STACKELBERG GAME THEORETICAL MODEL FOR OPTIMIZING AIRCRAFT MAINTENANCE ROUTING WITH MAINTENANCE STAFFING

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ABSTRACT

Despite the interdependence between the operational aircraft maintenance routing problem with flight delay consideration (OAMRPFD) and the maintenance staffing problem (MSP), they are solved separately. Therefore, the optimal plan of each problem will not be operated as planned. In this paper, our focus is the OAMRPFD along with the MSP, with two main objectives. Firstly, to develop an OAMRPFD model that reflects appropriately the flight delays. For this purpose, a new scenario-based stochastic programming model for OAMRPFD (SOAMRPFD) is proposed. Secondly, to handle the interdependence between SOAMRPFD and MSP, by proposing a coordinated configuration of SOAMRPFD and MSP that is formulated as a leader-follower Stackelbery game. In this game, SOAMRPFD acts as a leader and MSP acts as a follower. This game is enacted through a bi-level optimization model, which is solved by a bi-level nested ant colony optimization (ACO) algorithm. In order to demonstrate the superiority of the proposed model, a case study of major airline and maintenance companies located in the Middle East is presented.

Keywords: Aircraft routing problem, Maintenance staffing problem, Stackelberg game.

1 INTRODUCTION:

Aircraft maintenance routing problem (AMRP) has been well recognized as an effective mean for airline companies to build maintenance feasible routes for their aircraft [1]. it is one of the most studied problems with three focuses: tactical (TAMRP), operational (OAMRP), and operational with flight delay consideration (OAMRPFD). The TAMRP studies aim to generate specific rotations for each aircraft, while neglecting many of the operational maintenance constraints [2]. Using single rotation for each aircraft is not applicable due to lack of considering operational maintenance constraints. Therefore, the researchers shifted their focus from tactical side to operational side OAMRP, in order to generate routes consistent with the operational constraints [1]. However, the drawback of OAMRP

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is the ignorance of flight delay that is frequently happened in reality, resulting in generation of non-robust routes. For this reason, the researchers consider flight delay beside the operational side OAMRPFD, to produce robust routes [3]. Solving OAMRPFD provides a solution, which is a sequence of flight legs assigned to each aircraft, and that sequence is interrupted by maintenance visits in order to satisfy the operational requirements. To achieve this solution as planned, the airline company should send the scheduled arrival and departure times for its aircraft to the maintenance company. Based on the received scheduled times, the maintenance company has to solve the maintenance staffing problem (MSP), so that it can determine the team sizes required for the received aircraft, while taking into account the workforce capacity and the scheduled times of the aircraft [4]. From the above description, we can see that achieving the solution of OAMRPFD as planned, is the responsibility of the maintenance company to release the aircraft punctually from the maintenance station. Similarly, MSP's solution can be realized as planned, if the airline company send their aircraft on time, so that any disturbance to the staffing plan can be avoided. Therefore, OAMRPFD and MSP are closely interdependent on each other.

The focus of this paper is studying OAMRPFD along with MSP, and our contribution is as follow. Firstly, it is observed that OAMRPFD was formulated based on the expected value of the non-propagated delay. However, a drawback of this formulation is that it may not adequately reflect the final realization of non-propagated delay, as it is characterized by high level of uncertainty. This would result in facilitating the propagation of the delay and increasing its related costs. This situation motivates us to find better representation for the non-propagated delay, by proposing a scenario-based stochastic programming model for OAMRPFD (SOAMRPFD), as it has been proven one of the most successful ways to handle stochastic parameters [5]. Secondly, from the literature, one of the significant gaps is solving OAMRPFD and MSP separately. However, the pitfall of this separation is the ignorance of the interdependence between them. In this paper, for the first time, we attempt to fulfil this research gap, by proposing a coordinated configuration of SOAMRPFD and MSP that is formulated as a leader-follower Stackelbery game, in which SOAMRPFD acts as a leader and MSP acts as a follower. This game is enacted through a bi-level optimization model. In addition to these contributions, and to be consistent with the bi-level optimization model, a bi-level nested ACO algorithm is developed to derive optimal or near-optimal solutions for both problems.

The rest of the paper is organized as follow. The decision models of SOAMRPFD and MSP are presented in Sections 2 and 3, respectively. In Section 4, we elaborate the bi-level optimization model. A bi-level nested ACO algorithm is developed in Section 5. Section 6 reports a case study of major airline and maintenance companies. Conclusions of the study are given in Section 7.

