An Intelligent Fleet Condition-Based Maintenance Decision Making Method Based on Multi-Agent

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ABSTRACT

According to the demand for condition-based maintenance online decision making among a mission oriented fleet, an intelligent maintenance decision making method based on Multi-agent and heuristic rules is proposed. The process of condition-based maintenance within an aircraft fleet (each containing one or more Line Replaceable Modules) based on multiple maintenance thresholds is analyzed. Then the process is abstracted into a Multi-Agent Model, a 2-layer model structure containing host negotiation and independent negotiation is established, and the heuristic rules applied to global and local maintenance decision making is proposed. Based on Contract Net Protocol and the heuristic rules, the maintenance decision making algorithm is put forward. Finally, a fleet consisting of 10 aircrafts on a 3-wave continuous mission is illustrated to verify this method. Simulation results indicate that this method can improve the availability of the fleet, meet mission demands, rationalize the utilization of support resources and provide support for online maintenance decision making among a mission oriented fleet.

1. INTRODUCTION

When conducting a mission, an aircraft fleet consumes massive resources, especially maintenance manpower and resources. In practice, maintenance strategies usually combine the "fail and fix maintenance" with fixed preventive maintenance. The "fail and fix" strategy cannot prevent fatal accidents, which may endanger pilots' lives and reduce the mission availability, while fixed preventive maintenance strategy usually schedules excess maintenance actions to ensure availability, while ignoring the asynchronism of failures among a fleet and the shareability of maintenance resources, hence, cannot fully develop the overall efficiency of maintenance resources, causing a huge waste while cannot completely prevent failure (Jiang & Murthy, 2008). Besides, to ensure safety, a specific maintenance job is done at a specific site, which may lead to the incoordination between operational requirements and maintenance actions. In general, traditional "fail and fix" practice & fixed preventive maintenance practice are not completely suitable.

To tackle the difficult problem, Condition-Based Maintenance (*CBM*), which is based on the actual condition and development tendency of assets, is put forward (Bengtsson, 2004). The rapid development of Prognostics and Health Management (*PHM*) (Sun, Zeng, Kang & Pecht, 2012) approach and its application on battery (Goebel, Saha, Saxena, Celaya & Christophersen, 2008) and aero engine (Wen & Liu, 2011) makes *CBM* possible. In practice, an aircraft contains one or more Line Replaceable Modules (*LRM*) whose health condition development fit the deterioration process (Barata, Guedes, Marseguerra & Zio., 2002). *PHM* can help predict the Residual Useful Life (*RUL*) of deteriorating *LRMs* through condition monitoring, and help staff make maintenance decision. Through the application of *PHM*, a series of maintenance measures are provided in time, and the ideal *CBM* "need and fix" is achieved (Jardine, Lin & Banjevic, 2006). Moreover, since *RUL* can be estimated, maintenance actions can be performed dynamically according to operational requirements rather than in a fixed site. In a fleet, where maintenance tasks are heavy and resources are limited, the application of *CBM* can notably increase operational availability, reduce lifecycle costs and improve safety.

Traditional *CBM* is about safely extending maintenance intervals using *PHM* information, and is often applied to a single aircraft. Fleet oriented *CBM*, on the other hand, should consider many factors other than single aircraft *CBM*, such as mission requirement, maintenance teams, etc., to balance the whole fleet. Actually, the ideal process of fleet *CBM* is as follows: 1) Aircrafts obtain their *PHM* data. 2) The *PHM* data is transferred to the maintenance center. 3)

The maintenance center makes maintenance decisions. 4) The maintenance decisions are transferred to aircrafts and maintenance teams. 5) Maintenance action. So the fleet *CBM* problem is actually an "online" decision making problem. Besides, the fleet maintenance strategy is the combination of maintenance strategies for every single aircraft. For each single aircraft, the problem is to find the most suitable time and team while balancing the whole fleet, which is actually a routing problem. Routing problem has already proved to be N-P hard (Garey & Johnson. 1979), which is difficult to obtain the optimal or satisfying solution with the increase of problem scale. At present, the main solutions to fleet *CBM* problem include

1. Mathematical programming: Doganay and Bohlin (2010) studied the train fleet maintenance scheduling strategy & spare parts optimization with single station based on a mixed integer linear programming. Bai (2009) optimized the Life Limited Part (LLP) group maintenance schedule and the on-wing lifetime of an aero engine fleet based on immune particle swarm method.

2. Heuristic method: Reimann, Kacprzynski, Cabral and Marini (2009) designed a maintenance scheduling algorithm combining *CBM* with traditional fixed preventive maintenance using heuristic method, to reduce the maintenance cost of a fleet consisting of 50 aircrafts, and to predict the shortage of maintenance resources.

3. System simulation: Bivona and Montemaggiore (2005) tested different maintenance & management strategies based on system dynamics modeling and simulation. Dupuy, Wesely and Jenkins (2011) selected the best one out of three civil aviation fleet maintenance plans applying discrete event simulation with the help of ARENA®.

