Integrated maintenance and mission planning using remaining useful life information

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ABSTRACT

The modern world requires high reliability and availability with minimum ownership cost for complex industrial systems (high-value assets). Maintenance and mission planning are two major interrelated tasks affecting availability and ownership cost. Both tasks play critical roles in cost savings and effective utilization of the assets, and cannot be performed without taking each other into consideration. Maintenance schedule may make an asset unavailable or too risky to use for a mission. Mission type and duration affect the health of the system, which affects the maintenance schedule. This article presents a mathematical formulation for integrated maintenance and mission planning for a fleet of high-value assets, using their current and forecast health information. An illustrative example for a fleet of unmanned aerial vehicles is demonstrated and evolutionary-based solutions are presented.

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1. Introduction

Today's industry requires high availability for high-value assets (HVAs), such as aircraft, helicopters, power plants and unmanned aerial vehicles (UAVs). High availability can be achieved by avoiding failures through effective maintenance planning based on near real-time health monitoring. Even though maintenance planning and mission planning greatly affect each other, they are often considered and planned independently. This article presents an integrated methodology for maintenance and mission planning of a fleet of HVAs based on their current and forecast future health states.

Different mission types affect the health of assets differently. Some missions are harsh and lead to more degradation, whereas others are easy, with less degradation. For example, a 'combat' mission for an aircraft will degrade its health more than a 'cross-country' mission. Maintenance aims to enhance the asset's health by reducing the degradation caused by missions. Thus, it is important to perform mission and maintenance planning together because of their interacting nature.

Preventive maintenance involves real-time monitoring through sensors. Diagnostics aims to determine existing failure and prognostics aims to estimate the remaining useful life (RUL). Readers are referred to Lei *et al.* (2018) for a review on machine diagnostics and prognostics. RUL represents the time left before failure stops the system performing its intended function (Atamuradov *et al.* 2017).

Since maintenance planning is related to a defined future, the forecast health and RUL information should be incorporated in the maintenance planning. The estimated RUL is valuable only if it is used in mission and maintenance planning. Studies on maintenance planning have either ignored mission planning or received mission planning as an input. The opposite is also true. This article aims to address this gap in the literature by presenting a model for integrated maintenance and mission planning for a fleet of HVAs using RUL information on the assets of the fleet.

A literature review, model details, results and conclusions are presented in Sections 2–5, respectively.

2. Literature review

The literature on maintenance planning and mission planning is discussed in the following subsections.

2.1. Maintenance planning

Periodic maintenance (PM) is the most common approach to maintenance, and aims to reduce the consequences of failures by performing maintenance at regular intervals. Most of the research on PM covers the identification of the best maintenance period. A review of this work is presented by Ben-Daya, Duffua, and Raouf (2000). Other studies focus on finding the best grouping for maintenance actions (*e.g.* Ab-Samat and Kamaruddin 2014). Even though PM reduces the probability of failure, it leads to unnecessary maintenance in addition to necessary maintenance.

The maintenance period in PM is determined based on the reliability analysis of similar systems. Prognostics and health management (PHM) introduces new opportunities for more effective maintenance planning compared to PM. In PHM, monitoring data unique to the system under observation are used to identify the system health (Son *et al.* 2013; Sankararaman 2015). PHM recommends actions specific to the system under observation.

Industry today seeks maintenance solutions based on real-time health monitoring of assets (Hu *et al.* 2012). When a failure is detected through diagnostics, there is not much to plan. The failure should be fixed immediately to avoid higher failure consequences. Thus, planning requires forecasting the future health of the assets, which is performed through prognostics. Forecast health creates the opportunity to calculate the associated risk, which may be used for effective planning. Prognostics gives the RUL in the form of time to failure or the forecast probability of failure. Since the forecast involves uncertainty, the general approach of RUL in maintenance planning is in the form of failure probability (Camci 2009).

The classical approach to maintenance planning with RUL information is to set a threshold on the RUL values. Maintenance is scheduled when estimated RUL reaches the threshold (Javed, Gouriveau, and Zerhouni 2013; Sandborn and Wilkinson 2007; Haddad, Sandborn, and Pecht 2012). Although threshold optimization is possible (Marseguerra, Zio, and Podofillini 2002), the ineffectiveness of this approach for multiple components or multiple assets has been demonstrated (Camci 2009).

Maintenance scheduling using a genetic algorithm with RUL for a production system has been presented by Yang, Djurdjanovic, and Ni (2008). In this work, a cost function based on production rate is minimized for the best maintenance schedule. Tian and Liao (2011) presented a maintenance planning system for multiple components using a proportional hazards model. A dynamic model using the component health states and detected failures is presented in Bouvard *et al.* (2011). A version of the travelling salesman problem focusing on maintenance planning of HVAs located in different places with RUL was proposed by Camci (2014). The model has been expanded to better represent real maintenance planning for a set of geographically distributed assets (Camci 2015).

A dynamic maintenance planning method to handle changes in reconfigurable systems was presented by Xia *et al.* ("Reconfiguration-Oriented" 2017). There are also studies where maintenance is planned based on different criteria depending on the business need (Xia *et al.*, "Lease-Oriented" 2017; Xia *et al.* 2018). The throughput of a manufacturing system has been used as a constraint in a cost minimization problem to identify the best maintenance plan (Nahas and Nourelfath 2018). Liao, Zhang, and Jiang (2017) studied single-machine maintenance scheduling. Their model aims to meet the requirements of production scheduling and preventive maintenance. Lecerf, Allaire, and Willcox (2015) used the degradation of UAVs to estimate their capability through simulation.

