be completed considering that every aircraft leaving the ground is reliable and safe but also at the minimum cost [2].

A fleet of aircraft has pre-planned daily missions, and some unexpected failures during the pre- or after-flight check of individual aircraft. In addition to the unexpected faults, a wide range of scheduled maintenance activities must also be accomplished on time over a certain time period (ranging from a day to a year) to keep fleet availability at an appropriate level [3].

The MTSP becomes even more challenging when we consider the inherent uncertainty of maintenance tasks' duration, as well as limitations on resources, such as skilled labour, tools, space, and spare parts [4]. Moreover, the environmental and human factors in the presence of insufficient historical data make the pattern recognition of uncertain parameters so difficult. Not surprisingly, then, finding a robust solution covering a wide range of uncertainty as a proactive response to unexpected events has become a challenging issue [5].

In this paper, we propose a robust formulation for the aircraft fleet maintenance task scheduling to generate the solution satisfying all conservatism levels and uncertainty scenarios. In other words, for a certain level of conservatism, we would like to know which trade-off between labour requirements and fleet availability will cover the majority of disturbance scenarios of the tasks' duration?

Since the primary deterministic model has a specific structure (i.e., uncertain parameters appear in summation bounds) with a non-convex feasible space, the common robust optimization methods, e.g., polyhedral uncertainty [6] or cardinality constrained uncertainty [7], cannot be applied (see Appendix A). To cope with this drawback, our idea is to extract the set of all possible labour scenarios corresponding to various disturbance scenarios using Monte-Carlo sampling. That is, the samples are drawn from the bounded uncertainty set and then fed to the modified model (we name it ϵ-Conservative MTSP model or ϵ-CMTSP for short) to extract the set of possible labour scenarios. The first phase solves the ϵ-CMTSP model with the aim of minimizing the labour requirement, and the second phase solves the primary model to investigate the feasibility of the labour scenarios generated during the first phase.

The remainder of this paper is organized as follows. Section II briefly reviews related works and efforts and Section III explains the problem specifications and the deterministic mathematical modeling. In Section IV, the robust optimization approach is described and, in Section V, data generation, sensitivity analysis, and numerical results are reported. A conclusion and recommendations for future research are described in Section VI.

II. LITERATURE REVIEW

The MTSP has been investigated and extended by researchers from various points of view. For a comprehensive review of MTSP literature, see [8], [9], and [10]. To the best of our knowledge, Safaei *et al.* [11] is the pioneer study regarding the fleet availability considering the skilled-workforce requirements for military aircraft fleet. Recently, some studies have addressed maintenance scheduling for military aircraft fleets by focusing on daily mission and fleet availability. Verma and Ramesh [12] suggested a multi-objective model to optimize fleet reliability, cost, introduced criteria, non-concurrence of maintenance periods and maintenance start time measure in preventive maintenance tasks. Kozandis [13] proposed a flight and maintenance planning problem for a military fleet with the aim of maximizing the fleet availability and minimizing the total residual flight time. Kozanidis *et al.* [14] presented a heuristic approach to solve flight and maintenance planning of mission aircraft with the aim of maximum fleet availability over a given planning horizon, while also satisfying certain flight and maintenance requirements.

Qin *et al.* [15] presented a mixed-integer linear programming (MILP) mathematical model. Firstly, they integrated the interrelations between the maintenance schedule and aircraft parking layout plans. In the model, different maintenance hangar's parking limits, as well as the blocking of the aircraft rolling in and out route, are studied. Cui *et al.* [16] developed a mathematical model for aircraft maintenance routing problem to optimize the number of aircrafts and total remaining flying time. Deng *et al.* [17] investigated a practical dynamic programming-based approach to optimize the long-term maintenance check plan for a heterogeneous aircraft fleet. The suggested approach tries to optimize the wasted period in checks. Sanchez *et al.* [18] presented a multi-objective mixed-integer linear programming model and an iterative algorithm to run commercially viable and maintenance feasible flight and maintenance schedules.

Robust optimization has recently been the topic of many studies in which the exact distribution of uncertain parameters cannot be identified. This often occurs in practice, especially when information about the uncertain parameters is limited to insufficient historical data [19]. In the maintenance scheduling field, maintenance tasks are highly affected by human factors. That is, the tasks are performed by different individuals having various skill levels, tool proficiency, learning rates, and efficiency. In such a case, the maintenance tasks' duration might be bounded into an uncertainty set as a key idea in the robust optimization framework [20]. The goal is to find a schedule that is optimal for any realization of the uncertainty in a given set. In practice, this is equivalent to minimizing the deviation from the optimal solution in the worst-case scenario [21].

Robust optimization in the aviation industry used in several studies recently. Robust aircraft sequencing and scheduling problem studied while arrival and departure delays are uncertain. The problem solved using an artificial bee colony algorithm for robust ASSP model [22]. A two-stage optimization model proposed to manage the terminal traffic flow problem. After that, the model solved using a simulated annealing algorithm [23]. Finally, a two-stage mathematical model proposed to optimize an aircraft hangar maintenance planning problem while its MRO activities are outsourced. In order to solve the problem, a decomposition method deployed [24].

Airside operation research covers different fields in air transport management, including airspace and air traffic flow management, aircraft operation in the terminal maneuvering area, and surface traffic operation [25]. Högdahl *et al.* [26] developed a simulation-optimization approach to minimize travel time and delays in railway timetables. They also addressed the reliability of the estimation.

A cooperative game theory approach utilized for multi-level fleet maintenance planning. This approach is based on agent learning and the problem solved by a simulated annealing approach [27]. Furthermore, the game theory also used for fleet condition-based maintenance planning. The local and global optimal solutions were obtained by competition and cooperative game algorithms, respectively [28].

The majority of studies in maintenance scheduling have used stochastic optimization or simulation approaches to tackle uncertainty [29]–[32], and [11]. Other studies have used Markov decision analysis [33] or a combination of mathematical programming, simulation and data envelopment analysis [34]. However, in recent years, robust optimization for scheduling problems has been studied extensively by researchers [35]–[38], and [39].

From what has been discussed above, the MTSP is a hot topic in maintenance management to reduce operational costs of aircraft fleets. Furthermore, ignoring the problem uncertainties may result in infeasible solutions, which induced low service level and missed missions. Therefore, deploying an efficient, robust approach is necessary. In this paper, some gaps in the aircraft MTSP and robust optimization scope are fulfilled, with contributions as follows:

- Proposing a new robust optimization approach where the deterministic model has a non-convex feasible space (e.g., the uncertain parameter appears in summation bounds)
- Developing a robust model for a real-world aircraft MTSP
- Utilizing three generic uncertainty scenarios for the uncertain parameter (job processing time) to examine the robust optimization approach performance under different realizations.
- Presenting an approach that can be used for the class of uncertain problems in which the skilled-workforce and asset availability are major concerns.