4. Artificial Intelligence: Cycon (2011) discussed the technique Sikorsky Aircraft Corporation (SAC) is applying to incorporate *CBM* capabilities into all its products. By data collecting from all products and data mining, normal versus anomalous behavior is established, and man-in-the-loop support allows experts from various engineering and support services groups to quickly recommend appropriate maintenance actions. Zhou, Fox, Lee and Nee (2004) applied Multi-Agent technique and heuristic rules to solve the bus maintenance scheduling problem, which has equal optimality to reported studies and requires less computing time.

5. Multiple criteria analysis: Papakostas, Papachatzakis, Xanthakis, Mourtzis and Chryssolouris (2010) applied the multiple criteria (Cost, *RUL*, Operational Risk & Flight Delay) based on specific mission to select the best out of a set of generated maintenance plan alternatives using Monte-Carlo simulation.

But there are still shortages between those methods and dynamic environments where online maintenance decision making and scheduling is required when an aircraft fleet execute combat tasks. Especially in:

1. Those methods lack consideration into the relationship between the health condition of the entire fleet and that of a single aircraft, ignoring the potential shortage of maintenance resources, and the maintenance scheduling strategy is usually not optimal.

2. Due to the uncertainty of tasks and variety of aircrafts' health condition, maintenance strategy needs to be generated according to mission demands, aircrafts' health condition and resource limits. Those methods lack consideration into online decision making.

The fleet maintenance problem involves a lot of communication among aircrafts and maintenance teams, and Multi-Agent Modeling technique can imitate the communication and cooperation among agents to model complex systems (Budenske, Newhouse, Bonney & Wu, 2001), and has been successfully applied in many fields of manufacturing, especially dynamic and distributed scheduling problems. Through communication and cooperation can aircrafts and maintenance teams acquire the health condition of the whole fleet, and the working condition of maintenance teams. Meanwhile, the fleet maintenance problem is an N-P hard problem, and a common solution to N-P hard problems is heuristic searching. Heuristic rules can be integrated into agents to help overcome the N-P hardness, and is a guide to the intelligent allocation of maintenance tasks (Yang & Hu, 2007). In one word, Multi-Agent Modeling is suitable for solving the aircraft fleet maintenance problem.

This paper is the application of Multi-Agent System (*MAS*) to aircraft fleet maintenance scheduling. In this article, the idea of *MAS* and heuristic rules is adopted, and the dynamic intelligent maintenance decision making among an aircraft fleet with multiple maintenance teams is achieved to provide technical support for the online maintenance decision making. The purpose of this paper is to propose a multi-agent model, which can not only react to dynamic events, but can also generate schedules for maintenance jobs, to help design a fleet maintenance Decision Support System (DSS).

The remainder of this paper is organized as follows. Section 2 presents the description of the fleet maintenance problem. In Section 3, the *MAS* model for fleet maintenance scheduling is described, where the heuristic rules are put forward. The algorithm in which the dynamic problem is solved and schedules are generated is discussed in Section 4. Section 5 provides a case study of a mission oriented aircraft fleet to demonstrate the proposed method. Finally, concluding remarks and further study are provided in Section 6.

2. FLEET CBM PROBLEM DESCRIPTION

Consider an aircraft fleet containing m aircrafts and n maintenance teams ($n<m$) face continuous combat missions, in which a single mission requires l aircrafts (l is dynamic and $l \leq m$). Each aircraft contains p LRMs whose RUL can be estimated. All maintenance teams are of the same ability, namely the same LRM requires the same Mean Maintenance Time (*MMT*), while different LRMs require different MMTs. The basic assumptions of the problem are listed below.

1. The current mission is known, namely the upcoming mission and mission interval duration are known, while future missions are unknown.

2. Consider in-site maintenance only, so maintenance method is "replace and repair", and parts are repaired as good as new, namely the RUL of replaced LRMs reach the top.

3. The RUL of each LRM in each aircraft decreases with mission time, or RUL doesn't decrease without a mission. Moreover, due to the differences in historical missions, the initial RUL of different LRMs in different aircrafts are different.

4. Spare parts in each team are sufficient, namely spare parts are always available whenever a maintenance task is required.