None of the work cited above involves maintenance and mission planning using RUL. To the best of the authors' knowledge, this article addresses this problem for the first time in the literature.

2.2. Mission planning

Mission planning deals with methods that allow scheduling of a set of operations and tasks to achieve a main objective or function. It takes different constraints into account, such as the human and material resources needed in the mission. Several studies on mission planning have been reported in the literature, especially in the aerospace domain. Mission planning that integrates the efforts of space and ground systems for spacecraft has been presented by Harinath, Mahadevan, and Sarma (2008). Vachtsevanos *et al.* (2005) presented an overview of mission planning and analysis for UAVs. A hierarchical model was proposed, with different layers such as mission planning, trajectory generation and vehicle navigation. Similarly, Lin *et al.* (2014) proposed a hierarchical, three-level, decomposed framework to model the overall mission planning problem. In this framework, the first-level problem deals with the top-level mission scenario parameters, the second-level problem deals with the vehicle visiting strategy and the third-level problem deals with flying orbital missions.

A planning method using mixed-integer nonlinear programming is presented by Zhang *et al.* (2011). The method investigates single-phase parameters and phase-connecting parameters simultaneously. The method improves the rendezvous mission's overall performance. Evers *et al.* (2014) consider three extensions to the standard orienteering problem to model characteristics of practical relevance in planning reconnaissance missions of UAVs. A centralized–distributed hybrid control framework is proposed by Wei, Blake, and Madey (2013) for mission assignment and scheduling.

Mission planning and health monitoring are discussed together in Liu, Wang, and Liu (2009). Their article presents a mission-planning method for a flying robot to monitor the health of powerlines. The proposed method can determine the best checking order, the optimal space path and the best flight trajectory. Although health monitoring and mission planning are discussed together in the article, the mission planning and health monitoring are for different systems. Mission planning is done for the flying robot but the health monitoring targets powerlines using the flying robot. McClenaghan *et al.* (2013) present an integrated pathway for surgical missions and a report on its performance in action. Mission planning integrated with failure diagnosis system state is discussed in Balaban and Alonso (2013). The proposed method is based on partially observable Markov decision processes. The mission planning in that article is defined as the route of a UAV during a flight.

To the best of the authors' knowledge, mission planning using current and forecast health information on the fleet of assets incorporated with maintenance scheduling has not been presented previously. This article addresses this gap in the literature by proposing a methodology to deal with mission planning and maintenance scheduling together, using the current and forecast health of the assets.

3. Methodology

The problem involves assigning missions to assets and scheduling the maintenance of assets for a given period. There are *ss* number of mission types. For each mission type i, $S_{i,t}$ number of missions i is required at time t. There is a total of $\sum_{i=1}^{s} S_{i,t}$ missions to be performed at a given t. There are N number of assets to be assigned for each mission type. Assignment decisions are made through the decision variable ($Y_{i,j,k,t}$), which is a binary decision variable. It is equal to 1 if the kth mission in mission type j is assigned to asset i at time t; 0 otherwise. The second decision variable is used for maintenance scheduling (X_{it}), which is 1 if maintenance is scheduled for asset i at time t; 0 otherwise.

The problem is formulated as a cost (Z) minimization problem with three main terms: expected failure cost, maintenance cost and missed mission cost (Equation 1). Expected failure cost (FC) represents the expected consequence of a failure. Expected failure cost is the sum of expected failure costs of each asset, which is calculated as the product of the cumulative failure probability (CP_i) of asset i and its fixed failure cost (F_i), as shown in Equation (2). Fixed failure cost is the repair and downtime cost or the cost of loss of the asset due to failure. Maintenance cost (MC) is the product of unit maintenance cost (M_i) for asset i and the total number of maintenance events to be performed in the given period T, as in Equation (3). The total number of maintenance events is calculated as the sum of the binary decision variable (X_{it}). The last main term in the cost equation is the missed mission cost, which is the consequence of not performing a requested mission type at time t on time. Cost per time unit delay of not performing mission type j is C_j. The number of missed missions in mission type j at time t is represented by $MT_{j,t}$. Missed cost is the product of C_j and the sum of all mission types in the given period (T), as shown in Equation (4). The details of each term are discussed in detail below.

$$\text{Min } Z = FC + MC + MM \tag{1}$$

$$FC = \sum_{i=1}^{N} CP_i \times F_i \tag{2}$$

$$MC = \sum_{i=1}^{N} \left(M_i \times \sum_{t=1}^{T} X_{it} \right) \tag{3}$$

$$MM = \sum_{j=1}^{S} \left(C_j \times \sum_{t=1}^{T} MT_{j,t} \right) \tag{4}$$

First, the calculation of failure cost will be discussed. The cumulative failure probability (CP_i) used in the failure cost formula is calculated based on the effective failure probability (P_{ij}). The effective failure probability is obtained using two failure probability estimations and the maintenance schedule. The first failure probability estimation is a vector of failure probabilities obtained from the prognostics module for all assets at all time units within the given period (FP^1_{it}). This probability forecast is obtained from the current and forecast health of the asset based on the real-time monitoring, diagnostics and prognostics. The solid line in Figure 1 illustrates this probability estimation. This failure probability estimation will be true until maintenance is performed. When a maintenance action is performed, the estimation will become invalid because the component on which the analysis is based may be replaced or fixed. Thus, reliability analysis will be used to forecast the failure probability after maintenance (FP^2_{it}). Since no sensory data have been collected to identify and forecast the health of the asset (since the new component will be used after the maintenance event), it is acceptable to use the reliability data obtained from similar systems that have degraded after previous maintenance. The dashed line in Figure 1 illustrates the probability forecast based on the reliability information.