III. PROBLEM STATEMENT

The problem is associated with a fighter aircraft fleet with pre-planned daily missions. Each mission has a scheduled start and completion time and requires a fixed number of fighters. There is no time overlap between the missions, and delay on mission accomplishment is negligible. Each fighter must be inspected before the flight (pre-flight check) and after landing (after-flight check) for detection of possible faults. Major failures are referred to the repair shop, and minor ones are rectified while the aircraft holds on the flight line. The time for line rectifications is negligible. The scheduled maintenance activities must also be done at the shop. The labour resource is considered the highest priority since the workforce performing the maintenance tasks are highly paid and extremely skilled in special areas. The number of technicians of each skill in the shop and line is limited. The maintenance tasks' duration and the possibility of fault detection during pre- or after-flight checks are subject to uncertainty with known distributions. The maintenance tasks delegated to the shop should be scheduled in such a way that sufficient fighters are available on time to meet the demand of missions.

Considering a daily (24-hour) horizon, W scheduled missions must be accomplished with a fleet of identical fighters. The start time, ST_w, and end time, CT_w, of each mission is known. Each mission w ideally requires a_w fighters; however, ρ percentage of ideal requirement, i.e., $\rho \times a_w$, is a must. This is the minimum requirement to implement a mission. At the beginning of the horizon, M tasks (including scheduled maintenance or unscheduled repair jobs) are lined up in the repair shop from the past days, each associated with a down fighter. $e_{mk} = 1$ if task m is associated with kth fighter; otherwise, it equals zero. The technicians in the shop are divided into R different skills, and the number of available technicians for skill r is λ_r^{max}. The technicians are single-skill and specialized, e.g., weapon, avionic, mechanic, electrician, structural, etc., because the internal rules limit them to become licensed for at most one skill. λ_{mr} technicians of skill r are required to rectify task m. The number of time units required by skill r, pt_{mr} to perform task m is a stochastic parameter. Task preemption is not considered. The probability that a major fault is detected during the pre-flight check is ζ^1 and during the after-flight check, it is ζ^2 where usually $\zeta^2 \geq \zeta^1$. These values are extracted from the historical failures recorded in Computerized Maintenance Management System (CMMS)

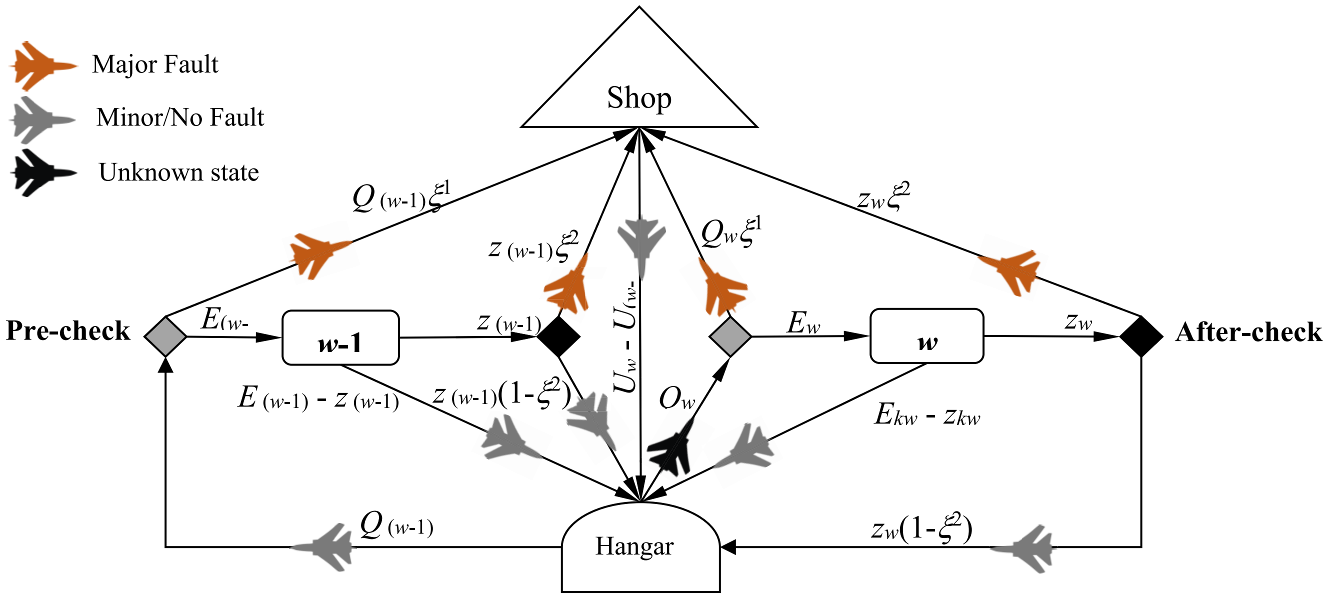

FIGURE 1. Schematic flow of aircraft between hangar, shop, and two consecutive missions.

database (for more information, see Safaei et al. [11]). Due to the high volume of the workload at the shop, the fighters with major faults detected or maintenance checks due over the current day are lined up in the shop to be scheduled over the next days. The rectified fighters will be sent to a hangar to be ready for upcoming missions. 'Hangar' is used as an intermediate buffer to house the available fighters for the next mission.

The objective is to optimally determine the completion time of the tasks where the fleet availability to accomplish the missions is maximized. The completion time of task m is calculated as $C_m = max_r \{c_{mr}\}$ where c_{mr} is the completion time of task m by skill r. The fleet availability per mission is defined as the percentage of demand satisfied. Hence, the objective function is to maximize the minimum fleet availability of missions, δ, where

$$\delta \leq \frac{z_w}{a_w} \forall w, \tag{1}$$

and decision variable z_w represents the number of fighters assigned to wth mission where $z_w \leq a_w$. Note that $\max_w \{\rho \times a_w\}$ is an explicit lower bound on (1) beyond which some missions cannot be implemented.