5. The estimation of RUL is accurate, so the case in which wrong strategy led by wrong estimations won't occur.

6. Each team can work on only one aircraft at one time, and each aircraft can be repaired by only one team at one time.

After the whole fleet return from the previous mission, each aircraft checks its own health condition, estimating RULs and comparing the RULs with maintenance thresholds to decide a possible maintenance. There can be one or more threshold (Camci, Valentine & Navarra, 2007), and in this article two thresholds are required, namely the Required Maintenance Threshold τ and the Opportunistic Maintenance Threshold T. Those two thresholds divide the aircraft into three health states. When $RUL \leq \tau$ the state is identified as the required maintenance state S_3 and a maintenance is required immediately. When $RUL>T$, the state is identified as the no maintenance state S_1 and no maintenance is scheduled. When RUL is between these two thresholds $\tau < RUL \leq T$, the state is identified as the opportunistic maintenance state S_2 and a possible maintenance task depends on the states of other aircrafts and the occupation of maintenance teams. T & τ can be set according to mission or by experience. For instance, τ must exceed the time before the aircraft returns from the next mission.
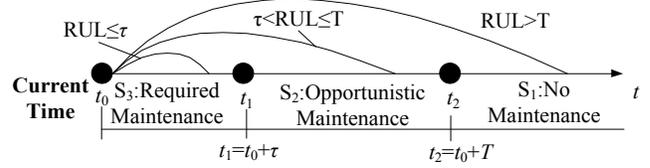

Figure 1. Maintenance thresholds and aircraft states

The objective of this problem is to maximize the availability of the fleet while the number of maintenance actions is satisfactory, and the basic constraints of the problem are:

1. The number of available aircrafts heading for the upcoming mission r must satisfy $r \geq l$.

2. The number of currently available teams s must satisfy $s \leq n$.

According to the description towards the problem above, when the fleet return from the previous mission, each aircraft checks its own health state S_t at the current time t_0, and reports to the maintenance center. The maintenance center verifies all the reports, organizes and coordinates maintenance tasks guided by a set of heuristic rules, and allocate maintenance tasks to suitable maintenance teams. Maintenance teams then execute maintenance tasks according to the maintenance center. When a maintenance task finishes, the fleet wait to execute the upcoming mission.

Each aircraft in the fleet will be repaired according to its condition. To all aircrafts, the combination of all maintenance decisions within the whole fleet forms a group of fleet CBM strategies aimed at utilizing the RULs of all aircrafts and the idle time of maintenance teams, in order to rationalize maintenance resources within the whole fleet.

3. THE FLEET CBM MODEL BASED ON MULTI-AGENT

The fleet CBM process involves a huge amount of communication among aircrafts, maintenance teams and the maintenance center. Moreover, maintenance teams and the maintenance center need to react to dynamic situations to make maintenance decisions and solve the problem, thus it can be regarded as a complex system (Zhang & Li, 2010), and one promising solution to complex systems is MAS. In MAS, an agent can be regarded as a self-directed software object with its own value system and a means to communicate with other agents (Baker, 1998), while the whole MAS can be regarded as "a loosely coupled network of problem solvers that work together to solve problems that are beyond the individual capabilities or knowledge of each problem solver" (Durfee, 1988). The fleet CBM process can be mapped into a similar MAS, where CBM strategies can be obtained via agents themselves and the communication between agents.

3.1. Model Framework

Through the analysis of the fleet *CBM* process, the physical entities can be abstracted into two types of agents, namely the Aircraft Agent (*AA*) and the Maintenance Agent (*MA*), and the dynamic process of management and coordination is abstracted into the Management and Coordination Agent (*MCA*).

AA is the abstract of an aircraft, it describes the inherent characteristics, the reliability characteristics, and is responsible for generating maintenance requirements. *MA* is the abstract of maintenance teams, and is responsible for specific maintenance process.

MCA is the abstract of the whole process of scheduling and intelligent allocating of maintenance tasks, it is driven by events, and is responsible for adjusting the whole process of maintenance, and obtaining the fleet maintenance strategy.

A 2-layer structure of *MAS* (Feng, Zeng & Kang, 2010) is applied to model the problem, each layer indicating the global scheduling and local scheduling, as shown in Figure 2.
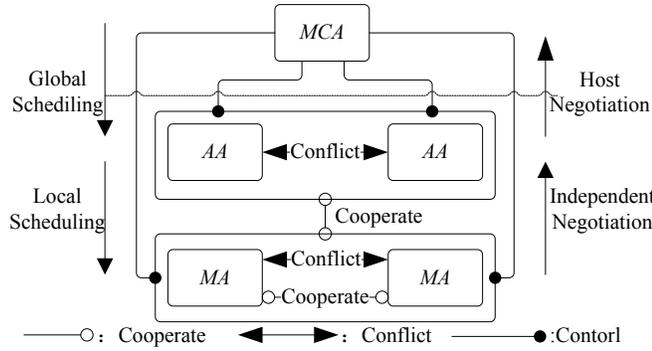

Figure 2. fleet *CBM MAS* model framework

Global Scheduling is conducted by *MCA*. When *MCA* receive the reports from *AA*s, it coordinates and controls the whole process and generates the overall maintenance strategy, to globally rationalize maintenance resources.

Local Scheduling is conducted between *AA*s and *MA*s, aimed at the negotiation in specific maintenance tasks.

