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Cooperative game approach based on agent learning for fleet maintenance oriented to mission reliability

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ABSTRACT

Fleet maintenance oriented to mission reliability is a multi-level maintenance planning problem that becomes highly difficult due to the various reliability models of equipment and fleet. A three-level decision structure for fleet maintenance is established, the objective is maintenance cost, the constraints is the reliability of fleet, and the variables are the maintenance statuses of line replaceable modules. Then, the fleet maintenance process is translated into game behavior among considerable equipment with different statuses. A cooperative game framework based on agent learning is developed. A convergence condition for optimization is proposed by a simulated annealing approach. In the game method, three types of learning signals and their evaluation rules are introduced to establish the equipment's reduced strategy space. Thus, the computation amount of game can be controlled, and the reliability constraints can be satisfied during the game process. Furthermore, the assessment method for the equipment payoff with a penalty factor is established, and the rapid search algorithm of Pareto optimal solution is provided on the basis of the total revenue of game. A case study is performed on a fleet of 15 aircrafts to prove that the proposed approach can reduce the maintenance cost effectively and can meet the fleet mission reliability requirements.

1. General introduction

Maintenance activities aim to restore an item for correction or to achieve better status (Shafiee & Chukova, 2013). The central issue in maintenance planning is the decision of when and how to organize maintenance activities (Li et al., 2016). The main maintenance strategies are corrective and preventive maintenance (Ding & Kamaruddin, 2015). For preventive maintenance, the time-based maintenance is gradually replaced with condition-based maintenance (CBM) in industry application (Keizer, Flapper, & Teunter, 2017; Sun, Zeng, Kang, & Pecht, 2012). Meanwhile, the maintenance actions can be classified according to the degree of repair, as follows: perfect maintenance; minimal maintenance; and imperfect maintenance (Wang & Pham, 2006). Furthermore, to make a practicable maintenance plan, some factors to consider include cost, resources, time, reliability, and availability (Gavranis & Kozanidis, 2015; Khatab, Aghezzaf, Djelloul, & Sari, 2017; Khatab, Ait-Kadi, & Rezg, 2014; Kozanidis, Gavranis, & Liberopoulos, 2014; Liu, Xie, Xu, & Kuo, 2016; Sikorska, Hodkiewicz, & Ma, 2011).

Generally, a maintenance action is carried out on a specific component, unit, or module. However, maintenance planning should be developed on equipment or fleet level, because one equipment must share the maintenance resources with other equipment in a fleet (Papakostas, Papachatzakis, Xanthakis, Mourtzis, & Chryssolouris, 2010; Rawat & Lad, 2015; Rawat & Lad, 2016; Schneider & Cassady, 2015). Many studies have focused on the equipment level, which involved repairing a set of components in accordance with their status and dependency; some typical topics include multi-component system problems (Chalabi, Dahane, Beldjilali, & Neki, 2016; Liu & Lv, 2015; Zhu, Fouladirad, & Bérenguer, 2016), opportunistic maintenance problem (Babishin & Taghipour, 2016; Zhang, Gao, Guo, Li, & Yang, 2017), and selective maintenance problem (Dao & Zuo, 2016; Khatab, Aghezzaf, Diallo, & Djelloul, 2017; Khatab et al., 2017). However, it is not enough to develop the maintenance planning on the equipment level; planning on the fleet level should also be performed to improve practical significance (Al-Thani, Ahmed, & Haouari, 2016; Feng, Bi, Zhao, Chen, & Sun, 2017; Kozanidis, 2009; Liang, Chaovalitwongse, Huang, & Johnson, 2011; Liu & Huang, 2010; Papakostas et al., 2010; Rawat & Lad, 2015; Rawat & Lad, 2016; Schneider & Cassady, 2015; Wijk, Andersson, Block, & Righard,

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2017; Yoo & Lee, 2016). In these studies, some of the topics only involve fleet and equipment levels, such as flight and maintenance (Kozanidis, 2009) and aircraft maintenance routing problems (Al-Thani et al., 2016; Liang et al., 2011). The problem and approach for these topics are similar to equipment level maintenance planning.

But in practice, an effective maintenance decision on fleet level should include at least three levels of fleet, equipment, and component (Feng et al., 2017; Liu & Huang, 2010; Papakostas et al., 2010; Rawat & Lad, 2015; Rawat & Lad, 2016; Schneider & Cassady, 2015). Thus, the maintenance planning on fleet level should determine when to repair which equipment and what the equipment's components are. Further, the fleet maintenance problem is NP-hard because the number of strategy will increase rapidly along with the number of equipment and components (Feng et al., 2017). The main methods for solving fleet level maintenance planning are as follows:

(1) Mathematical Programming (Moghaddam, 2013; Mollahassani-Pour, Abdollahi, & Rashidinejad, 2014; Safaei, Banjevic, & Jardine, 2011). This approach deals with the maintenance planning as an integer programming problem. The maintenance state or the working state of the object is the decision variable, and the variable is usually valued by 0 and 1. However, pure mathematical programming approach is invariably oversimplified, and the problem scale cannot be too large.
(2) Heuristic Algorithm: A heuristic algorithm can be used to solve a relatively large scale of planning in combination with other methods. Some typical approaches include genetic algorithm (Liu & Huang, 2010; Wijk et al., 2017), ant colony optimization (Berrichi, Yalaoui, Amodeo, & Mezghiche, 2010; Fetanat & Shafipour, 2011) simulated annealing approach (Doostparast, Kolahan, & Doostparast, 2015; Schlünz & Van Vuuren, 2013), and game approach (Feng et al., 2017; Pourahmadi, Fotuhi-Firuzabad, & Dehghanian, 2017). Furthermore, some special heuristic rules could be studied for a given problem (Kozanidis, 2009; Sikorska et al., 2011).
(3) System Simulation (Mattila & Virtanen, 2014; Sheng & Prescott, 2017): This method can deal with fleet maintenance for special system with different scales. The fleet maintenance process can be converted to a corresponding simulation model, and the solution can be obtained by combining with a certain search algorithm. However, the solution depends on the accuracy of the model
(4) Knowledge-based approach (Li et al., 2016; Vujanović, Momčilović, Bojović, & Papić, 2012). Similar to the simulation method, this can be applied to a specific system, and it can also address problem with different scale. The knowledge of maintenance planning is stored in the database, and then, the solution can be given according to the condition stipulated by certain rules.

For an operating fleet, a timely maintenance decision must be provided in the field to ensure the success of the subsequent mission with limited resources. Some limitations of existing studies on fleet maintenance include less consideration on CBM, simple reliability model, and inefficient algorithm. Consideration of these limitations complicates the fleet maintenance problem, making it more difficult to solve.

To bridge the abovementioned research gaps, the condition-based fleet maintenance (CBFM) problem is studied. This paper is organized as follows. Section 2 elucidates the description and modeling for CBFM with complex reliability models. Section 3 presents a solving framework, including the outer loop based on simulated annealing, and the inner loop based on agent learning, and cooperative game. Section 4 provides the evaluation approach of learning signal and cooperative game algorithm. Section 5 introduces the case study that concerns a fleet of 15 aircrafts along with analysis and discussion. Section 6 presents concluding remarks.

2. Problem description and modeling

2.1. Structure of Decision-making for CBFM

A fleet containing m the same equipment supported by q integrated support stations (ISSs) ($q < m$) is considered (Fig. 1). The mission preparation period is from time t_0 to t_d, and the end time of mission is t_a. To ensure fleet mission reliability, the number of equipment that must work is usually less than m and is denoted by l. Each equipment contains n key line replaceable modules (LRMs).

The LRM status can be measured in accordance with the remaining useful life (RUL). The RULs of all the LRMs in each equipment are used as input. The RULs of different LRMs differ because of the differences in working conditions, and can be monitored at time t_0. The RUL value can be predicted by data-driven, physics-based, or hybrid/fusion prognostics methods (Baraldi, Cadini, Mangili, & Zio, 2013; Cai, Zhao, Liu, & Xie, 2017; Si, Wang, Hu, & Zhou, 2011; Sikorska et al., 2011; Sun et al., 2012). The RUL results obtained from these methods are usually in three forms of mathematical expression, including point estimated value, interval estimated value, and random distribution, such as Normal, Log-normal, Weibull, inverse Gaussian distribution. Furthermore, the informational random distribution rather than the point and interval value is adopted to describe the RUL in this study.

The condition-based fleet maintenance (CBFM) involves three levels of decision making with time sequence, including LRM, equipment, and fleet levels, as shown in Fig. 2. As a dynamic decision-making problem, the decision results of different stages in CBFM have some dependencies.

On the LRM level, the maintenance decision for LRM should be made depending on its health status. According to the probability that the RUL of LRM cannot meet the requirement of mission, i.e. $\int_{t_0}^{t_a} f(t)$, the strategy of each LRM can be divided into three types, including necessary maintenance, opportunistic maintenance, and without maintenance.

$$SL = \begin{cases} SL_1 : \ \text{Necessary maintenance} & \int_{t_0}^{t_a} f(t)dt \geqslant \alpha \\ SL_2 : \text{Opportunistic maintenance} & \beta < \int_{t_0}^{t_a} f(t)dt < \alpha \\ SL_3 : \text{Without maintenance} & \int_{t_0}^{t_a} f(t)dt \leqslant \beta \end{cases} \tag{1}$$

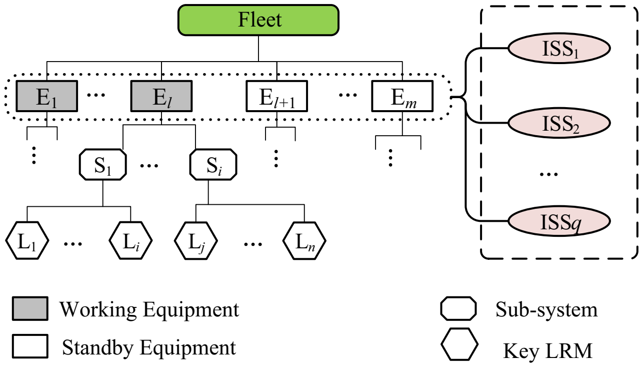

Fig. 1. System structure of CBFM problem.