A. PRIMARY MODEL

The primary model was formulated as a probabilistic network flow problem in which the fighters are flown among the missions, hangar and shop as nodes and major faults are treated as leakage in the system. The key idea is to determine the expected number of fighters available for mission w, i.e., E_w. This quantity is calculated using the following recursive function:

$$E_w = \left\{ \left(E_{(w-1)} - z_{(w-1)}\right) + \left(U_w - U_{(w-1)}\right) + z_{(w-1)} \left(1 - \zeta^2\right) \right\} \times \left(1 - \zeta^1\right) \ \forall w > 1, \tag{2}$$

with boundary condition

$$E_1 = (A + U_1) \times \left(1 - \zeta^1\right), \tag{3}$$

where A is the number of fighters available in the hangar at the beginning of the horizon, and U_w is the number of fighters released from the shop before time ST_w:

$$U_w = \sum_k \frac{\sum_1^M e_{mk} u_{mw}}{\sum_1^M e_{mk}}. \tag{4}$$

In Eq. (4), $u_{mw} = 1$ if task m is completed before the start time of mission w; otherwise $u_{mw} = 0$. The first term in (2), i.e., $\left(E_{(w-1)} - z_{(w-1)}\right)$, denotes the expected number of available fighters in the hangar after satisfying the demand of mission (w-1). The second term, i.e., $\left(U_w - U_{(w-1)}\right)$, is the number of fighters released from the shop between the starting times of missions w – 1 and w. The third term, i.e., $z_{(w-1)} \left(1 - \zeta^2\right)$, indicates the expected number of fighters released from after-flight check of mission w-1 with no major fault. The summation of the above three terms, $Q_w = \left(E_{(w-1)} - z_{(w-1)}\right) + \left(U_w - U_{(w-1)}\right) + z_{(w-1)} \left(1 - \zeta^2\right)$, is the expected inflow into the pre-flight check of mission w. Finally, Q_w is multiplied by $\left(1 - \zeta^1\right)$, the probability that a fighter successfully passes the pre-flight check and takes off without detection of any major fault. The calculation in (2) is schematically shown in Figure 1 for two consecutive missions, w -1 and w.

Note that the expected number of fighters available for a mission, $E_w = Q_w \left(1 - \zeta^1\right)$, is not necessarily the same number of fighters assigned to that mission, z_w. Moreover, the number of fighters assigned to a mission should not exceed the demand a_w. Hence, the following condition must hold:

$$z_w = min \{E_w, a_w\} \quad \forall w. \tag{5}$$

Using the above explanation, based on the optimization model proposed by Safaei *et al.* [11] the primary model is as follows:

P1 :

$\max Z_1 = \delta,$

Subject to:

(1)-(3), and

$$\sum_{t=1}^{T} y_{mrt} = 1 \ \forall m, r; pt_{mr} \neq 0 \tag{6}$$

$$\sum_{m=1}^{M} \left(\sum_{s=max\{1,t-pt_{mr}+1\}}^{t} y_{mrs} \right) \lambda_{mr} \leq \lambda_r^{max} \ \forall r, t, \tag{7}$$

$$\begin{cases} C_m \geq pt_{mr}(1+\epsilon) + \sum_{t=1}^{T} t y_{mrt} \ \forall m, r \\ C_m \leq pt_{mr}(1+\epsilon) + \sum_{t=1}^{T} t y_{mrt} + M^+(1-\alpha_{mr}) \quad \forall m, r \\ \sum_{m=1}^{M} \alpha_{mr} = 1 \quad \forall r \end{cases} \tag{8}$$

$$\begin{matrix} (C_m - ST_w) < (1 - u_{mw}) M^+ \\ (C_m - ST_w) \geq -u_{mw} M^+ \end{matrix} \quad \forall w, m, \tag{9}$$

$$U_w \leq \sum\nolimits_k \left(\frac{\sum_{m=1}^{M} e_{mk} u_{mw}}{\sum_{m=1}^{M} e_{mk}} \right) \forall w, \tag{10}$$

$$\begin{cases} z_w \leq E_w \\ z_w \leq a_w \end{cases} \quad \forall w, \tag{11}$$

$$y_{mrt}, u_{mw}, \alpha_{mr} \in \{0, 1\}; C_m, U_w \in \mathbb{Z}^+; E_w, z_w \in \mathbb{R}^+. \tag{12}$$

Model P1 is a time-indexed linear mixed-integer programming (MIP) model in which the planning horizon is divided into T time slots, each with restricted capacity per skill. The model's key decision variable, y_{mrt}, is to determine the starting time of the tasks over the horizon. That is, $y_{mrt} = 1$ if task m is started by skill r in time slot t where $1 \leq t \leq T$; otherwise, it equals zero. Constraint (6) ensures that each job by each required skill is started at only one of the time-slots over the horizon. Knapsack constraint (7) imposes that the capacity constraint per time slot and skill cannot be violated. The completion time of the tasks is calculated in Constraint set (8). The auxiliary variable α_{mr} helps us to fully satisfy the equality $C_m = max_r\{c_{mr}\}$, so that $\alpha_{mr^*} = 1 \Leftrightarrow C_m = c_{mr^*}$ where $c_{mr} = pt_{mr} + \sum_{t=1}^{T} t y_{mrt}$, is the completion time of task m by skill r and r^* is r for which c_{mr} is maximized M+ in constraints (8) and (9) represents the big M. Constraint (9) determines whether a task is completed before the starting time of a mission. Using this, inequality (10) calculates the number of aircraft that their maintenance task is completed before each mission. Constraints (10) and (11) represent the linear forms of Equations (4) and (5). Finally, (12) imposes the variables' integrality.

IV. ROBUST FORMULATION

Using the dual counterpart of the primary problem to determine the worst-case scenario is a common practice in the majority of the robust optimization methods. As such, P1 might be formulated as the following dual form to minimize the required labour size, given the minimum expected fleet availability, δ; $(\delta \geq \rho)$, per mission:

$$\text{P2}: \quad \text{Min } Z_2 = \sum_{r=1}^{R} \lambda_r^{max}, \tag{13}$$

Subject to:

(1)-(3), (6)-(11), and

$$y_{mrt}, u_{mw}, \alpha_{mr} \in \{0, 1\}; C_m, U_w, \lambda_r^{max} \in \mathbb{Z}^+; E_w, z_w \in \mathbb{R}^+ \tag{14}$$

In Constraint (1), entity δ obviously cannot be greater than the percentage of aircraft which successfully pass the pre-flight check, i.e., $\delta \leq 1 - \zeta^1$. This is actually a reasonable assumption given the resource scarcity. In practice, it rarely happens that E_w exceeds the demand a_w. If the success rate of the pre-flight check is, for example, $\alpha\%$ (in our case $= 1 - \zeta^1$), the minimum expected fleet availability cannot be rationally greater than $\alpha\%$. Therefore, $\left(1 - \zeta^1\right)$ is a fair upper bound on δ. P2 has R-1 variables more than P1, which does not lead to a significant increase in complexity. However, having δ as input parameter facilitates our efforts to incorporate the concept of robustness into the formulation