2 SOAMRPFD DECISION MODEL

SOAMRPFD aims to generate maintenance feasible routes for each aircraft. SOAMRPFD's formulation is based on the connection network, which is one of the commonly used network for AMRP [1]. To formalize the representation of the proposed SOAMRPFD, we first define the sets, parameters and decision variables that are frequently used throughout this paper as follow.

<u>SOAMRPFD decision model</u>

Sets

$i, j \in NF$:	Set of flight legs.
$k \in K$:	Set of aircraft.
$m \in MT$:	Set of maintenance stations.
$a \in A$:	Set of airports.
$v \in \{1, \dots, V\}$:	Number of maintenance operations that should be performed by each aircraft.
$\xi \in \Xi$:	Set of disruption scenarios.

$\{o,t\}$: Dummy source and sink nodes of the connection network.

Parameters

DT_i: Departure time of flight leg i.

AT_i: Arrival time of flight leg i.

TRT: Turn-around time.

O_{ia}: Origin binary indicator of flight leg i such that $O_{ia} = 1$ if the origin of flight leg i and the airport a are the same, and 0 otherwise.

D_{ia}: Destination binary indicator of flight leg i such that $D_{ia} = 1$ if the destination of flight leg i and the airport a are the same, and 0 otherwise.

FT_i: Flight duration of flight leg i.

T_{max}: Maximum flying time between two successive maintenance operations.

NPD_{ik}^{ξ}: Non-propagated delay of an aircraft k that covered flight leg i, under scenario ξ.

Mb_{ma}: Maintenance binary indicator of maintenance station m such that $Mb_{ma} = 1$ if the maintenance station m located at airport a, and 0 otherwise.

MAT: Time required to perform the maintenance operation assumed by airline company.

M: A considerable big number.

p^{ξ}: Probability for realization of scenario ξ.

C_{pD}: Per minute propagated delay cost.

PD_{ijkv}^{ξ}: Propagated delay caused when aircraft k covered flight leg i and will cover flight leg j, before performing maintenance operation number v, under scenario ξ.

PD_{ikv}^{ξ}: Total propagated delay of the route covered by aircraft k caused from the beginning of coverage until covering flight leg i, before performing maintenance operation number v, under scenario ξ.

Decision variables

$x_{ijkv}^{\xi} \in \{0,1\}$: =1 if flights legs i and j are covered by aircraft k, before performing maintenance operation number v, under scenario ξ, and 0 otherwise.

$y_{imkv}^{\xi} \in \{0,1\}$: =1 if aircraft k covers flight legs i then perform maintenance operation number v, at maintenance station m, under scenario ξ, and 0 otherwise.

$z_{mjkv}^{\xi} \in \{0,1\}$: =1 if aircraft k covers flight legs j after performing maintenance operation number v, at maintenance station m, under scenario ξ, and 0 otherwise.

$RTAM_{kv}^{*\xi} > 0$: The ready time for aircraft k to continue covering another flight leg, after performing the maintenance operation number v, under scenario ξ.

<u>MSP decision model</u>

Sets

$f \in \{1,\dots,F\}$: Set of flights that their aircraft will be maintained.

$s \in S$: Set of shifts.

$\{o',t'\}$: Source and sink node of the layered graph.

Parameters

SAT_{fm}^{ξ}: Scheduled arrival time of flight f, at maintenance station m, under disruption scenario ξ.

SDT_{fm}^{ξ}: Scheduled departure time of flight f, at maintenance station m, under disruption scenario ξ.

w_{sm}^{l}: Minimal team size (number of worker) that can be formed, during shift s, at maintenance station m.

w_{sm}^{u}: Maximal team size (number of worker) that can be formed, during shift s, at maintenance station m.

wf_s^{max}: Capacity of workforce available during shift s.

l_f: Workload (man-hours) required to maintain aircraft that covers flight f.

C_{wfsm}: Cost incurred when w workers assigned to maintain aircraft that covers flight f, during shift s, at maintenance station m.

CW_d: Per minute penalty cost paid for aircraft time delay in the maintenance station.

Decision variables

wf_{fsm}^{ξ}: Number of worker (team size) assigned to maintain aircraft that covers flight f, during shift s, at maintenance station m, under disruption scenario ξ.

