Agent-based Formation Flight Coalition under Incomplete Information

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Abstract—The continued increasing air traffic demand and the corresponding fuel consumption urge the innovations of technologies and operating modes in commercial aviation community. Formation flight, due to its potential for reducing fuel use, are widely recognized as one of the most effective ways to improve aviation fuel saving. This study addresses the commercial formation coalition problem under incomplete information. First, a mathematical formulation is redefined to fit well the agent-based computation. Second, a BDI agent-based formation coalition model is developed to capture the structural characteristics of formations and the mental and behavioral characteristics of flights under incomplete information. Third, a Bayesian negotiation algorithm is constructed, within which Harsanyi transformation is used to transform the formation coalition problem under incomplete information to a Bayesian-equivalent coalition problem under imperfect information. Experiments indicate that the model proposed in this study is fast convergent and produces an equitable formation flight economy split among fleets. Besides, the unknown information prediction accuracy is better than MAS cooperative coalition model.

Keywords- Commercial aviation; Formation flight; Coalition; Negotiation; BDI; Incomplete information

INTRODUCTION

The increasing global air traffic demand in commercial aviation sector not only aggravates the air traffic delay, but also creates more serious energy and environment problems. Research conducted by the International Airport Association indicates that the passenger demand is expected to reach 9.1 billion and cargo demand 214 million tons in 2025, which in turn will result in 1.4 billion tons of CO₂ emissions, increasing concerns for energy demand and environment crisis[1]. In 2009, the European Union urged its member states to cut down CO₂ emissions to half of the 2005 level by 2050[2]. The aviation sector will inevitably to take strategies to run down its share of CO₂ emissions. Flying in formation like migrating birds saving energy, the amount of which varies sharply based on different conditions but is very impressive[3], over long distances was suggested by many scholars. NASA, Airbus, Boeing and some researchers have pioneered studies on aerodynamic basics and fuel saving of formation flying in commercial aviation community[4-13]. Commercial formation flight is recommended to be patterned into echelon form with the longitudinal spacing varying from 5 to 40 spans, termed as extended formation flight. Leader shall be rotated among all flights with the optimized interval to make sure each will achieve a fair fuel saving. There are many interesting issues in this area, e.g., aerodynamic coupled effects[4-13], precision wake detection and estimation[14-17], peak-seeking control based on drag reduction[18-20], formation coalition[21-22], formation path planning[9-13,23], and etc. However this study only addresses the formation coalition problem.

Formation coalition is interpreted as when, where and with who flights are planned to join and break away from a formation, with the objective of maximizing the overall fuel savings. However, formation paths shall be created in advance to evaluate the fuel economy of each specific formation. Therefore, the formation coalition problem and the formation path planning problem are highly correlated and NP-hard[24]. Ribichini formulated the problem as three related sub-problems, presented a multi-agent coalition algorithm and solved it via the greedy method[22]. Kent built a mixed integer programming model for large-scale formation coalition and solved it based on simulated annealing[10]. Later, he incorporated wind impacts into the model[11]. Xu developed a bi-level formation flight path planning framework in which heterogeneous aircraft drag models are involved[12]. He also significantly reduced the problem’s complexity by restricting the search space inside the intersections of all the candidate
flight performance and fuel-efficiency envelopes[13]. Xu and Meng presented a mathematical model of the formation path planning problem along with related geometric deductions[23]. Meng, Xu and Zhao developed a Multi-agent System (MAS) model addressing the commercial formation coalition problem under incomplete information[21].

This thesis is organized as follows: Section 1 introduces present research achievements of formation flight in commercial aviation community. Section 2 builds the basic MAS framework to fit well agent-based computation. Section 3 implements the BDI-agent model and develops an agent-based negotiation algorithm under incomplete information. Experiments are made in Section 4 to validate the efficiency of the BDI-agent based formation coalition model and negotiation algorithm. Conclusions and suggestions for future work are made in Section 5.