Note that the uncertain parameter pt_{mr} appears in summation bounds in Constraint (7). Moreover, the feasible set of P2 is not convex because of the form of Constraints (8) and (9), which are formulated using the big-M method. Therefore, recent robust optimization methods, e.g., ellipsoidal uncertainty [6] or polyhedral constrained uncertainty [7], cannot be applied. For instance, the latter method requires a linear dual form (for inner maximization sub-problem) to compute the worst-case scenario, while P2 has a non-linear dual counterpart due to the specific structure of Constraint (7). Moreover, the duality gap, as a result of the non-convexity of the feasible set, creates a gap between the optimal solution of the inner maximum sub-problem and its dual counterpart; therefore, the aforementioned methods cannot be implemented in practice.

A. CONSERVATIVE FORMULATION FOR P2

Since a straightforward robust formulation for P2 does not exist, we have to establish a procedure to achieve the list of all feasible labour scenarios corresponding to possible disturbance vectors. To this end, we modify P2 in such a way that the abovementioned list can be extracted using Monte-Carlo sampling. That is, we use Monte-Carlo simulation to take samples from the uncertainty set bounded by conservatism level ϵ and feed the samples to a modified version of P2 (ϵ-Conservative MTSP or ϵ-CMTSP), to extract the set of all feasible labour scenarios. As the uncertainty set is a norm-bounded set, we will have a finite number of scenarios.

To construct ϵ-CMTSP, we first define the worst-case scenario using the concept of weak flow conservation proposed by [40] for robust network flow problems. Using this concept, we prove there is an explicit relationship between the conservatism level and δ in Eq. (1) as both are determined by an individual decision maker. This relationship enables us to embed the conservatism into P2 without increasing the complexity. Moreover, to incorporate the robustness into the model, we investigate the conditions under which a solution of P2 is still feasible when we change the conservatism level. We first provide an interval representation of the uncertain quantity pt_{mr}, as follows:

$$pt_{mr} \in \left[pt_{mr}(1-\epsilon), pt_{mr}(1+\epsilon)\right], \tag{15}$$

where pt_{mr} represent the nominal (most likely) value and $0 \leq \epsilon \leq 1$ is the conservatism level, which controls the uncertainty aspects of processing times. We say a solution is robust (to the processing times' perturbation) if it satisfies (1) under all realizations of the disturbances pt_{mr} within Interval (15).

In practice, it is unlikely that all aircraft available for a mission, Q_w, fail simultaneously during the pre-flight check. Hence, to control the level of conservatism, we define $\Gamma_w(\Gamma_w \leq Q_w)$ as an upper bound on the number of aircraft with a major fault detected during pre-flight check of mission w. In this case, the set of all possible scenarios is defined as:

$$\Theta_w^1 := \left\{\mu = (\mu_k) \in \{0,1\}^{Q_w} \mid \sum\nolimits_{k=1}^{Q_w} \mu_k \leq \Gamma_w\right\}. \tag{16}$$

The binary variable μ_k indicates whether or not aircraft k ($k = 1, \ldots, Q_w$) fails. We define robustness using the idea proposed by [40], i.e., weak flow conservation, for robust network flow problems. Given directed graph G=(V,E) with node set V and arc set E, the weak flow conservation constraint imposes that for each node $v \in V$, the net flow $\sum_{e\in\delta^-(v)} x_e - \sum_{e\in\delta^+(v)} x_e$, i.e., Inflow – Outflow, must be greater than zero where x_e is the flow on arc $e \in E$ and $\delta^-(v)$ and $\delta^+(v)$ denote the set of arcs entering and leaving node v respectively. In other words, the weak flow conservation implies that the amount of flow entering a node is at least the amount of flow leaving it. Thus, we can have excess at some node, but a deficit is not allowed at any node except Source. Their objective was to seek the flow from Source to Sink with maximum net flow. The same idea can be applied to our network flow problem (Figure 1) in which the objective is to maximize the inflow into each mission (node). That is, for each mission w, the inflow (# of fighters passing the pre-flight check and entering the mission) must be greater than the outflow (minimum expected demand). Thus, a robust solution must guarantee:

$$Q_w - \sum\nolimits_{k=1}^{Q_w} \mu_k \geq a_w \times \delta. \tag{17}$$

To construct our ϵ-CMTSP, we substitute $1-\rho$ for δ in P2. Then, we investigate the conditions under which a solution of P2 is still feasible when we change ϵ. Consider solution $\dot{Y} = (\dot{Y}_{mrt})$ a feasible solution of P2 and let $\dot{\Psi}_w := \{m | ST_w \geq \dot{C}_m\}$ to be the set of tasks completed before time ST_w where $\dot{C}_m = max_r\{\dot{c}_{mr}\}$ and $\dot{c}_{mr}$ is the completion time of task m by skill r. We say $\dot{Y}$ is robust if slack time $(ST_w - C_m)$ covers the effect of disturbances pt_{mr} $\forall r$ on completion time. The key idea is that the additive uncertainty in processing time may postpone the completion time; however, the slack times are long enough to absorb this additive uncertainty without changing the primary schedule. Hence, $\dot{Y}$ should satisfy Constraint (1) as well as the following constraints under various disturbance scenarios corresponding to intervals (15).

1. $ST_w \geq \hat{C}_m \; \forall\, w, m \in \Psi_w;\; \hat{C}_m = max_r\{\dot{c}_{mr} + pt_{mr} \times \epsilon\}$
2.

$$\sum_{m=1}^{M}\left(\sum_{s=max\{1,t-pt_{mr}(1+\epsilon)+1\}}^{t} \dot{y}_{mrs}\right)\lambda_{mr} \leq \lambda_r^{max} \;\forall\, r, t. \tag{18}$$

Given conservatism level ϵ, the above conditions ensure sufficient slack times are available to cover the uncertainty part of pt_{mr}, i.e., $pt_{mr} \times \epsilon$, while the workforce constraints are still satisfied. In the first condition, $ST_w \geq \hat{C}_m$ can be rewritten as $(ST_w - \dot{C}_m) \geq \left(\hat{C}_m - \dot{C}_m\right)$ so that the left-hand side is the slack time and the right-hand side is the effect of uncertainty on completion time. To formulate the robust model, Constraint (8) is turned into the following linear form, representing the first condition in (18):

$$\begin{cases} C_m \geq pt_{mr}(1+\epsilon) + \sum\limits_{t=1}^{T} ty_{mrt} \quad \forall m, r \\ C_m \leq pt_{mr}(1+\epsilon) + \sum\limits_{t=1}^{T} ty_{mrt} + M^+(1-\alpha_{mr}) \,\forall m, r \\ \sum\limits_{m=1}^{M} \alpha_{mr} = 1 \quad \forall r \end{cases} \tag{19}$$