$RTAM_{fm}^{\xi} > 0$: Actual ready time for the aircraft that covers flight f to leave the maintenance station m, under disruption scenario ξ.

The optimization model for SOAMRPFD, as a leader, is formulated as below:

$$min \sum_{\xi\in\Xi} p^{\xi} \left(\sum_{v\in V} C_{pD} \left(\sum_{k\in K} \sum_{i\in NF} \sum_{j\in NF} PD_{ijkv}^{\xi}\, x_{ijkv}^{\xi}\right)\right) \quad (1)$$

Subject to

$$PD_{ijkv}^{\xi} = PD_{ikv}^{\xi} + (NPD_{ik}^{\xi} - (DT_j - AT_i - TRT))^{+} \quad \forall\, i \in NF, \forall j \in NF, \forall k \in k, \forall v \in V, \forall \xi \in \Xi \quad (2)$$

$$\sum_{k\in k} \left(\sum_{j\in NF\cup\{t\}} \sum_{v\in V} x_{ijkv}^{\xi} + \sum_{m\in MT} \sum_{v\in V} y_{imkv}^{\xi}\right) = 1 \quad \forall\, i \in NF, \forall \xi \in \Xi \quad (3)$$

$$\sum_{j\in NF\cup\{o\}} x_{ijkv}^{\xi} + \sum_{m\in MT} z_{mikv}^{\xi} = \sum_{j\in NF\cup\{t\}} x_{ijkv}^{\xi} + \sum_{m\in MT} y_{imkv}^{\xi} \quad \forall\, i \in NF, \forall k \in k, \forall\, v \in V, \forall \xi \in \Xi \quad (4)$$

$$\sum_{j\in NF} \sum_{v\in V} y_{jmkv}^{\xi} = \sum_{j\in NF\cup\{t\}} \sum_{v\in V} z_{mjkv}^{\xi} \quad \forall m \in MT, \forall k \in k, \forall \xi \in \Xi \quad (5)$$

$$AT_i + TRT - DT_j \le M(1 - x_{ijkv}^{\xi}) \quad \forall\, i \in NF, \forall j \in NF, \forall k \in k, \forall v \in V, \forall \xi \in \Xi \quad (6)$$

$$\sum_{k\in k} x_{ijkv}^{\xi} \le \sum_{a\in A} D_{ia} O_{ja} \quad \forall\, i \in NF, \forall j \in NF, \forall v \in V, \forall \xi \in \Xi \quad (7)$$

$$\sum_{k\in k} y_{imkv}^{\xi} \le \sum_{a\in A} D_{ia} Mb_{ma} \quad \forall\, i \in NF, \forall m \in MT, \forall v \in V, \forall \xi \in \Xi \quad (8)$$

$$\sum_{k\in k} z_{mjkv}^{\xi} \le \sum_{a\in A} Mb_{ma}\, O_{ja} \quad \forall m \in MT, \forall j \in NF, \forall v \in V, \forall \xi \in \Xi \quad (9)$$

$$RTAM_{kv}^{*\xi} - DT_j \le M\,(1 - z_{mjkv}^{\xi}) \quad \forall m \in MT, \forall j \in NF, \forall k \in k, \forall v \in V, \forall \xi \in \Xi \quad (10)$$

$$RTAM_{kv}^{*\xi} = \sum_{i\in NF\cup\{o\}} \sum_{m\in MT} (AT_i + MAT) z_{mjkv}^{\xi} \quad \forall k \in k, \forall v \in V, \forall \xi \in \Xi \quad (11)$$

$$RTAM_{kv}^{*\xi} = \sum_{f\in F} \sum_{i\in NF\cup\{o\}} \sum_{m\in MT} RTAM_{fm}^{\xi}\, z_{mjkv}^{\xi} \quad \forall k \in k, \forall v \in V, \forall \xi \in \Xi \quad (12)$$

$$\sum_{i\in NF\cup\{o\}} \sum_{j\in NF} FT_j\, x_{ijkv}^{\xi} \le T_{max} \quad \forall k \in k, \forall v \in V, \forall \xi \in \Xi \quad (13)$$