MATHEMATICAL FORMULATION

A. Problem Formulation

In our previous work, the formation flight coalition problem was formulated as an WGSMT construction problem[8-13]. The formation path can be represented by a WGSMT tree, \( Y(D,R,B,A,W) \), spanning the departure aerodrome set, \( D = \{ d(j) | j = 1,2,\ldots,m \} \), and the arrival aerodrome set, \( A = \{ a(j) | j = 1,2,\ldots,n \} \) (Fig 1). The rendezvous node set, \( R = \{ r(j) | j = 1,2,\ldots,m \} \), includes a series of optimized nodes after which fleets from different departure nodes or previous rendezvous nodes fly in formation. The breakaway node set, \( B = \{ b(j) | j = 1,2,\ldots,n-1 \} \), is a series of optimized Steiner nodes, paired with rendezvous nodes, after which fleets leave the formation for their own arrivals or the subsequent breakaway nodes. \( W \) is the arc weight set determined by fleet size. The objective is to minimize the total weighted geodesic distance of \( Y(D,R,B,A,W) \) by optimizing the formation schedule.

![Figure 1 WGSMT formation flight path. White circles are origin nodes and pink circles are Steiner nodes.](image)

To capture the topological features of the formation path, the process of constructing \( Y(D,R,B,A,W) \) is abstracted as the recursive construction of \( Y(k) = \{ (o(k), g(k), q(k)) | i = 1, 2,\ldots,n(k) \} \) until \( Y(k) \) converges. In \( Y(k) \), \( o(k) \) is \( i \)'s current position, \( g(k) \) is \( i \)'s current goal-reachable position, \( q(k) \) is \( i \)'s formation size and \( n(k) \) is the number of formations at generation \( k \). A formation at \( k \) is regarded as a candidate fleet at \( k+1 \).

The equivalent range[23] is introduced to represent the fuel economy of formation flight as

\[
D^e(o_i(k),g_i(k)) = w_i(k)D(o_i(k),g_i(k))
\]

which can be explained as the endurance flying solo while burning the same amount of fuel flying in formation. In (1), \( D^e(o_i(k),g_i(k)) \) is the equivalent range from \( o_i(k) \) to \( g_i(k) \) and is shortened for \( D^e(o_i,g_i) \) thereafter; \( w_i(k) \) is the fuel efficiency of formation flight as

\[
e_i(q_i(k)) = 2q_i(k)/(q_i(k) + 1)
\]

This formula is based on some idealized conditions, e.g., the air is assumed to be inviscid and incompressible, the formation is constrained to fly at the maximum Lift/Drag point of a single aircraft, and the horse-shoe model is used to deduce the conclusion[25]. However since this study does not intend to evaluate the fuel savings exactly, we build it as a basis for optimizing formation coalition in a decentralized way for simplification.

At \( k=0 \), \( Y(k) = \{ (o(k),g(k),q(k)) | i = 1,2,\ldots,n \} \), \( o(k) \) \( \in \) \( D \), \( g(k) \) \( \in \) \( A \), \( q(k) \) \( \in \) \( N \).

At each \( k=0 \), any fleet \( i \) needs to select a partner \( j \) from \( Y(k) \) to form a formation to maximize both sides’ utility based on the strategies both take:

\[
\max_{j \neq i(k)} \left[ \pi(i) (1 - \pi(j)) q_i(k) e^g_i(k) + (1 - \pi(i)) \pi(j) q_j(k) e^g_j(k) \right]
\]

where

\[
e^g_i(k) = u_i^g(k)/D(o_i,g_i)
\]

denotes fleet \( i \)'s utility factor in formation \( <i,j> \), and

\[
u_i^g(k) = D(o_i,g_i) - \left[ D^e_i(o_i,r_i) + D^e_i(r_i,b_i) + D^e_i(b_i,g_i) \right]
\]
is fleet \( i \)'s utility in formation \( <i,j> \). \( \pi \in [0,1] \) denotes fleet \( i \)'s strategy of selecting a partner where 0 indicates \( i \) is definitely uncooperative, and 1 indicates \( i \) is definitely cooperative. \( r_i(k) \) and \( b_i(k) \) each separately denotes the rendezvous node and breakaway node of \( <i,j> \).