Moreover, Constraint (7) is replaced by Constraint (20). Finally, the ϵ-CMTSP model has the following form:

ϵ-CMTSP:

Min $Z_2 = \sum_{r=1}^{R} \lambda_r^{max}$,

Subject to:

(2), (3), (9)–(11), (14); (18), (19), and

$$\frac{z_w}{a_w} \geq 1 - \forall w. \tag{20}$$

Constraint (20) is the revised version of (1). ϵ-CMTSP does not change the computational tractability as it has the same size and complexity as P2. As pointed out earlier, ϵ-CMTSP is used in tandem with Monte-Carlo sampling to extract all labour scenarios corresponding to the possible disturbance vectors. In this case, each disturbance vector $\Phi : \{pt_{mr} + \Delta_{mr}\} \in \mathbb{R}^{M \times R}$ is a point in a polyhedral uncertainty set structured by intervals (15) where Δ_{mr} is a random number with an unknown pattern within interval $[-\epsilon \times pt_{mr}, +\epsilon \times pt_{mr}]$. The overall uncertain space is covered by the polyhedral, an intersection of intervals (15) in $M \times R$-dimension space, so that the conservatism level is an adjustable parameter controlling the size of the uncertainty set. Assuming a sufficient number of simulation runs, all labour scenarios generated using the sampling-optimization procedure guarantee (20). However, a question remains: "Does each individual solution guarantee (20) under all uncertainty scenarios"? To investigate this question, each solution of ϵ-CMTSP is fed to the primary model P1 to check whether it guarantees $Z_1 \geq 1 - \rho$ under various uncertainty scenarios. In this case, P1 is considered a classical stochastic programming model in which the uncertain parameters follow known probability distributions. Thus, we say a feasible solution of ϵ-CMTSP is robust if it is also feasible for P1 by satisfying $Z_1 \geq 1 - \rho$ for all possible uncertainty scenarios. The above methodology is the key idea behind our new hybrid simulation-optimization approach to cope with the main drawback of one-way sampling-then-optimization procedure, i.e., lack of probabilistic Guarantees.

B. A HYBRID SIMULATION-OPTIMIZATION APPROACH FOR PROBABILISTIC GUARANTEES

The proposed hybrid simulation-optimization (HSO) approach consists of two phases:

1) Sampling: In this phase, ϵ-CMTSP is iteratively solved to extract the list of all possible feasible labour scenarios. At each iteration of this phase, the disturbance vectors are uniformly sampled from interval (15) and ϵ-CMTSP is solved. The optimal solution of ϵ-CMTSP is a labour scenario like $\Lambda : (\lambda_1^{max}, \lambda_2^{max}, \ldots, \lambda_R^{max}) \in \Pi$, where Π is the finite set of all possible labour scenarios. In Appendix B, we proof that Π cannot be infinite and thereby all its elements can be generated through the uniform sampling over a finite number of trails. To facilitate our analysis, we consider three levels of conservatism and use the linguistic abbreviations shown in TABLE 1 to display them.
2) Probabilistic Feasibility Check: In this phase, primary model P1 is iteratively solved for each scenario $\Lambda \in \Pi$; assuming pt_{mr} follows a known uncertainty pattern. That is, given scenario Λ, at each iteration of the Monte-Carlo sampling procedure, P1 is solved when pt_{mr} are randomly drawn from a specific uncertainty pattern. We say labour scenario $\Lambda \in \Pi$ will be robust conservatism level ϵ; if $Z_1^*(\Lambda; pt_{mr}; n) \geq 1 - \forall n$ where $Z_1^*(\Lambda; pt_{mr}; n)$ is the optimal objective value of P1 in nth run. To incorporate the above theoretical interpretation into the simulation results, we say scenario $\Lambda \in \Pi$ is feasible if the feasibility rate (or equivalently, guarantee of probability) over runs has an average greater than 0.95 and a standard deviation less than 0.05.

TABLE 1. Conservatism Levels.

Level	Description	ϵ
L	Low	5%
M	Medium	15%
H	High	30%

For a rough approximation, we adopt three generic uncertainty structures for pt_{mr} as normal, abnormal, and mysterious situations represent by normal, beta, and uniform distributions, respectively. 'Normal' refers to situations in which the uncertain parameter is normally distributed around the nominal value. 'Abnormal' refers to situations where the uncertain parameter has extreme values very close to its lower or upper bounds with a high probability. 'Mysterious' refers to the situations where the behavior of the parameter is very difficult to identify; in this case, we give the same probability to all possible values (absolute ignorance). These situations are schematically shown in Figure 2. Having these definitions, we consider the possible uncertainty scenarios for pt_{mr} as presented in TABLE 2.

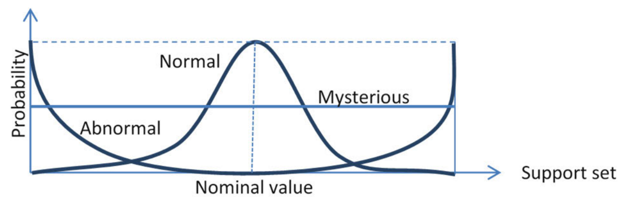

FIGURE 2. Generic uncertainty scenarios for pt_{mr}.

TABLE 2. Generic uncertainty scenarios for pt_{mr}.

	pt_{mr}
Normal	$N[\dot{pt}_{mr}, \grave{o} \times \dot{pt}_{mr}]$
Abnormal	$\dot{pt}_{mr}(1-\int) + Beta(0.5, 0.5) \times 2 \times \int \times \dot{pt}_{mr}$
Mysterious	$\mathrm{Unif}((1-\grave{o}) \times \dot{pt}_{mr}, (1+\grave{o}) \times \dot{pt}_{mr})$

The distribution parameters are set in such a way that the range of variability of pt_{mr} is the same as the intervals (15). Distribution Beta(0.5,0.5) represents the abnormal scenarios within interval (0, 1), which is mapped into the intervals (15) using the linear transmission shown in TABLE 2. Thus, the second phase will be run for each labour and uncertainty scenario, given conservatism level ϵ.