3.2. Heuristic Rule-based Agent Negotiating Mechanism

The Contract Net Protocol (*CNP*) (Smith, 1980) is one of the most widely used agent negotiating mechanisms. Through imitating the "Calling-Bidding-Winning-Signing" process in economic behavior, *CNP* realizes the allocation, dynamic adjusting and converting of tasks among agents (Tang, Zhu, Li & Lei, 2010). Based on the *CNP*, the rationalization of the fleet *CBM* strategies is achieved.

In this article, all agents are assumed rational and friendly, their communication manifest cooperation and conflicts, which means that an agent is willing to cooperate with other agents, and maximize its own profit if possible. That

assumption caters for practical situations. For instance, each aircraft wishes to be repaired as early as possible. A maintenance team needs cooperation to repair all aircrafts, but wishes to repair as many aircrafts as possible.

Since the *MAS* model applies the 2-layer structure, the negotiating between agents is also divided into two layers, namely the Host Negotiating and the Independent Negotiating. As proved above, the problem of a fleet maintenance with multiple maintenance teams is N-P hard, it's difficult to obtain the satisfying solution. So in each layer, negotiation must follow its corresponding heuristic rules, as described below.

3.2.1. Heuristic Rules in Independent Negotiation

In Independent Negotiation, idle *MA*s communicate with *AA*s to obtain local maintenance strategies, the alternative maintenance decision making heuristic rules are listed below.

1. Aircrafts in the required maintenance state S_3

- The shortest total waiting time principle: all aircrafts in the required maintenance state S_3 are scheduled to shorten the average waiting time, or to even the working time of all maintenance teams. This rule is marked "Rule 11a".

- The most repairs within limited interval principle: once a maintenance team is idle, a maintenance task is performed on the aircraft with the shortest *MMT*. This rule is marked "Rule 11b".

- Single team with widest repair time margin principle: as many aircrafts are repaired by as few maintenance teams as possible, so as to leave the most teams idle, in case unexpected failures occur. This rule is marked "Rule 11c".

2. Aircrafts in the opportunistic maintenance state S_2

- The most repairs within limited interval principle: once a maintenance team is idle, a maintenance task is performed on the aircraft with the shortest *MMT*. This rule is marked "Rule 12a".

3.2.2. Heuristic Rules in Host Negotiation

In Host Negotiation, the *MCA* communicates with *AA*s to obtain global maintenance strategies, generates a group of local maintenance tasks and dispatches tasks to corresponding *MA*s. The whole process is listed below:

Assume that the number of aircrafts needed for the upcoming mission is l_n. *AA*s first report their health states S_t to the *MCA*. The *MCA* analyses all data reported and confirms the number of *AA*s in the required maintenance state S_3 m_3, the number of *AA*s in the opportunistic maintenance state S_2 m_2, and the number of *AA*s in the no maintenance state S_1 m_1. The *MCA* then calculates the

number of repairable aircrafts within the interval m_4 according to Rule 11a, Rule 11b and Rule 11c respectively, and gets the maximum number m_4, and the optimal rule is expressed as $Pro(Rul_i)$. The number of combat-ready AAs $m_a = m_1 + m_2 + m_4$. The alternative maintenance decision making heuristic rules are shown in Figure 3.
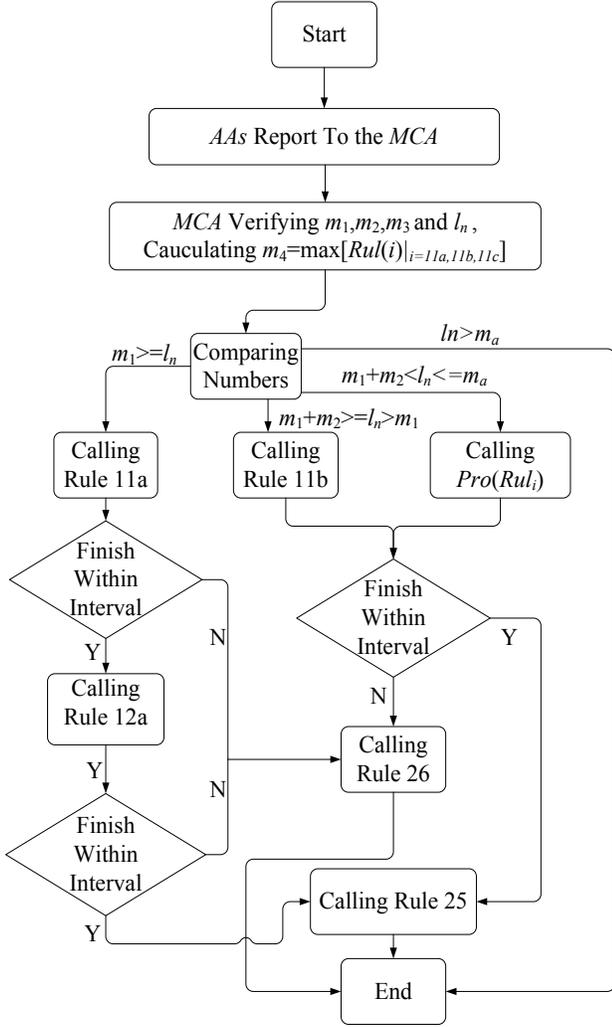

Figure 3. The flow chart of generating maintenance tasks

Based on the analysis above, the alternative maintenance decision making heuristic rules are listed below.