Two key constraints are included in the model.
Maximum allowed equivalent range. Both fleets’ utilities in formation $<i, j>$ shall not be less than that they fly solo with an extra fraction of $e$ at least

$$u_i^j(k) \geq eD_i(o_i, g_j)$$  \hspace{1cm} (4)

$$u_j^i(k) \geq e_jD_j(o_j, g_i)$$  \hspace{1cm} (5)

where $0 \leq e, e_j \leq 1$ is the minimum expected utility factor of fleet $i$ and fleet $j$. Let

$$e_i^j(k) = u_i^j(k) / D_i(o_i, g_j)$$

and

$$e_j^i(k) = u_j^i(k) / D_j(o_j, g_i)$$

which represent $i$’s and $j$’s utility fractions in formation $<i, j>$, then constraint (4) and (5) can be rewritten as $e_i^j(k) \geq e_i$ and $e_j^i(k) \geq e_j$.

Maximum allowed formation size. Any fleet’s size must not be greater than the maximum formation size, $q_{\text{max}}$ , ensuring that no unintentional formation breakaways might occur due to cumulative tracking errors from possible maneuvers.

$$q_i(k) \leq q_{\text{max}}$$  \hspace{1cm} (6)

$$q_j(k) \leq q_{\text{max}}$$  \hspace{1cm} (7)

To be noted that the prior distributions of $\pi_i$ and $e_i$ are private information which endows the formation coalition process with the background of incomplete information. Therefore there exists a risk of failing to reach an agreement on forming a formation coalition for any fleet.

At the beginning of each $k$, those having formed formation coalitions at $k-1$ will update their state vectors and $\Upsilon(k)$ will be reconstructed consequently. A state $s_i(k)$ of $i$ at $k$ includes $i$’s current position $o_i(k)$, current goal-reachable position $g_i(k)$ and fleet size $q_i(k)$, and

$$s_i(k) = (o_i(k), g_i(k), q_i(k))$$  \hspace{1cm} (8)

Algorithm 1 WGSMT updating algorithm

Step1: $k=k+1$, $\Upsilon(k) = \{ \}$ ;

Step2: Update the current positions and goal-reachable positions of all fleets.

For any $i$ and $j$ who have formed a formation $<i, j>$ at $k-1$, $f = <i, j>$

$$s_j(k) = \{r_j(k-1), b_j(k-1), q_j(k-1) + q_j(k-1)\}$$  \hspace{1cm} (10)

$$\Upsilon(k) = \Upsilon(k) U s_j(k)$$  \hspace{1cm} (11)

For any $i$ who has not joined any formation at $k-1$,

$$f = i$$  \hspace{1cm} (12)

$$s_j(k) = s_i(k-1)$$  \hspace{1cm} (13)

$$\Upsilon(k) = \Upsilon(k) U s_j(k)$$  \hspace{1cm} (14)

When the sequence $\{\Upsilon(1), \Upsilon(2), \ldots, \Upsilon(k)\}$ converges due to either “maximum allowed equivalent range” or “maximum allowed formation size” being satisfied for all formations, we then have one or more formation paths represented by WGSMT trees included in $\Upsilon(k)$.

B. Formation coalition rules

Two formation coalition rules are considered in our framework:

- Cooperative rule (Fig. 2). If $i$ and $j$ rendezvous into $<i, j>$ at $r_o(k)$ and break away from $<i, j>$ at $b_o(k)$, where $r_o(k)$ and $b_o(k)$ are the paired WGSMT nodes joining $\{o_i(k), o_j(k)\}$ and $\{g_i(k), g_j(k)\}$, then the next state vector of $<i, j>$, $(o_i(k+1), g_i(k+1))$, shall be replaced by $(r_o(k), b_o(k))$.

In this case, each side shares the utility corresponding to its fleet size. Cooperative is denoted as “C”.

- Semi-cooperative rule (Fig. 3). If $j$ leaves $o_i(k)$ for $o_i(k)$ to join $<i, j>$ and breaks away from $<i, j>$ at $g_i(k)$, then the next state vector of $<i, j>$, $(o_i(k+1), g_i(k+1))$, shall be replaced by $(o_i(k), g_i(k))$. In this case, $i$ gains more than it would be while $j$ gains less than it would be based on the cooperative rule. Semi-cooperative is denoted as “SC”.