Phase 1 will be terminated whenever set Π becomes stable; that is, a new labour scenario is not inserted into the set after a specific number of iterations, i.e., π_1. Phase 2 will be terminated whenever the number of iterations exceeds a predetermined value, i.e., π_2. The outcome of our HSO is set Ω, the set of all labour scenarios which are feasible for both primary and robust models and for all uncertainty scenarios under a certain conservatism level, where $\Omega \subset \Pi$. We define $B(\epsilon) \in \Omega$, Best Robust Labour Scenarios, as the labour scenario with minimum size under level ϵ. Our ultimate goal is to find $\omega \in \Omega$, the labour scenario with minimum size satisfying all conservatism levels; we refer it as 'Robust Optimal Labour Scenarios' (ROLS).

A robust region for decision-making purposes can be concluded as Figure 3. This region determines the range of conservatism levels (ψ in Figure 3) which are satisfied by specific labour size or the range of robust labour sizes (Υ in Figure 3) given a conservatism level. The cross point of two ranges, ψ and Υ, denotes the minimum robust labour size at conservatism level ϵ; $B(\epsilon)$. In this case, the ROLS is the minimum labour size satisfying all conservatism level, as shown in Figure 3.

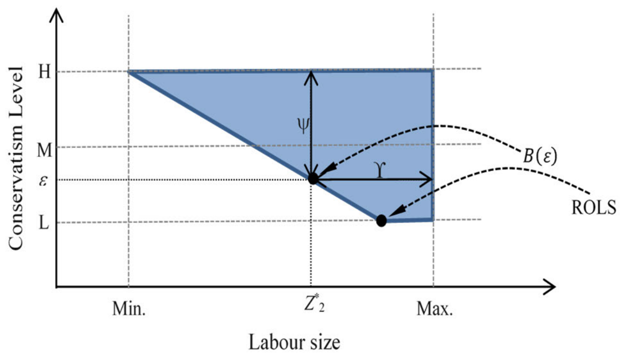

FIGURE 3. Robust Region.

The proposed HSO flow chart is depicted in Figure 4.

TABLE 3. Numerical examples.

Instance	# Tasks	# Missions	Missions' schedule
1	20	4	(8:00 am – 10:00 am) (10:00 am – 12:00 pm) (12:00 am – 2:00 pm) (2:00 pm – 4:00 pm)
2	50	4	(8:00 am – 10:00 am) (10:00 am – 12:00 pm) (12:00 am – 2:00 pm) (2:00 pm – 4:00 pm)
3	70	4	(8:00 am – 10:00 am) (10:00 am – 12:00 pm) (12:00 am – 2:00 pm) (2:00 pm – 4:00 pm)
4	70	5	(8:00 am – 10:00 am) (10:00 am – 12:00 pm) (12:00 am – 2:00 pm) (2:00 pm – 4:00 pm) (4:00 pm – 6:00 pm)
5	80	5	(8:00 am – 10:00 am) (10:00 am – 12:00 pm) (12:00 am – 2:00 pm) (2:00 pm – 4:00 pm) (4:00 pm – 6:00 pm)
6	80	6	(8:00 am – 10:00 am) (10:00 am – 12:00 pm) (12:00 am – 2:00 pm) (2:00 pm – 4:00 pm) (4:00 pm – 6:00 pm) (6:00 pm – 8:00 pm)
7	90	6	(8:00 am – 10:00 am) (10:00 am – 12:00 pm) (12:00 am – 2:00 pm) (2:00 pm – 4:00 pm) (4:00 pm – 6:00 pm) (6:00 pm – 8:00 pm)
8	100	6	(8:00 am – 10:00 am) (10:00 am – 12:00 pm) (12:00 am – 2:00 pm) (2:00 pm – 4:00 pm) (4:00 pm – 6:00 pm) (6:00 pm – 8:00 pm)

V. EXPERIMENTAL RESULTS

In order to examine the performance of proposed simulation-optimization approach, we use five real-world numerical examples adopted from Safaei *et al.* [11] reported in TABLE 3. In these examples, the number of tasks range between 20 and 100 for whole fleet and the number of daily missions range between 4 and 6. The number of skills is fixed and equals R = 3, representing three trades: 1- Weapons and armament electrical, 2- Airframe mechanical, airframe electrical and propulsion, and 3- Avionics/electronics.

The required number of fighters per mission a_w is given; however, the mission may be accomplished with at least %50 of total demand under the worst-case scenario, i.e., $\rho = 0.5$. According to the failure data analysis, the nominal value pt_{mr} is drawn from a log-normal distribution with location parameter $\mu = 2$ and shape parameter $\sigma = 3$. Moreover, the relationship $\zeta^2 \approx 7 \times \zeta^1$ is concluded from the data where $\zeta^1 = 0.028$. Models P1 and P2(ε) are solved, and the HSO approach is coded using the CPLEX solver embedded in GAMS 24.2.3 software and run on a x64-based system with Intel(R) Core(TM)2 duo CPU P8700 @ 2.53 GHz. The proposed HSO approach is solved per numerical example and per conservatism level, as shown in TABLE 1. The stoppage parameters π_1 and π_2 are experimentally set to 100 and 1000.

The results obtained from the first phase of the HSO approach are reported in TABLE 4. This table contains the possible labour scenarios satisfying the given conservatism level for different instances. However, there is no guarantee on their feasibility over the second phase.

Hereafter, to facilitate analysis, we aggregate the labour scenario $\left(\lambda_1^{max}, \lambda_2^{max}, \lambda_3^{max}\right)$ as a single indicator labour size, $\sum_{r=1}^{3} \lambda_r^{max}$ (same as P2's objective function – Eq. 13). As such, in accordance with the interval representation of uncertain parameters; we consider the minimum and maximum values of labour size per conservatism level, as reported in TABLE 5 and schematically shown in Figure 3. The shaded areas (bounded by minimum and maximum labour sizes) in Figure 5 denote the possible values for ROLS, i.e., the labour