The objective function (1) is the minimization of the total expected cost of propagated delay. Constraints (2) describe the calculation of the propagated delay. In order to ensure covering all the flight legs, constraints (3) are cast, which indicate covering each flight leg exactly by one aircraft. In order to keep the circulation of the aircraft throughout the network, the balance constraints (4) and (5) are formulated. To connect two flight legs by using same aircraft, that connection should be feasible in terms of time and place considerations, as described by constraints (6) and (7). On the other hand, to prepare a maintenance visit for the aircraft, we formulate constraints (8) that consider the locations of the maintenance stations. After finishing the maintenance operation, the aircraft should resume covering its route. For this purpose, constraints (9), (10), (11) and (12) are cast. It should be noted that constraints (12) are considered the link between SOMARPFD and MSP. Forcing the aircraft that needs maintenance to undergo maintenance operations cannot be fulfilled through coverage and balance constraints. Therefore, the operational restrictive constraints (13) are cast.

3 MSP DECISION MODEL

MSP is to determine the workforce team sizes required to perform the maintenance operations to the aircraft. MSP presented in this section is formulated based on a layered graph, which is commonly used in the literature for handling the staffing problem and worker allocation problem [6].

The optimization model for MSP, as a follower, is formulated as below.

$$min \sum_{m \in MT} \sum_{s \in S} \sum_{f \in F} C_{wfsm}\, wf_{fsm}^{\xi} + \sum_{f \in F} CW_d \left(RTAM_{fm}^{\xi} - SDT_{fm}^{\xi} \right) \qquad (14)$$

Subject to

$$RTAM_{fm}^{\xi} = (SDT_{fm}^{\xi} - (SAT_{fm}^{\xi} + TRT + l_f / wf_{fsm}^{\xi}))^{+} \qquad \forall f \in F, \forall m \in MT \qquad (15)$$

$$\sum_{f \in F} wf_{fsm}^{\xi} \leq wf_{s}^{max} \qquad \forall s \in S, \forall m \in MT \qquad (16)$$

$$SAT_{fm}^{\xi} = \sum_{k \in K} \sum_{i \in NF} \sum_{v \in V} AT_i \, y_{imkv}^{\xi} \qquad \forall f \in F, \forall m \in MT \qquad (17)$$

$$SDT_{fm}^{\xi} = \sum_{k \in K} \sum_{j \in NF} \sum_{v \in V} RTAM_{kv}^{*\xi} \, z_{mjkv}^{\xi} \qquad \forall f \in F, \forall m \in MT \qquad (18)$$

The objective function (14) is the minimization of the total worker cost and the penalty cost paid due to time delay happen to the aircraft in the maintenance station. Constraints (15) represent the calculation of the real ready time for the aircraft when leaving the maintenance station. In order to allocate the workers properly to perform maintenance operation, the worker capacity in each visible shift should be respected, as explained by constraints (16). Acting as a follower to build efficient staffing plan requires MSP to receive some information from the airline company. For this purpose, linkage constraints (17) and (18) are cast.

4 JOINT CONFIGURATION OPTIMIZATION

In this section, we present joint optimization model for the coordinated configuration of SOAMRPFD and MSP. This model is modelled as a leader-follower bi-level optimization model, known as Stackelberg game, in which the SOAMRPFD as a leader constitutes the upper-level optimization model, and the MSP as a follower forms the lower-level optimization model. The bi-level optimization model can be summarized as follow:

$$min \sum_{\xi \in \Xi} p^{\xi} \left(\sum_{v \in V} C_{pD} \left(\sum_{k \in K} \sum_{i \in NF} \sum_{j \in NF} PD_{ijkv}^{\xi} \, x_{ijkv}^{\xi} \right) \right) \qquad (19)$$

Subject to constraints (2) - (13)

Where given decision variables (y_{imkv}^{ξ}, z_{mjkv}^{ξ} and $RTAM_{kv}^{*\xi}$) used to solve:

$$min \sum_{m \in MT} \sum_{s \in S} \sum_{f \in F} C_{wfsm}\, wf_{fsm}^{\xi} + \sum_{f \in F} CW_d \left(RTAM_{fm}^{\xi} - SDT_{fm}^{\xi} \right) \qquad (20)$$

Subject to constraints (15) - (18)

From the above formulation, it is observed that SOAMRPFD makes decision regarding the maintenance visits for its aircraft. With these results as an input, MSP determine its staffing plan to satisfy the required maintenance operations. Next, MSP responds to the upper-level by providing its decisions. If the decisions influence the initial routing plan, SOAMRPFD further adjusts its decisions by resolving the model. This process keeps iterated until reaching the Stackelberg equilibrium, in which both players are unwilling to adjust their decisions. In this way, the optimal setting for the coordinated configuration are derived.