In addition to failure forecasts from prognostics and reliability analysis, the forecast failure probability of the asset will depend on the maintenance schedule. The failure probability will be obtained from prognostics until the maintenance is carried out, and will be based on the reliability data after the maintenance event. Consider a case in which the maintenance is an oil change. The prognostics module analyses the quality of the oil and predicts the oil's RUL. This prediction is valid until the oil is changed. After the oil change, the prediction of oil quality should rely on the reliability data because monitoring data are obtained from already replaced oil. If the oil change is scheduled for next week, the quality of the oil for the following week cannot be based on the monitoring data of the oil currently in use.

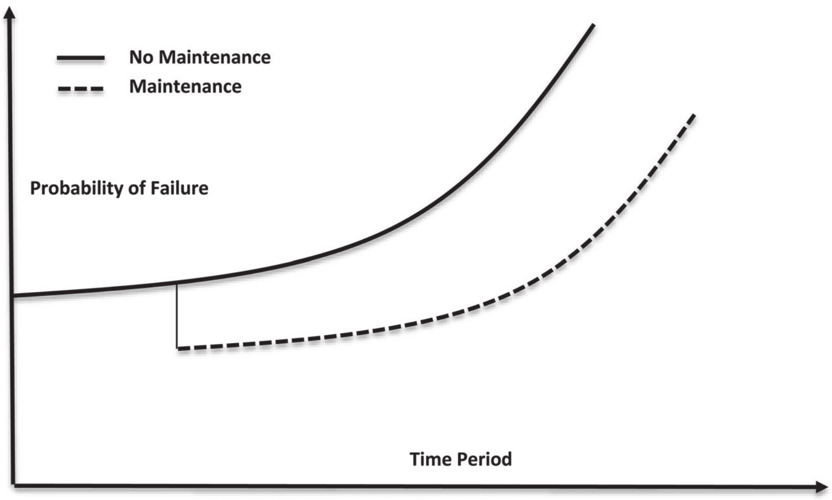

Figure 1. Effect of maintenance on failure probability.

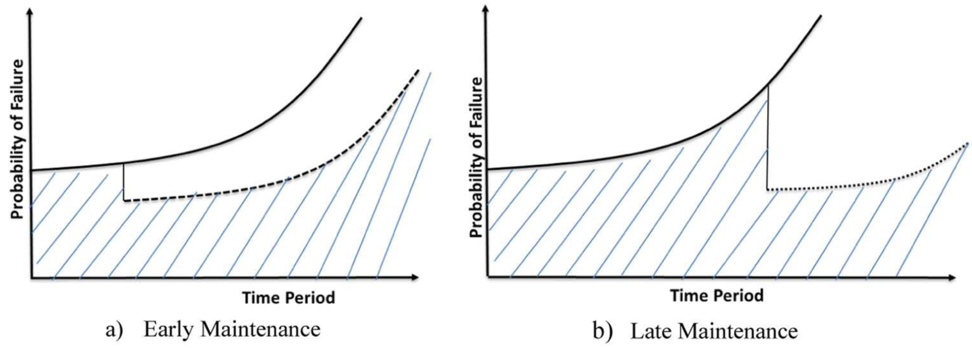

Figure 2. Cumulative failure probability based on prognostics, reliability forecasts and maintenance time: (a) early maintenance; (b) late maintenance.

The effect of maintenance time (performing maintenance earlier or later) is demonstrated in Figure 2. In Figure 2, the failure probability forecast obtained from the prognostics module (solid line) determines the failure probability until the maintenance event. After the maintenance has been carried out, the probability forecast from the reliability analysis (dashed line) becomes effective. The cumulative failure probability (CP_i) is the area under the effective failure probability (P_{it}) (solid line before maintenance; dashed line after maintenance). Figure 2(a) shows a case where the maintenance is performed earlier, whereas Figure 2(b) shows another case with later maintenance. The cumulative failure probability (CP_i) (area under effective probability; shaded area) is greater in Figure 2(b) since the maintenance has been performed later. The effect of maintenance time (early or late) is quantified using cumulative failure probability (CP_i) in the objective function. Note that FP^1_{it} and FP^2_{it} are input parameters to the model used to calculate the effective failure probability forecast (P_{it}) and cumulative probability (CP_i) based on a given maintenance schedule.

The effective failure probability is received either from the prognostics module (FP^1_{it}) or from reliability analysis (FP^2_{it}). If there is no maintenance scheduled for the asset before time t, then the effective failure probability is calculated as $P_{ij} = FP^1_{i,j}$. If there is at least one maintenance event before time t, then the effective failure probability is obtained from the reliability data, as shown in the 'after maintenance' part of Figure 3. The time index of the failure probability obtained from reliability analysis

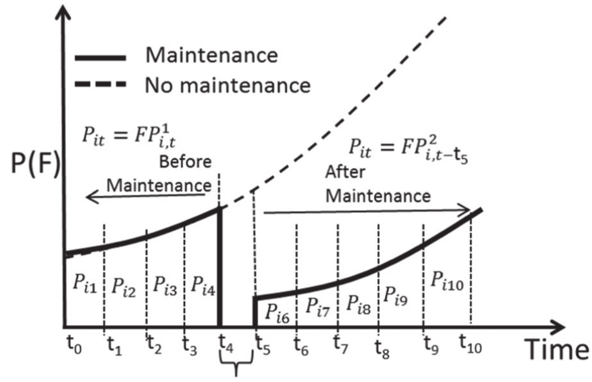

Figure 3. Failure probability with and without maintenance.