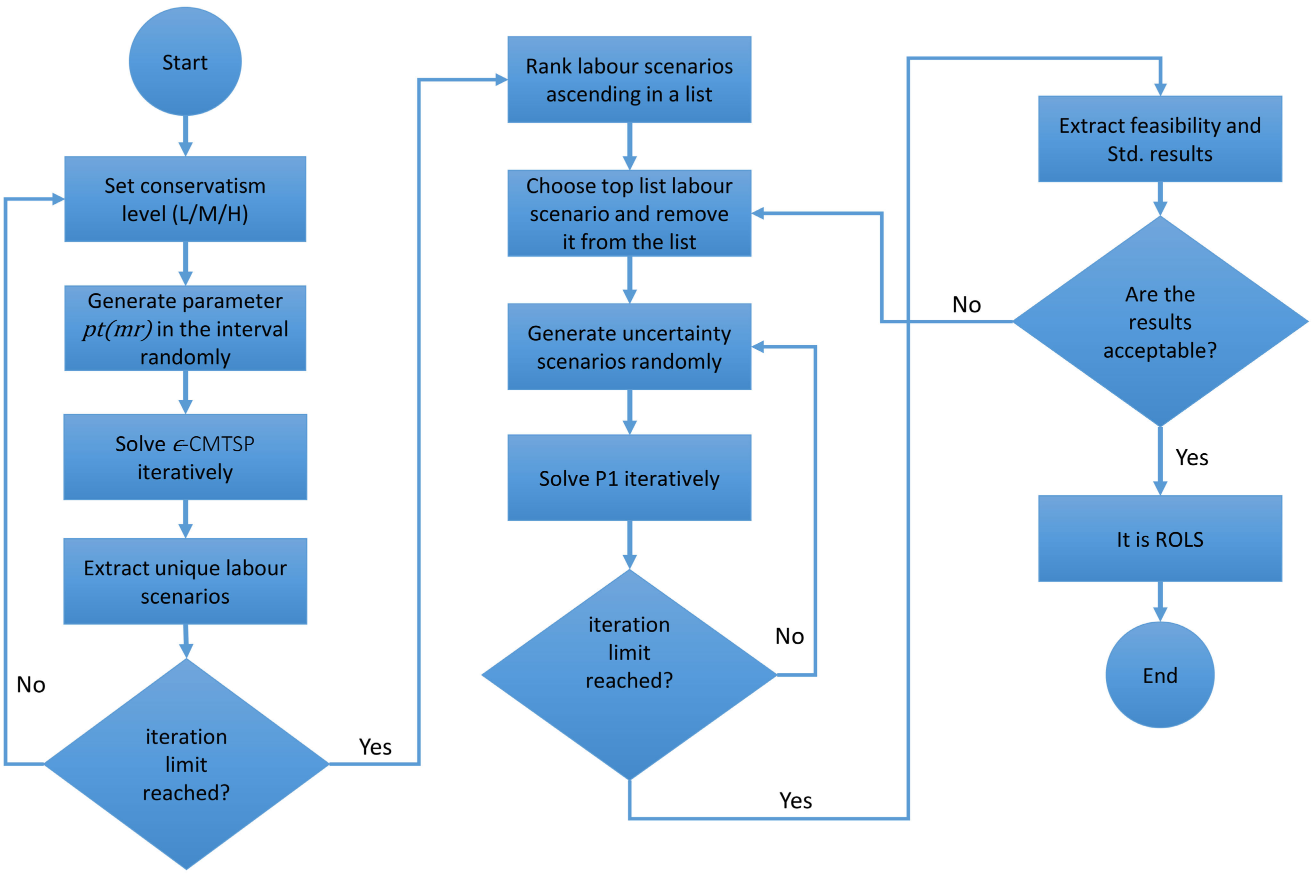

FIGURE 4. The HSO flow chart.

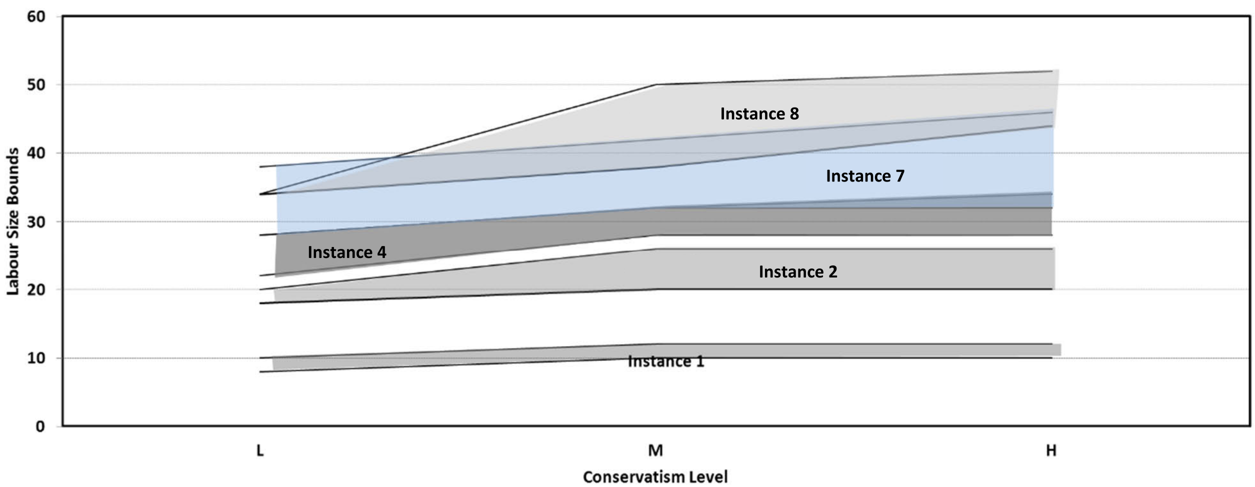

FIGURE 5. Min/Max labour size per conservatism level – Shaded areas indicate the possible values for ROLS.

scenario(s) with minimum size covering all conservatism levels and uncertainty scenarios, as an outcome of the second phase.

To investigate the feasibility of the aggregated labour sizes provided in TABLE 4, we run the second phase of our HSO approach; the outputs are summarized in TABLE 6 for instance 1 and 2. This table reports the average (Avg.) and standard deviation (StDev.) of feasibility rates over π_2 simulation runs associated with all possible labour sizes (TABLE 4) under various conservatism levels and uncertainty scenarios. As reported in this table, the most pessimistic labour size scenario (2,6,4)=12 chose as ROLS

TABLE 4. Output of phase 1 in the form of $(\Lambda_1^{max}, \Lambda_2^{max}, \Lambda_3^{max})$ – HSO approach.