5 SOLUTION METHOD

In this section, we propose solving the bi-level optimization model by using bi-level nested ACO algorithm. This is because SOAMRPFD and MSP are essentially formulated based on network representation, for which ACO has proven to be advantageous for large and complex network based problems [7].

5.1 ACO for upper-level optimization

The ACO adopted to solve SOAMRPFD consists of two main parts, which are as follow:

- Route construction. This part is conducted by the help of ants (i.e. each ant simulates an aircraft $k \in K$) such that each ant constructs its route by the usage of state transition rule, stated in Eq. (21).

$$j = \begin{cases} arg\_max_{l \in N_i^k} \left\{ \left[\tau_{ij}{}^{\xi}\right]^{\alpha} \left[\eta_{ij}{}^{\xi}\right]^{\beta} \right\} & if\ q \leq q_0 \\ J & if\ q > q_0 \end{cases} \qquad \textbf{(21)}$$

Where $N_i^k$is the set of potential flight legs that can be selected by the ant k.The terms $\tau_{ij}{}^{\xi}$ and $\eta_{ij}{}^{\xi} = 1/(C_{pD} * PD_{ijkv}^{\xi})$ are the pheromone trial and the heuristic function of the network arcs, respectively. The two parameters α and β represent the relative importance of the pheromone trial and the heuristic function, respectively. q_0 is the exploration threshold parameter $(0 \leq q_0 \leq 1)$ and q is a uniformly distributed random number $[0{\sim}1]$. Typically, the ant selects the next flight leg j based on the value q. If $q \leq q_0$, then selects the flight leg j in according to Eq. (21). On the other side, if $q > q_0$, the ant picks the flight leg j according to the following probability rule:

$$P_{ij}^k = \left[\tau_{ij}{}^{\xi}\right]^{\alpha} \left[\eta_{ij}{}^{\xi}\right]^{\beta} / \sum_{l \in N_i^k} \left[\tau_{ij}{}^{\xi}\right]^{\alpha} \left[\eta_{ij}{}^{\xi}\right]^{\beta} \qquad if\ j \in N_i^k \qquad \textbf{(22)}$$

- Update the pheromone trail. It can be done in accordance with the following rule:

$$\tau_{ij,new}^{\xi} = (1-\rho)\tau_{ij,old}^{\xi} + \Delta\,\tau_{ij}{}^{\xi} \qquad \textbf{(23)}$$

Where ρ is the evaporation rate parameter$(0 < \rho < 1)$. The first term $(1-\rho)\tau_{ij,old}^{\xi}$ is used each iteration, so that a uniform reduction of the phermones can be achieved. The second term $\Delta\,\tau_{ij}{}^{\xi}$ represents the pheromone quantities, under disruption scenario ξ. This term is only used to update all the edges included in the best so far solution, by following the rule in Eq. (24).

$$\Delta\,\tau_{ij}{}^{\xi} = Q/cost\left(A_{best}^{\xi}\right) \qquad if\{i,j\} \subseteq A_{best}^{\xi} \qquad \textbf{(24)}$$

Where Q is the control factor of laying the pheromone. The $cost\left(A_{best}^{\xi}\right)$ is the lowest propagated delay cost from the beginning until now, while handling disruption scenario ξ.

5.2 ACO for lower-level optimization

ACO adopted to solve MSP is similar to that one proposed to solve the upper level ACO except the heuristic function. There are two types of heuristic functions. First, the heuristic function for worker cost ($\eta_{bfw,worker}^{\xi} = 1/(wf_{fsm}^{\xi} * C_{wfsm})$), whereas the second is the heuristic function for the penalty cost paid due to the time delay ($\eta_{bfw,delay}^{\xi} = 1/CW_d(RTAM_{fm}^{\xi} - SDT_{fm}^{\xi})$).