Figure. 2 Cooperative rule

![Figure 2 Cooperative rule](image)

Figure. 3 Semi-cooperative rule

![Figure 3 Semi-cooperative rule](image)
A. Agent model based on BDI

Our previous research constructed a MAS coalition model to deal with the commercial formation scheduling problem under incomplete information. In our previous framework, a formation is termed as a coalition, a flight or more flights with the same origin-destination (OD) are termed as a fleet. Fleets are differentiated into elites and everymen based on their fleet size and OD locations in air route network. An elite agent has either the authority to decide whether to agree upon forming a cooperative coalition or to initiate a negotiation to form a semi-cooperative coalition. An everyman agent can only agree upon a cooperative coalition or initiate negotiation to form a semi-cooperative coalition. The coalition barrier between elites and everymen is set to avoid a partial optimal solution. The coalition is recursively conducted until there a maximum formation size has been reached or there is no possibility to achieve acceptable utility factor with any of existing agents.

An apprehension for the previous model is that, while increasing the success rate of forming a formation, the barrier of coalition among agents of same class may decrease the global economy of flying in formation. In this study, coalitions are conducted between any two agents irrespective of their classes. Those agents of same class form a cooperative coalition while those agents of different class only form a semi-cooperative coalition.

Moreover we implemented the agent model based on BDI (Belief, Desire, Intention) architecture which provides an effective way to capture the agent’s mental state of deliberating the rational negotiation set and selecting an intended partner. BDI model was firstly proposed by Rao and Georgef[26] and thereafter was developed into a number of modified models[27-32]. In our BDI-based formation coalition model, agent conducts a cycle of observing environment, updating beliefs, deliberating desires and intentions and carrying out intended plan. The agent's possible world is generated by its beliefs and derived from its desires. Only one of the rational desires, usually the best desire at present, will be chosen as the intention and must be the consistent subset of its desires and beliefs. After a coalition is formed, agents assume their roles, e.g., leader, cooperator or follower, and update their states. It is the leader who takes over the total resource of all coalition members and participates in formation coalition at next generation.

The pseudo code of the BDI-based agent model is given below.

Properties (SetAccess=Protected)

agentid; % Agent’s identification number
orig; % Origin state, agent’s current position
goal; % Goal state, agent’s current goal reachable position
resource; % Resource, fleet size in this study
socialreputation; % Social class, determined by agent’s social reputation
utilityfactor; % Utility factor
leader; % A pointer of agent’s leader
cooperator; % A pointer of agent’s cooperator
follower; % A pointer of agent’s follower
message; % The message box
quit_flag; % The flag indicating agent’s activity

Properties (SetAccess=Private)

mimin; % The membership of the minimum expected utility factor belonging to e_min
mmmax; % The membership of the minimum expected utility factor belonging to e_max
pcooperative; % The membership of strategy type belonging to cooperative
pcooperative_min; % The expectation of all other agents’ utility type belonging to e_min
pcooperative_max; % The expectation of all other agents’ utility type belonging to e_max
uncooperative; % The membership of strategy type belonging to uncooperative
uncooperative_min; % The expectation of all other agents’ strategy type belonging to uncooperative
uncooperative_max; % The expectation of all other agents’ strategy type belonging to uncooperative
BeliefSet; % Storing agent’s beliefs
DesireSet; % Storing agent’s desires
Intention; % Storing agent’s intention

Methods(SetAccess=Protected)

Agent; % Creating an agent object
Belief; % Calculating utilities in all possible games
Desire; % Deliberating all partners with Bayesian rationality
Intention; % Deliberating all partners with Bayesian rationality
SendMessage; % Sending a message to the best partner with the Bayesian rationality
HandleMessage; % Handling received messages.
Some terminologies in the model are explained as:

- **Social classes**: *elite*, *everyman*.

  In the beginning of each $k$ generation, agents are differentiated into *elites* and *everymen* based on their social reputations. Elite has higher social reputation and the utility of forming a coalition with it will be optimistic for the majority of agents. Everyman has a lower social reputation and the utility of forming a coalition with it might not be promised for the majority of agents. The *social reputation* is calculated by the agent’s fleet size, i.e. resource in our framework, and the aspect ratio, which is defined by the ratio of its lateral deviation from the geometric center of all agents’ state space to its equivalent range [21].

- **Agent roles**: *leader*, *cooperator*, *follower*.

  In a cooperative coalition, formed between agents of same class, the agent who earns a higher social reputation usually assumes the leader. The other assumes the cooperator.

  In a semi-cooperative coalition, formed between agents of different class, elite assumes the leader while everyman assumes the cooperator.