1. If $m_a < l_n$, then mission fails. This rule is marked "Rule 21".

2. If the number of AAs in the no maintenance state S_1 satisfies $m_1 \geqslant l_n$, then AAs in the no maintenance state S_1 are put on mission first, and AAs in the required maintenance state S_3 are repaired according to Rule 11a. When current task finishes, AAs in the opportunistic maintenance state S_2 are repaired according to Rule 12a, where AAs with the shortest MMT are repaired with high priority. This rule is marked "Rule 22".

3. If $m_1 < l_n \leqslant m_1 + m_2$, then AAs in the required maintenance state S_3 are repaired according to Rule 11b. This rule is marked "Rule 23".

4. If $m_1 + m_2 < l_n \leqslant m_1 + m_2 + m_4$, then AAs in the no maintenance state S_1 and the opportunistic maintenance state S_2 are put on mission first, and AAs in the required maintenance state S_3 are repaired according to $Pro(Rul_i)$. This rule is marked "Rule 24".

5. When the interval ends, each aircraft checks its health state again, and reports to the MCA. Then the MCA analyses the reported data and select l_n AAs with the shortest RUL out of all combat-ready AAs (AAs in the opportunistic maintenance state S_2, AAs in the no maintenance state S_1 and repaired AAs) to execute the mission. This rule is marked "Rule 25".

6. When mission starts, if there exists still AAs in the opportunistic maintenance state S_2 required maintenance state S_3 among all the left-over AAs, then those AAs are repaired according to Rule 11a and Rule 12a respectively. This rule is marked "Rule 26".

3.2.3. Agent Behavior in fleet CBM

Based on the analysis of the process of fleet CBM, the MAS model framework and the heuristic rules on solving maintenance strategies, the Agent Ability Chart (Feng, 2009) in fleet CBM is established, which finally defines agents' attributes and behaviors of function & fault, laying the foundation of solving the maintenance strategies.
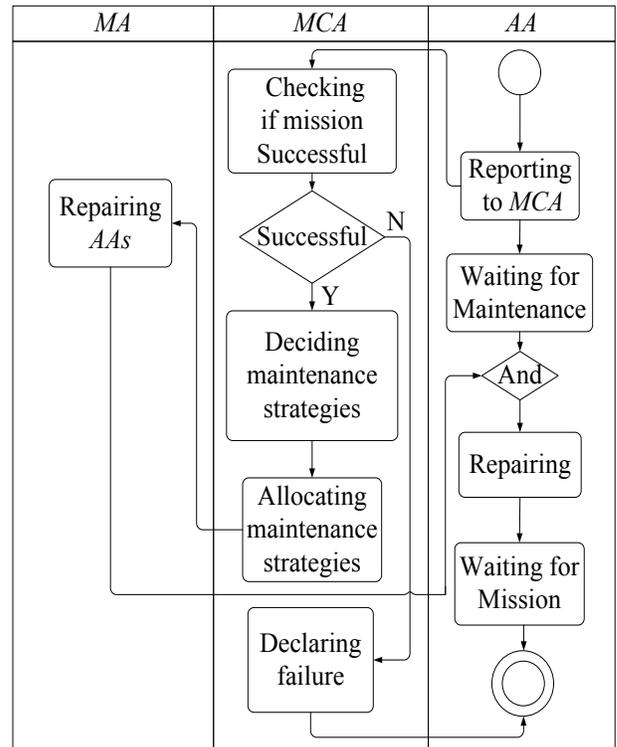

Figure 4. The Agent ability chart in fleet CBM

4. MAINTENANCE STRATEGY SOLVING ALGORITHM

AUML (Bauer, Müller & Odel, 2001), based on object oriented design, is a typical agent oriented modeling technique. It provides a uniform agent oriented modeling mechanism, and doesn't restrict too much on modeling process. The process of fleet *CBM* can be realized through the communication between *AA*s and *MA*s. With the help of AUML, the negotiating models between agents are established based on *CNP*.

Since the *CBM* model involves communication between and within layers, the problem is relatively complex. As space is limited, three of the most typical maintenance schemes are illustrated. These three corresponding algorithms are listed below.

4.1. The Shortest Total Maintenance Waiting Time Maintenance Scheme Negotiating Algorithm

This scheme is relatively integrated, which involves cooperative and competitive negotiations. The algorithm is listed below.