5.3 Bi-level nested ACO algorithm

In this section, we propose a bi-level nested ACO algorithm, which starts with upper-level ACO in order to solve SOAMRPFD and take decisions regarding the routing plan and maintenance visits (refereed as y_{imkv}^{ξ}, z_{mjkv}^{ξ} and $RTAM_{kv}^{*\xi}$). Upper-level solution is sent to the lower-level ACO as an input in order to solve MSP and take decisions regarding the staffing plan (referred as wf_{fsm}^{ξ} and $RTAM_{fm}^{\xi}$). All the lower-level best solutions are sent back to the upper-level ACO to re-run it and adjust its solution. This process iterates until both leader and follower reach the Stackelberg game equilibrium.

For computational efficiency, we set the stopping criteria for upper and lower-level ACOs to be happened when the solution improvement is capped for successive 100 iterations, or when the number of iterations exceeds the maximum number of iterations (i.e. 500 iterations). If both stopping criteria are satisfied, then the nested algorithm is terminated, and the Stackelberg equilibrium is derived.

6 CASE STUDY

To demonstrate the importance of the proposed model, we present a case study based on data acquired from major airline and maintenance companies located in the Middle East, as shown in Table 1.

Table 1: Data collected from airline and maintenance companies.

<u>**Airline company**</u>
Number of flight legs=240.
Fleet size=30.
Number of airports=8.
Turn-around time (TRT) =45 minutes.
Maximum flying time (T_{max}) =40 hours.
Time required to perform maintenance (MAT) =8 hours.
Per minute propagated delay cost (C_{pD}) = 75 if propagated delay is less than or equal 15 minutes, or it is equal 125 for longer propagated delays.
<u>**Maintenance company**</u>
Number of maintenance stations=4.
Minimal team size (w_{Sm}^{l}) = 10 workers.
Maximal team size (w_{sm}^{u}) = 5 workers.
Capacity of workers (wf_s^{max}) =100 workers.
Potential team size (wf_{fsm}^{ξ}) are 5, 6, 7, 8, 9, and 10, and its corresponding cost (C_{wfsm}) are 670,730,800,870,950, and 1020.
Per minute aircraft time delay penalty cost (CW_d) =100.
Workload required to maintain aircraft (l_f) =50 hours.

6.1 Results of Stackelberg game joint optimization

The near optimal solutions for the joint SOAMRPFD and MSP are determined by implementing the nested ACO algorithm. For computational efficiency and meaningful problem context, the number of disruption scenarios is capped at as 100 equally likely scenarios. The nested ACO algorithm adopts pheromone trail importance of 1, heuristic function importance of 2, exploration threshold of 0.95, evaporation rate of 0.05, and control factor for pheromone laying of 0.01. Regarding the ant size, the upper-level ACO adopts the size that equals the number of aircraft. On the other hand, the lower level ACO sets the size to be equal the number of flights that their aircraft will be maintained. The results obtained from the nested ACO algorithm show that after 350 iterations, the upper-level ACO converges and returns its best result, whereas the lower-level ACO converges and its best result is achieved after 450 iterations. Since these results constitute the situation in which both companies are unwilling to change their decisions, the Stackelberg equilibrium is achieved to be 1804.25 for the airline company and 27146.96 for the maintenance company.

6.2 Performance analysis

To demonstrate the advantage of leader-follower Stackelberg model (LFS), we conduct computational experiments in order to compare LFS performance with another traditional optimization method called non-joint optimization method (NJOP), which treats each problem of SOAMRPFD and MSP separately. The results show that LFS model outperforms the NJOP model by 15.61% (1804.25 vs. 2137.98), while handling SOAMRPFD, whereas the outperformance of LFS model over NJOP model is 18.70% (27146.96 vs. 33391.08), while handling the worker and penalty costs of the maintenance company. Therefore, it is clear from these results that the proposed LFS model improves the results obtained by the airline and maintenance companies significantly. This echoes the importance of the coordinated configuration of SOAMRPFD and MSP to be implemented in reality.

7 CONCLUSION

In this paper, we propose a joint optimization model for coordinated configuration of SOAMRPFD and MSP by using leader-follower Stackelberg game. In this game, SOAMRPFD plays a leader's role for minimization the propagated delay cost. On the other hand, MSP acts as a follower that responds rationally to the leader's decision. In order to achieve the Stackelberg equilibrium, a nested ACO algorithm was presented. The case study of major airline and maintenance companies located in the Middle East verifies the superiority of the proposed model. The results demonstrate significant saving in the costs of both companies.

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