should be shifted by the time difference between the last maintenance and the corresponding time index. For example, a failure probability estimate for the next 50 time units is obtained from the prognostics module and maintenance is scheduled at time 14. The failure probability for time units 1–13 is equal to the failure estimations obtained from the prognostics module, and is $P_{i,1:13} = FP^1_{1:13}$. The failure probability at time unit 14 is 0 ($P_{i,14} = 0$), since this is the maintenance time. The failure probability for time units 15–50, obtained from reliability analysis, is $P_{i,15:50} = FP^2_{1:36}$. The thick solid line in Figure 3 shows the effective failure probability. Equation (5) presents the formulation of the failure probability selection process. If maintenance is scheduled at time t, then the failure probability is 0. Otherwise, it is calculated with probabilities obtained from prognostics and reliability analysis. $T(m)$ represents the latest maintenance before time t.

$$P_{it} = \begin{cases} 0 & \text{If } X_{it} = 1 \\ FP^1_{i,t} \times \max\left(0; 1 - \sum_{r=1}^{t-1} X_{ir}\right) + FP^2_{i,t-T(m)} \times \min\left(1; \sum_{r=1}^{t-1} X_{ir}\right) & \text{If } X_{it} = 0 \end{cases}$$
$$\forall t = 1 : T, \quad \forall i = 1 : N \tag{5}$$

It is assumed that the failure probability is constant within a time unit. If the time unit is a day, then the failure probability within a day does not change. The time unit should be narrow enough compared to the expected life of the asset. For example, a week is narrow enough for a component with an expected life of 20 years, but not narrow enough for a component with life expectancy of 1 month. The degradation within a week for the component with a 20 year life expectancy can be ignored. The time unit should also be large enough to allow maintenance of multiple assets. Too narrow a time unit will increase the complexity of the optimization, whereas too large a time unit will reduce the optimality of the result. Failure probability in a time unit is basically the shaded area between the previous time unit and the current time unit, shown as $P_{i1}, P_{i2}, \ldots P_{i10}$ in Figure 3. The cumulative failure probability within the time period T is calculated as the union of failure probabilities in the time units in the period T, as shown in Equation (6). For simplicity, it is assumed that the failure probabilities used in the union calculation are independent.

$$CP_i = \bigcup_{t=1}^{T} (P_{i,t}), \quad \forall i = 1 : N \tag{6}$$

The second term in the cost formula is the maintenance cost. Each asset may have a distinct unit maintenance cost (M_i). The total number of maintenance actions performed for an asset is calculated as the sum of binary variables for all time units in the given time period. Summation of the maintenance costs of all assets gives the total maintenance cost, as in Equation (3).

The third term in the cost formula is the missed mission cost. C_j (delay cost for mission type j) is multiplied by the sum of delay times for mission type j ($\sum_{t=1}^{T} MT_{j,t}$). The total missed mission cost is the sum of all missed mission cost types. The number of missed mission type j at time t is calculated as the difference between the required number of mission type j at time t ($RM_{j,t}$) and the total number of assets assigned to mission type j at time t, as shown in Equation (7).

$$\boldsymbol{MT_{j,t} = RM_{j,t} - \sum_{k=1}^{RM_{j,t}} \left(\sum_{i=1}^{N} Y_{i,j,k,t} \right), \quad \forall t = 1 : T, \quad \forall j = 1 : ss} \tag{7}$$

It is important not to have a negative value for $MT_{j,t}$. Thus, a constraint is introduced to the model in (8) to ensure its non-negativity.

$$RM_{j,t} - \sum_{k=1}^{RM_{j,t}} \left(\sum_{i=1}^{N} Y_{i,j,k,t} \right) \geq 0, \quad \forall t = 1 : T, \forall j = 1 : ss \tag{8}$$

There is a special constraint for maintenance capacity. The number of assets scheduled for maintenance for a given time unit is restricted by the capacity of the maintenance depot. This may be due to limitations of available space or personnel. Equation (9) shows the capacity constraint, where c_j is the capacity of the maintenance depot at time unit t.

$$\sum_{i=1}^{n} X_{i,t} \leq c_t \quad \forall t = 1 : T \tag{9}$$

Another constraint ensures that at any time t, an asset can be on maintenance or on mission or idle. Thus, no asset can be maintained and assigned in the same time unit. The first term in (10) shows an asset's maintenance schedule and the second term shows its assignment to any mission. The equation does not allow the sum of these numbers to be greater than 1. If the sum is 1, then the asset is either assigned to a mission or scheduled for maintenance. If the sum is 0, then the asset is idle, meaning that the asset is not scheduled for maintenance and no mission has been assigned.

$$X_{a,b,t} + \sum_{j=1}^{MS_t} \left(\sum_{k=1}^{RM_{j,t}} (Y_{i,j,k,t}) \right) \leq 1 \quad \forall t = 1 : T, \forall i = 1 : N \tag{10}$$

It is also possible to limit the use of assets for specific missions. For example, the model can define an upper limit for usage of an asset for specific mission types. The total number of assignments of asset i to mission type j is calculated as the sum given in (11), which is forced to be less than or equal to the limit ($L_{j,i}$).

$$\sum_{t=1}^{T} \left(\sum_{k=1}^{RM_{j,t}} (Y_{i,j,k,t}) \right) \leq L_{j,i} \quad \forall j = 1 : MS_{\boldsymbol{t}}, \forall i = 1 : N \tag{11}$$