	Conservatism level		
Instance	L	M	H
1	(2,4,2) (2,4,4)	(2,4,4) (2,6,4)	(2,4,4) (2,6,4)
2	(4,8,6) (4,10,6)	(4,10,6) (4,12,8) (6,12,8)	(4,10,6) (4,12,8) (6,12,8)
3	(4,10,6) (6,12,6)	(4,12,8) (6,12,8) (6,16,8)	(4,12,8) (6,12,8) (6,14,8)
4	(4,12,6) (6,14,8)	(6,14,8) (6,16,8) (8,16,8)	(6,14,8) (6,16,8) (8,16,10)
5	(6,14,8) (6,14,10)	(6,16,8) (6,16,10) (8,18,12)	(6,14,10) (8,14,10) (8,16,10)
6	(6,14,8) (8,14,8) (8,16,8)	(6,16,10) (8,16,10) (8,18,10)	(6,16,10) (8,16,12) (8,18,12)
7	(6,14,8) (6,16,10) (8,18,12)	(6,16,10) (8,18,12) (10,20,12)	(6,16,10) (8,18,12) (8,20,12) (10,20,12)
8	(8,16,10) (10,20,14)	(8,18,12) (10,18,12) (10,18,14) (10,20,14) (12,22,16)	(10,20,14) (10,22,14) (12,24,16)

TABLE 5. Min/Max labour sizes per instance and conservatism level (concluded from Table 4).

Instance	Labour Size	Conservatism Level		
		L	M	H
1	Max	10	12	12
	Min	8	10	10
2	Max	20	26	26
	Min	18	20	20
3	Max	24	30	28
	Min	20	24	24
4	Max	28	32	34
	Min	22	28	28
5	Max	30	38	34
	Min	28	30	28
6	Max	32	36	38
	Min	28	32	32
7	Max	38	42	46
	Min	28	32	32
8	Max	44	50	52
	Min.	34	38	44

value because the other labour scenario do not have acceptable performance under all uncertainty scenarios. However, ROLS value is not necessarily the most pessimistic labour size scenario. As can be seen in instance 2, labour size (4,12,8)=24 shows an acceptable performance and determined as ROLS value. Finally, comparing different solutions originated from different conservatism levels (L, m and H), it can be concluded that due to the problem uncertainty low conservatism solutions result high infeasibility rate. Therefore, ignoring or underestimating the problem uncertainty yields low quality solutions.

TABLE 6. Output of phase 2 for instance 1 and 2.

Instance	Labour size scenario	Uncertainty scenario	Feasibility	StDev.	ROLS
1	(2,4,2)=8	Normal	0.04	0.05	
		Abnormal	0.03	0.03	
		Mysterious	0.05	0.04	
	(2,4,4,)=10	Normal	0.9	0.13	
		Abnormal	0.86	0.15	
		Mysterious	0.88	0.16	
	(2,6,4)=12	Normal	1	0	
		Abnormal	1	0	✓
		Mysterious	1	0	
2	(4,8,6)=18	Normal	0.07	0.1	
		Abnormal	0.05	0.07	
		Mysterious	0.09	0.12	
	(4,10,6)=20	Normal	0.99	0.01	
		Abnormal	0.99	0.01	
		Mysterious	0.93	0.07	
	(4,12,8)=24	Normal	0.99	0.01	
		Abnormal	0.99	0.01	✓
		Mysterious	0.99	0.01	
	(6,12,8)=26	Normal	1	0	
		Abnormal	1	0	
		Mysterious	1	0	

TABLE 7. ROLS values.

Instance	ROLS labour scenario $(\lambda_1^{max}, \lambda_2^{max}, \lambda_3^{max}) = \sum \lambda_m^{max}$	Uncertainty scenario	Feasibility	StDev.
3	(6,12,8)=26	Normal	0.95	0.02
		Abnormal	0.97	0.03
		Mysterious	0.99	0.04
4	(6,14,8)=28	Normal	0.98	0.02
		Abnormal	0.96	0.05
		Mysterious	0.95	0.05
5	(8,14,10)=32	Normal	1	0
		Abnormal	0.99	0.01
		Mysterious	0.99	0.01
6	(8,18,12)=40	Normal	1	0
		Abnormal	1	0
		Mysterious	0.99	0.01
7	(10,20,12)=42	Normal	1	0
		Abnormal	1	0
		Mysterious	1	0
8	(10,20,14)=44	Normal	1	0
		Abnormal	1	0
		Mysterious	1	0

In TABLE 7, the summary results of phase 2 for the other data instances are presented. Indicated ROLS values show that the proposed HSO robust optimization enables us to find a high-quality solution that is not too conservatism, but its feasibility under different uncertainty scenarios and levels is guaranteed. Therefore, the proposed approach presents solutions which are not corresponding to hard-worst case solution.

VI. CONCLUSION AND REMARKS

This paper has presented an approach to robust scheduling of the maintenances tasks of fighter aircraft fleets with daily missions where the tasks' duration are subject to uncertainty. The sole objective is to maximize the fleet operational availability for the planned missions, while the available skilled labour is the main constraint. The tasks are either scheduled maintenance activities or unexpected repair jobs when a fault is detected during pre- or after-flight check of each mission. The probability of the fault detection is known.

Because of the primary mathematical model's specific structure, it cannot be extended to create a robust framework using the existing methods. Thus, we modify the primary model to generate a finite set of the solutions corresponding to the uncertainty set. This can be done using a sampling-optimization procedure. In this procedure, Monte-Carlo simulation is used to take samples from the uncertainty set; the samples are iteratively fed to the modified model to extract the set of feasible solutions. However, the procedure does not guarantee the probabilistic feasibility; i.e., we cannot ensure the feasibility of the solutions under particular distributional assumptions for the disturbance vectors. Thus, we propose a hybrid simulation-optimization approach to overcome the problem. This approach consists of two phases: 1- generating the list of all solutions corresponding to the uncertainty set using Monte-Carlo sampling-optimization; 2- checking the probabilistic feasibility of the abovementioned solutions under three general uncertainty scenarios: normal, abnormal, and mysterious. Using this approach, we determine the optimal robust solutions, i.e., the solutions with minimum cost satisfying all conservatism levels and uncertainty scenarios. The obtained results reveal that our approach is not sensitive to the uncertainty scenarios or to the problem size; validating the performance of the proposed approach to solve a class of robust scheduling problems in which the availability of assets for planned programs is a concern while the tasks' duration is subject to unknown uncertainty behaviors. Our hybrid simulation-optimization approach may be applied to other robust optimization problems in which either a dual counterpart for the primary model does not exist or the feasible space has a non-convex form.

Spare part inventory management plays a critical role in maintenance management. Therefore, integrating spare part inventory and maintenance task scheduling in this approach is recommended for future research. Furthermore, the proposed approach can be utilized in commercial airlines by considering related assumptions. Finally, proposing an online robust maintenance scheduling approach is an interesting research field to enhance model performance.

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