- **Communication among agents**

  Messages are managed via mailbox mechanism. The arbitrator manages a public mailbox in which each agent has a private room, identified by a unique identification code, to be used for receiving and transmitting negotiation messages.

**B. Agent-based negotiation for formation coalition based on incomplete information**

Although agent’s utility is calculated based on the common rules which make each individual’s utility public information, the agent does not know if its proposal will be accepted by its preferred partner because the minimum utility factor each would accept and the strategy each takes are private beliefs [33]. In this case, the formation coalition problem is a dynamic cooperative coalition game with incomplete information. Harsanyi transformation builds the fundamental framework for playing games with incomplete information [34-36]. By using Harsanyi transformation, a coalition game with incomplete information can be transformed to a Bayesian-equivalent game with imperfect information. The imperfect information an agent keeps is expressed through its subjective confidence of the opponent’s utility and strategy types.

Consider a formation coalition game $G$ with $m$ elites and $n$ everymen, where $I = \{i = 1, \ldots, m\}$ is the elite set and $J = \{j = 1, \ldots, n\}$ is the everyman set. $E = \{0, 1\}$ is the range space of the minimum expected utility factor. $\Pi = \{0, 1\}$ is the range space of the strategy type. $R$ is the set of social rules applied in formation coalition process.

The key to Harsanyi transformation is that each agent assigns and revises the subjective confidence of other agent’s unknown information based on the prescribed triggered events. When this task is completed, agent can assess the utility splits with opponents in all possible coalitions and thereafter deliberates negotiation set. The process is carried out based on Bayesian approach.

Agent initially believes that any other agent’s unknown information obeys a basic probability profile

$$
P = \left( p_e, p_n \right) = \left((p^0_k, p^1_k), (p^0_n, p^1_n)\right)^T$$

of $e$ and $n$ satisfying

$$p^0_k + p^1_k = 1$$

and

$$p^0_n + p^1_n = 1.$$  

$(p^0_k, p^1_k)$ is the basic probability profile of agent’s utility type belonging to $E$ in the statistical sense. $(p^0_n, p^1_n)$ is the basic probability profile of agent’s strategy type belonging to $\Pi$ in the statistical sense. For any $i \in I$ , let the profile of $i$’s utility type and strategy type be $P_i^* = (p^0_i, p^1_i)$ and $P_{ij}^* = (p^0_{ij}, p^1_{ij})$. Let

$$J_i = \{ (e^i_j, \pi^i_j) \mid j \in J \}$$

be $j$’s unknown information set that $i$ knows to be

$$P_{ij}^* = \left( (p_{ij}^{0e}, p_{ij}^{0e}), (p_{ij}^{1e}, p_{ij}^{1e}) \right)$$

in $i$’s own expectations, where

$$P_{ij}^* = (p_{ij}^{0e}, p_{ij}^{0e})$$

and

$$P_{ij}^* = (p_{ij}^{1e}, p_{ij}^{1e}).$$

At $k=0$, $P_{ji}^* = P_i^*$. In conjunction with the negotiation process, $i$ revises $P_{ij}^*$ by observing each previous negotiation outcome.

If $i$ is rejected by $j$, there might be two independent causes, $A$ and $B$, contributing to the event, deemed a *fail*, where

- $A$ is interpreted as “the membership grade of $e_i$ belonging to 0 was overestimated by $\delta_e$ and that belonging to 1 was underestimated by $\delta_e$, with the confidence level $p_{ij}^{e,\text{fail}}$.”

- $B$ is interpreted as “the membership grade of $\pi_j$ belonging to 0 was overestimated by $\delta_{\pi}$ and that belonging to 1 was underestimated by $\delta_{\pi}$, with the confidence level $p_{ij}^{\pi,\text{fail}}$.”
If both $e^j_i \geq e_i$ and $e^j_i \geq e^*_{ij}$ hold, then $j$ is its rational negotiation partner where

$$e^j_{ij} = P^j_{ij}(0, 1)^T$$

However, $i$ does not know if $j$ would accept the proposal because it does not know $j$’s strategy type and utility type exactly. In this case, it has to assess the utility split in coalition $<i, j>$ based on its own strategy type and its expectation of $j$’s strategy type using formula (17).

$$e^j_{ij} = p^*_{ij} e_i^j + p^{e,0}_{ij} + p^{e,1}_{ij} e^j_{ij}$$

where $e^j_{ij}$ and $e'_{ij}$ is both agent’s utility factor in coalition $<i, j>$ and can be definitely determined by the geometric law. Agent $i$ can then select the best partner to maximize $e^j_{ij}$.