The model described above involves a single asset type. However, there may be different types of assets in a fleet. It may not be possible to assign some asset types to some mission types. So that the model can handle such a requirement, different asset types have been defined. Each asset type has a different number of assets in the fleet, represented by N_i. Thus, the total number of assets is equal to the sum of the number of assets in each asset type ($N = \sum_{a=1}^{A} N_a$, where A is the number of asset types). Note that the notation of assignment decision variables should also be changed from $Y_{i,j,k,t}$ to $Y_{a,b,j,k,t}$, which represents the assignment of the bth asset of asset type a to the kth mission of mission type j. Also note that the number of decision variables does not change with this notation if the total number of assets is the same. In order not to assign asset type h to mission type v, the sum of all the binary decision variables representing the banned assignment should be equal to 0, as in (12).

$$\sum_{b=1}^{N_h}\left(\sum_{t=1}^{T}\left(\sum_{k=1}^{RM_{b,t}} Y_{h,b,v,k,t}\right)\right) = 0 \tag{12}$$

The optimization model discussed above is given as a full formula below. The objective is to find the best maintenance and mission schedule that minimizes the total cost by satisfying the given constraints.

Objective function:

$$\text{Min } Z = \sum_{a=1}^{A}\sum_{b=1}^{N_a}\left(CP_{a,b} \times F_{a,b} + M_{a,b} \times \sum_{t=1}^{T} X_{a,b,t}\right) + \sum_{j=1}^{S}\left(C_j \times \sum_{t=1}^{T} MT_{j,t}\right)$$

Constraints:

(1) $CP_{a,b} = \bigcup_{t=1}^{T} (P_{a,b,t}) \quad \forall a = 1 : A, \forall b = 1 : N_a$

(2) $P_{a,b,t} = \begin{cases} 0 & If X_{a,b,t} = 1 \\ FP^1_{a,b,t} \times \max\left(0, 1 - \sum_{t=1}^{j-1} X_{a,b,t}\right) & \\ +FP^2_{a,b,t-T(m)} \times \min\left(1, \sum_{t=1}^{j-1} X_{a,b,t}\right) & If X_{a,b,t} = 0 \end{cases}$

$\forall t = 1 : T, \forall a = 1 : A, \forall b = 1 : N_a$

(3) $MT_{j,t} = RM_{j,t} - \sum_{k=1}^{RM_{j,t}}\left(\sum_{a=1}^{A}\left(\sum_{b=1}^{N_a}(Y_{a,b,j,k,t})\right)\right) \quad \forall t = 1 : T, \forall j = 1 : ss$

(4) $RM_{j,t} - \sum_{k=1}^{RM_{j,t}}\left(\sum_{a=1}^{A}\left(\sum_{b=1}^{N_a}(Y_{a,b,j,k,t})\right)\right) \geq 0 \quad \forall t = 1 : T, \forall j = 1 : ss$

(5) $\sum_{a=1}^{A}\left(\sum_{b=1}^{N_a}(X_{a,b,t})\right) \leq c_t \quad \forall t = 1 : T$

(6) $X_{a,b,t} + \sum_{j=1}^{S}\left(\sum_{k=1}^{RM_{j,t}}(Y_{a,b,j,k,t})\right) \leq 1 \quad \forall t = 1 : T, \forall a = 1 : A, \forall b = 1 : N_a$

(7) $\sum_{t=1}^{T}\left(\sum_{k=1}^{j}(Y_{a,b,j,k,t})\right) \leq L_{j,a,b} \quad \forall j = 1 : S, \forall a = 1 : A, \forall b = 1 : N_a$

(8) $\sum_{b=1}^{N_h}\left(\sum_{t=1}^{T}\left(\sum_{k=1}^{RM_{b,t}} Y_{h,b,v,k,t}\right)\right) = 0$ for given h and v

Decision variables (model output):

$X_{a,b,t}$ Binary decision variable indicating if maintenance is scheduled for the bth asset in asset type a at time t

$Y_{a,b,j,k,t}$ Binary decision variable indicating if the kth mission of mission type j has been assigned to the bth asset in asset type a at time t

Input parameters:

N_a Number of assets in asset type a

A Number of asset types in the fleet

T Time period when the maintenance schedule and mission assignment will be performed

ss Number of mission types

Table 1. Binary variables.

		Time				
		1	2	3	4	5
UAV1	Mission 1	0	1	1	0	0
	Mission 2	0	0	0	0	1
	Maintenance	1	0	0	1	0
UAV2	Mission 1	1	0	0	0	0
	Mission 2	0	1	1	0	0
	Maintenance	0	0	0	0	1
New format	UAV1	01	10	10	01	11
	UAV2	10	11	11	00	01

Note: UAV = unmanned aerial vehicle.

MS_j Number of missions in mission type j
$F_{a,b}$ Failure cost of the bth asset in asset type a (repair, downtime cost)
$M_{a,b}$ Maintenance cost of the bth asset in asset type a; it is expected that $M_{a,b} < F_{a,b}$
C_j Cost of delaying the mission type j by one time unit
$RM_{j,t}$ Required number of missions for mission type j to be completed at time t
c_t Maximum number of assets that can be maintained at unit time t
$L_{j,a,b}$ Maximum number of times the bth asset in asset type a can be assigned to mission type j
$FP^1_{a,b,t}$ Failure probability forecast obtained from the prognostics module for the bth asset in asset type a at time t
$FP^2_{a,b,t}$ Failure probability forecast after maintenance obtained from reliability analysis for the bth asset in asset type a at time t

Calculated parameters in the model:

N Number of assets in the fleet
TMS Total number of missions required to be completed in given period
$CP_{a,b}$ Cumulative failure probability of the bth asset in asset type a within a given period
$P_{a,b,t}$ Effective failure probability of the bth asset in asset type a at time t
$MT_{j,t}$ Missed mission type j at time t

The computational complexity of the model is directly related to the number of decision variables. For a given problem, the model will involve $N \times T \times TMS + N \times T$ number of binary variables. The first term is the number of assignment decision variables ($N \times T \times TMS$) and the second term is the number of scheduling decision variables ($N \times T$). To reduce the number of decision variables, the decision variables are combined. A given asset at a given time can be assigned to a mission, maintained or left idle. Thus, TMS number of states is needed for missions, and two states are needed, one for maintenance and one for being idle. Assignment of an asset at a given time can be represented as a binary string of size $\log(TMS + 2)$. Table 1 gives examples of binary variables. The new decision variable format reduces the number of binary variables to $N \times T \times \log(TMS + 2)$.