4.1.1. Cooperative Negotiation

Cooperative negotiation is required before a maintenance task starts. It's aimed at calculating the whole maintenance time needed and allocating each *MA* its corresponding maintenance time.
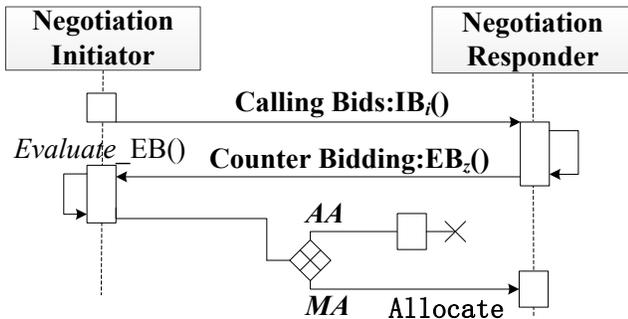

Figure 5. The cooperative negotiation mechanism

Step 1: The negotiation initiator calling for bids.

The first idle *MA i* (a random *MA* if there exists more than one) calls other *MA*s and all *AA*s for bids $IB_i(t_i|ta_i,tb_i)$, where t_i represents the latest bid time allowed, ta_i represents the earliest idle time of other *MA*s (Time to finish current task), tb_i represents the maintenance duration needed.

Step 2: The negotiation responders counter-bidding.

*MA*s and *AA*s assess their own status and counter-bid before t_i. The counter-bids from *MA*s are represented as $EB_j(t_j|ta_j)$, where t_j represents the waiting time, ta_j

represents the earliest idle time. While the counter-bids from *AA*s are represented as $EB_k(t_k|tb_k)$, where t_k represents the waiting time, ta_k represents the maintenance time needed.

Step 3: The negotiation initiator responding to all counter-bids

The negotiation initiating *MA* counts all counter-bids. Assume that m is the number of counter-bids from *MA*s and n is the number of counter-bids from *AA*s. Then based on the Shortest Total Maintenance Waiting Time Principle, The negotiation initiating *MA* calculates the Allocated Maintenance Time (*AM*T) to *MA j* through function *Evaluate_EB*(),

$$AMT_j = (\sum_1^m ta_j + \sum_1^n tb_k)/m - ta_j \tag{1}$$

and responds to each *MA* its *AMT*.

4.1.2. Competitive Negotiation

Competitive negotiation is required during the process of specific maintenance tasks. It's aimed at confirming maintenance strategy and realizing maintenance tasks.
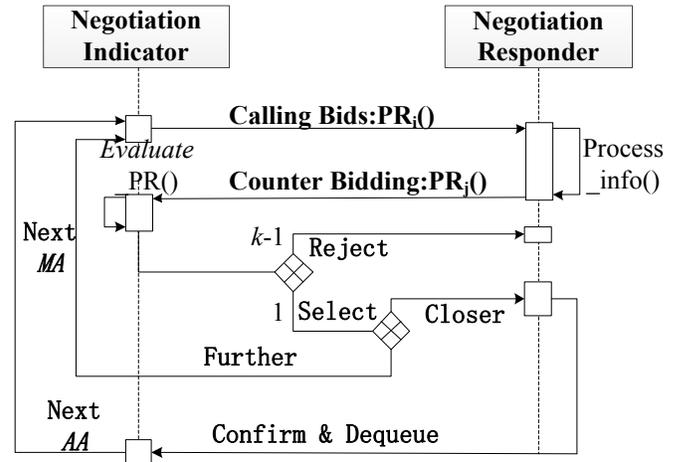

Figure 6. The competitive negotiation mechanism

Step 1: *MA* calling for bids.

The first idle *MA i* (a random *MA* if there exists more than one) calls all *AA*s for bids $PR_i(T_i|AMT_i)$, where T_i represents the latest bid time allowed, AMT_i represents the allocated maintenance time.

Step 2: *AA*s counter-bidding.

*AA*s assess their own status through function *Process_info*(). If it's within the candidate queue, then counter-bid before t_i. The counter-bids from *AA*s are represented as $PR_j(T_j|MMT_j)$, where T_j represents the waiting time, MMT_j represents the maintenance time needed.

Step 3: *MA* assessing all counter-bids

MA counts all counter-bids and assesses them through function *Evaluate_EB*(), ranking all counter-bidding *AA*s according to the length of *MMT* and selecting the candidate *a* with the closest *MMT* to *AMT*.

Step 4: *MA* judging whether to stop bidding.

MA updates its *AMT*: $AMT_{temp}=AMT-MMT_a$ for the moment. If abs (AMT_{temp}) < abs (AMT), then *MA* updates the $AMT=AMT_{temp}$ and responds to the selected *AA* and the selected *AA* then dequeues, repeat Step1 ~ Step3. Else, *MA* stops the current process of bidding and starts repairing all selected *AA*s.

Step 5: Other *MA*s start bidding according to the idle time order (a random *MA* if there exists more than one), repeat Step1 ~ Step4.

4.2. The Most Repairs Within the Limited Interval Maintenance Scheme Negotiating Algorithm
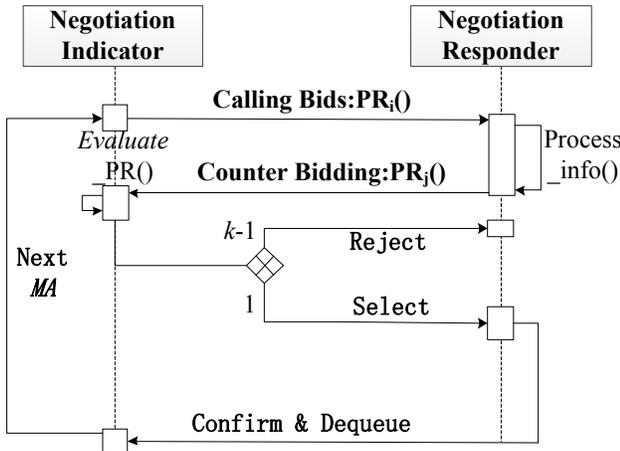

Figure 7. The most repairs within the limited interval maintenance scheme negotiation mechanism

Step 1: *MA* calling for bids.

The first idle *MA i* (a random *MA* if there exists more than one) calls all *AA*s for bids $PR_i(T_i|LMT_i)$, where T_i represents the latest bid time allowed, LMT_i represents the longest maintenance time.

Step 2: *AA*s counter-bidding.

*AA*s assess their own status through function *Process_info*(). If it's within the candidate queue, then counter-bid before t_i. The counter-bids from *AA*s are represented as $PR_j(T_j|MMT_j)$, where T_j represents the waiting time, MMT_j represents the maintenance time needed.

Step 3: *MA* assessing all counter-bids

MA counts all counter-bids and assesses them through function *Evaluate_EB*(), ranking all counter-bidding *AA*s according to the length of *MMT* and selecting the candidate *a* with the shortest *MMT*. Then repair task starts, when task finishes, *MA* updates its $LMT=LMT-MMT_a$.

Step 4: The repaired *AA* then dequeues. Other *MA*s start bidding according to the idle time order (a random *MA* if there exists more than one), repeat Step1 ~ Step3.

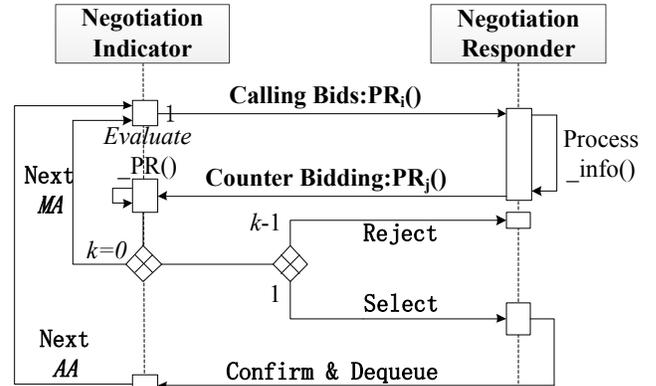### 4.3. Single Team with Widest Repair Time Margin Maintenance Scheme Negotiating Algorithm

Figure 8. Single team with widest repair time margin maintenance scheme negotiation mechanism

Step 1: *MA* calling for bids.

The first idle *MA i* (a random *MA* if there exists more than one) calls all *AA*s for bids $PR_i(T_i|LMT_i)$, where T_i represents the latest bid time allowed, LMT_i represents the longest maintenance time.

Step 2: *AA*s counter-bidding.

*AA*s assess their own status through function *Process_info*(). If it's within the candidate queue, then counter-bid before t_i. The counter-bids from *AA*s are represented as $PR_j(T_j|MMT_j)$, where T_j represents the waiting time, MMT_j represents the maintenance time needed.

Step 3: *MA* assessing all counter-bids

MA counts all counter-bids and assesses them through function *Evaluate_EB*(), ranking all counter-bidding *AA*s according to the length of *MMT* and selecting the candidate *a* with the closest *MMT* to *LMT*. Then the selected *AA* dequeues.

Step 4: *MA* updates its $LMT=LMT-MMT_a$ and repeats Step1 ~ Step3, till there's no suitable candidate. Then stop bidding and start repairing all selected *AA*s.

Step 5: Other *MA*s start bidding according to the idle time order (a random *MA* if there exists more than one), repeat Step1 ~ Step4.