4. Results and discussion

This section presents the implementation of the proposed mathematical model on mission and maintenance planning of a fleet of HVAs using simulated data. The implementation is performed using two cases. The first case aims to demonstrate the capability of finding the global optimum solution for a small problem with a fleet of four UAVs. The second case aims to demonstrate the effectiveness of the method over a longer time period. The cases involve different scenarios to enable understanding and analysis of the terms and factors in the objective function and the constraints of the proposed approach.

4.1. Case 1: Small-size fleet with short planning period

This case demonstrates maintenance and mission planning for a small fleet with two UAV types, with one UAV of each type (*i.e.* a total of two UAVs, $tN = 2$) and one mission type (*i.e.* a total of one missions, $tMS = 1$). The planning time horizon is set to 4 time units ($T = 4$) (*e.g.* days, weeks or months). The number of decision variables is 16 ($tN \times T \times \log(tMS + 2)$). The total number of potential maintenance and mission planning is 2^{16}, given 16 binary decision variables. It is possible to find the global best planning option among this number of potential options. Thus, this case is used to demonstrate the effectiveness of the proposed solution by comparing the best solution found with nonlinear optimization and the global best. The parameters used in the model are shown in Table 2. Parameters that are not related to cost have been determined as in previous studies (Camci 2014, 2015). Cost-related parameters have been determined based on the authors' best engineering judgement.

The cost of all potential maintenance schedule and mission planning was calculated and the best option is presented below. The best solution is shown in Table 3, in which UAV2 is assigned to mission 1 at all times and UAV1 is assigned to mission 1 at times 1 and 3. Thus, the required missions at all times (*i.e.* 2, 1, 2, 1 at given times) have been assigned to UAVs. The rows in the table show UAVs and the columns show the time units. 'Mis1' refers to assignment of a UAV in the corresponding row to mission 1 at the corresponding time in the column. 'Maint' refers to the maintenance scheduled for the corresponding UAV at the given time unit. This solution leads to a total cost of \$1409.20 (expected failure cost: \$1309.20; maintenance cost: \$100; missed mission cost: \$0). Note that the failure probability of UAV1 reaches 0.49 before the maintenance event at time unit 2. After maintenance, the failure probability starts at 0.01 and reaches 0.1 at the end of the planned time period. The cumulative failure probability for UAV1 is 0.541, which is calculated as the union of 0.49 and 0.1. The expected failure cost of UAV1 is 649.2 (0.541×1200). The failure probability of UAV2 is 0.6 since no maintenance is scheduled. The expected failure cost of UAV2 is 660 (0.6×1100). The total expected failure cost is 1309.2.

The proposed optimization model was implemented to find the optimum solution for this case. The model was run 10 times and the best solution was found for all 10 runs, with an average computational time of 6.74 s (maximum = 13.44 s; minimum = 5.41 s). Note that finding the global best solution through iterations of all possible solutions (*i.e.* $2^{16} = 65{,}536$) took 26.67 s.

Table 2. Input parameters for the small fleet case.

Parameter		UAV1			UAV2
Failure cost		1200			1100
Maintenance cost		100			100

Parameter		Time 1	2	3	4	5
Required number of missions		2	1	2	1	N/A
Maintenance capacity		5	5	5	5	N/A
Assignment limit		5	5	5	5	N/A
Assignment restrictions		N/A	N/A	N/A	N/A	N/A
Cost of not performing a mission		300,000	300,000	300,000	300,000	N/A
Failure probabilities						
FP1	UAV1	0.42	0.49	0.55	0.64	0.71
	UAV2	0.4	0.45	0.5	0.55	0.6
FP2	UAV1	0.01	0.05	0.1	0.15	0.2
	UAV2	0.02	0.08	0.16	0.21	0.23

Note: UAV = unmanned aerial vehicle; FP1 = failure probability before maintenance; FP2 = failure probability after maintenance; N/A = not applicable.

Table 3. Optimum maintenance (Maint) and mission (Mis) planning for the small fleet case.

	Time			
Assets	1	2	3	4
UAV1	Mis1	Maint	Mis1	–
UAV2	Mis1	Mis1	Mis1	Mis1

Note: UAV = unmanned aerial vehicle.

Table 4. Optimum maintenance (Maint) and mission (Mis) planning for scenario 1 of the small fleet case.

	Time			
Assets	1	2	3	4
UAV1	Mis1	Mis1	Mis1	Mis1
UAV2	Mis1	Maint	Mis1	–

Note: UAV = unmanned aerial vehicle.

Table 5. Optimum maintenance (Maint) and mission (Mis) planning for scenario 2 of the small fleet case.

	Time			
Assets	1	2	3	4
UAV1	Maint	Mis1	Mis1	Mis1
UAV2	Mis1	Mis1	Mis1	Mis1

Note: UAV = unmanned aerial vehicle.