5. CASE STUDY

A typical continuous mission of a fleet is presented to verify the proposed fleet *CBM* decision making strategy. Assume a fleet consisting of 10 aircrafts, each monitoring the condition of two *LRM*s and predicting their corresponding *RUL*s, which carries on a 3-wave mission. The time property of the mission is listed in Table 1

No.	Start Time (*h*)	Mission (*h*)	Interval (*h*)
1	1	2	2
2	5	3	1
3	9	2.5	-

Table 1. Time property of the mission

During the mission, there exist two maintenance teams to support the whole fleet. The maintainability (*MMT*) of the two *LRM*s are listed in Table 2

LRM Sorts	MMT (*h*)
LRM_1	0.5
LRM_2	1

Table 2. Reliability and maintainability data

To effectively verify this method, assume that some aircrafts are in the no maintenance state S_1 while others are in the opportunistic maintenance state S_2, hence all aircrafts can take part in the first mission, and no maintenance is considered before the first wave. The initial *RUL* of all aircrafts in the fleet are listed in Table 3

Aircraft / LRM	1	2	3	4	5
LRM_1	16.3	8.5	12.6	5.6	19.1
LRM_2	18.1	18.2	5.9	10.9	19.2

Aircraft / LRM	6	7	8	9	10
LRM_1	5.1	19.1	16.0	8.4	15.8
LRM_2	19.4	9.7	5.8	18.3	19.1

Table 3. The initial *RUL* of the fleet

Since the future missions are unknown, the maintenance thresholds can be decided as: τ is the time before the aircraft return from the next mission, and T is $T = 2 \times \tau$. On each inspection, the maintenance thresholds are listed in Table 4

Maintenance thresholds(*h*)	First Inspection	Second Inspection
τ	3	2.5
T	6	5

Table 4. Maintenance thresholds on each inspection

Assume that the first wave requires 8 aircrafts, the second wave requires 6 and the third wave requires all aircrafts. Based on our former assumptions and the maintenance decision making rules, maintenance strategies can be obtained as listed in Table 5, where the 2nd and 3rd column indicates the number of aircrafts repaired in the team. For instance, "3,4" means aircraft 3 and 4 are repaired in team 1. The 4th column indicates the spared aircrafts from the mission, for instance, "1,5" indicates aircraft 1 and 5 are spared from this mission. The 5th column indicates whether this mission is successful.

Waves	Queue 1	Queue 2	Spared	Mission Succeed
1	null	null	1,5	Y
2	3,4	6,8	1,5,6,8	Y
3	2,9	7	null	Y

Table 5. Fleet maintenance strategies.

Traditional *CBM* methods, which concentrates more on "timely" maintenance decision making rather than "online", can hardly make maintenance decisions online, so is not comparable with the *MAS* method. To make the comparison possible, *MAS* is applied to model traditional *CBM* policy, which assumes that an aircraft is repaired only when it comes to the required maintenance state S_3, relies on a single threshold, and ignores the states of the whole fleet and the maintainability of limited teams. Assume that the initial state, mission time property and maintainability of teams are the same, and the fleet maintenance strategies are listed in Table 6

Waves	Queue 1	Queue 2	Spared	Mission Succeed
1	null	null	1,5	Y
2	null	null	1,5,6,10	Y
3	3	4,6	8	N

Table 6. Single threshold fleet maintenance strategies

The table shows that before the 3rd wave, aircraft 3,4,6,8 all need repairing, and the total time required is 3*h*, which exceeds the maximum time teams can offer, so mission fails.

The case above shows that the 2-thresholds *CBM* policy is superior to traditional single-threshold *CBM* policy in both flexibility and results.

6. CONCLUSION

In this paper, a fleet *CBM* intelligent decision making method based on *MAS* and heuristic rules is proposed, which is a technical support for fleet online maintenance decision making, and can help design a fleet maintenance Decision Support System (DSS). A fleet consisting of 10 aircrafts and 2 teams is illustrated to verify the correctness and feasibility of this method.

To avoid the local optimal solution, host negotiating is proposed to coordinate the global maintenance strategies, which can not only guarantee the correctness and feasibility of the solution, but also optimize the global maintenance strategy.

A 2-thresholds *CBM* policy is proposed, and results show that the 2-thresholds *CBM* policy is superior to traditional single-threshold *CBM* policy in both flexibility and results, while the requirement to decide maintenance threshold is much higher.

This method mainly concentrates on the strategy itself. With suitable improvement, this method can be modified to optimize maintenance resources.

This method is based on an assumption that the *RUL* estimation is accurate, and the maintenance strategies are based on accurate *RUL*s. Considering the defects in failure prognostics technology, further study needs to discuss the relationship between the accuracy of the *RUL* estimates and the availability of the fleet, where *PHM* uncertainty management will be considered.

NOMENCLATURE

AA	Aircraft Agent
AMT	Allocated Maintenance Time
CBM	Condition-Based Maintenance
CNP	Contract Net Protocol
LMT	Longest Maintenance Time
LRM	Line Replaceable Module
MA	Maintenance Agent
MAS	Multi-Agent System
MCA	Management and Coordination Agent
MMT	Mean Maintenance Time
PHM	Prognostics and Health Management
RUL	Remaining Useful Life

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