The model will be discussed with several scenarios by changing some of the parameters given in the base scenario above. In scenario 1, consider that an incipient failure is detected in UAV2 and its failure probabilities in the planning horizon are increased as follows: 0.6, 0.7, 0.8, 0.9, 0.95. The increase in the expected failure cost for UAV2 leads to maintenance, and the optimum maintenance and mission planning changes, as shown in Table 4. UAV2 is set for maintenance at time 2 and UAV1 is used mostly to satisfy the mission requirements. The total cost of such a plan is calculated as \$1774.80 (expected failure cost: \$1674.80; maintenance cost: \$100). The optimization model was run 10 times and the best solution presented below was found in all runs. The average computation time is 5.92 s (maximum = 6.8 s; minimum = 5.4 s).

Scenario 2 demonstrates the trade-off between not meeting a mission requirement and failure cost. To force the assignment of all UAVs for the mission, the mission requirement for all times is changed to 2. However, the failure cost for UAV1 and UAV2 has been increased to \$12,000 and \$11,000. The cost of not meeting a mission is changed to \$1000. Thus, the optimum solution offers an early maintenance for the asset, for which the reduced failure cost is more than the sum of the maintenance cost and missed mission cost. The total cost of the optimum solution in scenario 2, shown in Table 5, is \$13,784 (expected failure cost: \$12,684; maintenance cost: \$100; missed mission cost: \$1000).The presented optimization model was run 10 times and eight of these runs led to the optimum solution. The other two runs led to a local optimum solution with the total cost of \$14,192, which schedules the maintenance of UAV1 to time 2 instead of time 1.

Scenario 3 is based on scenario 2 and involves a different requirement of only one mission at time 2. Thus, maintenance should be scheduled at time 2 since only one UAV mission is required at this time. The optimum solution given in Table 6 leads to a total cost of \$13,192.The optimization model was run 10 times and the optimum solution was found in six of the runs. The other four runs identified a local optimum with the cost of \$13,202, which schedules maintenance for both UAVs, leading to reduced cost but at the price of missing one mission. The computational time for this scenario is similar to the previous cases.

Table 6. Optimum maintenance (Maint) and mission (Mis) planning for scenario 3 of the small fleet case.

	Time			
Assets	1	2	3	4
UAV1	Mis1	Maint	Mis1	Mis1
UAV2	Mis1	Mis1	Mis1	Mis1

Note: UAV = unmanned aerial vehicle.

Table 7. Parameters for the large fleet case.

		Assets			
		UAV type 1		UAV type 2	
Parameter		UAV1	UAV2	UAV3	UAV4
Failure cost		12,000	12,000	13,000	13,000
Maintenance cost		100	100	100	100
Assignment limits					
Mission type 1		10	10	10	10
Mission type 2		10	10	10	10
Weibull distribution parameters					
FP2	Alpha	3	2.8	2.5	0.7
	Beta	2	1.7	1.8	2.1
	Starting input	0.1	0.1	0.1	0.1
FP1	Starting input	0.6	0.6	0.6	0.6
	Increase	0.2	0.3	0.4	0.25

Note: UAV = unmanned aerial vehicle; FP2 = failure probability after maintenance; FP1 = failure probability before maintenance.

Table 8. Mission type parameters for the large fleet case.

Assignment restrictions	Asset type 1	Asset type 2	Cost of not performing mission
Mission type 1	N/A	N/A	300,000
Mission type 2	N/A	N/A	300,000

Note: N/A = not applicable.

4.2. *Case 2: Large-size fleet*

Case 2 involves two types of missions and UAVs. The fleet has two UAVs in both UAV types and two missions in one mission type. The parameters for the UAVs are given in Table 7. The failure and maintenance costs of each UAV are given first. Then, the assignment limits of UAVs to mission types are displayed. The failure probabilities before and after maintenance are obtained from a Weibull distribution, using the alpha and beta parameters given in the table. The starting input is the input parameter to calculate the corresponding failure probability. The degradation is obtained by increasing the input parameter by 0.1 in each time unit. The failure probability before maintenance uses the same alpha and beta parameters for a given UAV as the failure probability after maintenance. The differences are the starting point and probability increase defined in Table 7.

The maintenance capacity for the planning horizon is set as five for each time unit. Mission type parameters are shown in Table 8.

The number of parameters is 80 ($tN \times T \times \log(tMS + 2) = 4 \times 10 \times 2$)). The number of combinations is 2^{80} (1.20893E + 24), which is quite large. The optimization model was run 10 times. Table 9 shows the results of these runs. The proposed maintenance and mission schedule for the best solution obtained is presented in Table 10. The average computational time taken to obtain these results is 1093 s (minimum = 902 s, maximum = 1333 s).

Scenario 1 discussed above requires 29 missions distributed over the given time period with a length of 10 time units. In scenario 2, the total number of missions required over the time period is

Table 9. Total costs of 10 runs for scenario 1 in the large fleet case.

Results of 10 runs									
1	2	3	4	5	6	7	8	9	10
25,857	25,846	26,352	26,940	25,301	24,794	24,758	26,133	27,523	25,214
Max: 27,523		Min: 24,758		Average: 25,871.80		Stuck in solution with penalty: 0			

Table 10. Maintenance (Maint) and mission (Mis) planning of scenario 1 in the large fleet case.

		Time									
		1	2	3	4	5	6	7	8	9	10
UAV type 1	UAV1	Maint	Mis1	Mis2	Mis2	Mis1	Mis1	Maint	Mis2	Mis1	Mis1
	UAV2	Mis1	Mis2	Mis1	Maint	Mis1	Mis1	Mis1	Mis1	Maint	Mis2
UAV type 2	UAV3	Maint	Idle	Mis2	Mis2	Mis2	Mis2	Mis1	Mis2	Mis2	Mis2
	UAV4	Mis1	Maint	Mis1	Mis2	Mis2	Mis2	Mis2	Idle	Idle	Mis2
Required	Mis1	2	1	2	0	2	2	1	1	1	1
	Mis2	0	1	2	3	2	1	1	2	1	3
Performed	Mis1	2	1	2	0	2	2	1	1	1	1
	Mis2	0	1	2	3	2	1	1	2	1	3

Note: UAV = unmanned aerial vehicle.

Table 11. Total costs of 10 runs for scenario 2 in the large fleet case.

Results of 10 runs with 1000 generations									
1	2	3	4	5	6	7	8	9	10
33,307	32,542	31,253	625,978*	27,023	328,404*	33,168	32,750	30,627	30,170
Max: 625,978		Min: 27,023		Average: 120,522		*Stuck in solution with penalty: 2			
Results of 10 runs with 3000 generations									
1	2	3	4	5	6	7	8	9	10
34,736	28,588	27,869	33,194	26,865	327,003*	28,323	28,323	32,883	29,203
Max: 327,003	Min: 26,865		Average: 59,699		*Stuck in solution with penalty: 1				

increased to 34 (Table 12). Finding the solution in this scenario, with a higher number of required missions, is more difficult. The model was run 10 times, changing only the required missions. The average computational time for scenario 2 is 885 s (minimum = 802 s; maximum = 931 s). It can be seen in Table 11 that the GA may become stuck in solutions with missed mission penalty values in two of the 10 runs. Runs 4 and 6 lead to solutions with an inability to assign UAVs to two and one missions, respectively (marked with asterisks in Table 11). The scenario was run 10 times, changing the number of generations from 1000 to 3000. The average computational time of these runs increases to 4742 s, (minimum = 2760 s; maximum = 8111 s). The increase in the number of generations in the GA leads to better results even for more complex problems involving more mission requirements, at the price of higher computational time. As can be seen from Table 11, the maximum, minimum, average and number of solutions with penalty have been reduced with the higher number of generations.Table 12 displays the maintenance and mission plan obtained as a result of the best solution obtained for scenario 2. This result proposes that UAV1 be maintained at time 2, UAV2 at times 2 and 6, UAV3 at times 4 and 9, and UAV4 at time 8.

In scenario 3, the restriction of assigning a UAV for a given mission is demonstrated. The total number of allowable assignments of UAV1 to mission 1 is set to 0. All other parameters are set the same as the base scenario for this case. The solutions with penalty cannot assign a UAV for a required mission. Table 13 displays the results of 10 runs for scenario 3. Table 14 displays the maintenance and mission plan for scenario 3. As seen from the results, UAV1 has not been assigned to mission 1 owing to the introduced limitation. This is true for the results of all 10 runs.

Table 12. Maintenance (Maint) and mission (Mis) planning for scenario 2 of the large fleet case.

		Time									
		1	2	3	4	5	6	7	8	9	10
UAV type 1	UAV1	Mis1	Maint	Mis2	Mis2	Mis2	Mis1	Mis1	Mis2	Mis1	Mis2
	UAV2	Mis2	Maint	Mis2	Mis2	Mis1	Maint	Mis2	Mis1	Mis1	Mis1
UAV type 2	UAV3	Mis1	Mis1	Mis1	Maint	Mis2	Mis1	Mis1	Mis2	Maint	Mis2
	UAV4	Mis2	Mis2	Mis1	Mis2	Mis1	Mis2	Mis2	Maint	Mis2	Mis2
Required	Mis1	2	1	2	0	2	2	2	1	2	1
	Mis2	2	1	2	3	2	1	2	2	1	3
Performed	Mis1	2	1	2	0	2	2	2	2	2	1
	Mis2	2	1	2	3	2	1	2	1	1	3

Note: UAV = unmanned aerial vehicle.

Table 13. Total costs of 10 runs for scenario 3 of the large fleet case.

Results of 10 runs									
1	2	3	4	5	6	7	8	9	10
28,777	25,689	26,122	26,753	28,320	26,300	325,333*	326,299*	324,914*	26,486
Max: 326,299		Min: 25,689		Average: 116,499		*Stuck in solution with penalty: 3			

Table 14. Maintenance and mission plan in scenario 3 for large fleet case.

		Time									
		1	2	3	4	5	6	7	8	9	10
UAV type 1	UAV1	Idle	Maint	Miss2	Miss2	Miss2	Miss2	Miss2	Maint	Idle	Miss2
	UAV2	Maint	Miss1	Miss1	Miss2	Miss2	Miss1	Maint	Miss2	Miss1	Miss1
UAV type 2	UAV3	Miss1	Miss2	Miss2	Maint	Miss1	Miss1	Maint	Miss1	Idle	Miss2
	UAV4	Miss1	Maint	Miss1	Miss2	Miss1	Miss2	Miss1	Miss2	Miss1	Miss2
Required	Mis1	2	1	2	0	2	2	1	1	1	1
	Mis2	0	1	2	3	2	1	1	2	1	3
Performed	Mis1	2	1	2	0	2	2	1	1	1	1
	Mis2	0	1	2	3	2	1	1	2	1	3

5. Conclusion

This article presents a methodology to perform mission and maintenance planning together, using current and forecast health information on the HVA. The main contribution of this article is the mathematical modelling for integrated maintenance and mission planning. The presented method is a nonlinear optimization model with binary decision variables representing maintenance scheduling of assets in time units over the planning horizon and their assignments to the required missions. The method has been applied to two simulated cases with different scenarios.

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