C. Agent-based framework for formation coalition

Agent’s BDI calculating and updating process is depicted in Fig. 4. The world state is the common knowledge all agent knows, e.g., social rules, the basic distributions of unknown information, all agents’ current states and goal reachable states, which is the start point of BDI calculation for all agents. A belief of $i$ is defined by a possible coalition $<i, j>$ as well as the utility split in $i$’s expectation. A desire of $<i, j>$ is a rational belief that both $i$ and $j$ achieve the minimum expected utilities at least in $i$’s expectation. An intention of $i$ is the best desire of $i$ in $i$’s expectation.

![Diagram](Image)

The MAS coalition and evolving process is depicted in Fig. 5. The candidate flight plans are used to create agents
with properties, events and methods. Some properties, e.g., agent states, fleet size, reputation, social class level, roles in organization, are public information and can be accessible by other agents. While other properties, e.g., utility and strategy types, beliefs, desires and intentions, are private information and cannot be accessible by other agents. After MAS being initialized, the arbitrator differentiates all candidate agents into elites and everymen based on their social reputations and immediately declares the start of coalition process. At each MAS evolving generation, all agents conduct BDI calculations, deliberate the best partners, negotiating to form coalitions, revising the expectations of unknown information based on triggered events, and updating organizations. Whenever there is no possibility to form a coalition for an individual agent, it will then quit MAS. When all agents quit, the arbitrator declares the end of MAS evolving process.

EXPERIMENTS AND RESULTS

Experiments were conducted on Matlab 2012b platform. Object oriented programming techniques were used to implement agent model. Comparisons were made in four aspects between MAS cooperative coalition algorithm and the BDI-based formation coalition model.

A. Data preparation

See [21], 100 intercontinental flights were selected to validate the proposed BDI-based formation coalition model against the MAS cooperative coalition model. Uniform rejection sampling method\(^{[37]}\) is introduced to produce a series of normal random numbers which are subsequently transformed into the utility factor and the strategy profiles. Other simulation parameters are listed in TABLE I.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Settings</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>(q_{\text{max}})</td>
<td>10</td>
<td>Maximum allowed formation size</td>
</tr>
<tr>
<td>(p_i^{f,\text{fail}}, p_i^{f,\text{fail}})</td>
<td>(0.7,0.7)</td>
<td>The basic probability of a fail event due to over- or under-estimation of unknown information’s profile.</td>
</tr>
<tr>
<td>(p_i^{o,\text{omit}}, p_i^{o,\text{omit}})</td>
<td>(0.3,0.3)</td>
<td>The basic probability of an omit event due to over- or under-estimation of unknown information’s profile.</td>
</tr>
<tr>
<td>([e^u, e^s])</td>
<td>(0.0,0.2)</td>
<td>The range space of utility type</td>
</tr>
<tr>
<td>(P_k)</td>
<td>(0.5,0.5)</td>
<td>The basic profile of all agents’ utility type</td>
</tr>
<tr>
<td>(\mu_e)</td>
<td>0.1</td>
<td>The expectation to generate random utility types for all agents</td>
</tr>
<tr>
<td>(\sigma_e)</td>
<td>0.033</td>
<td>The standard variation to generate random utility types for all agents</td>
</tr>
<tr>
<td>([\text{uncooperative, cooperative}])</td>
<td>[0,1]</td>
<td>The range space of strategy type</td>
</tr>
<tr>
<td>(P_{\Pi})</td>
<td>(0.5,0.5)</td>
<td>The basic profile of all agents’ strategy type</td>
</tr>
<tr>
<td>(\mu_{\Pi})</td>
<td>0.5</td>
<td>The expectation to generate random strategy types for all agents</td>
</tr>
<tr>
<td>(\sigma_{\Pi})</td>
<td>0.067</td>
<td>The standard variation to generate random strategy types for all agents</td>
</tr>
<tr>
<td>(Z_0)</td>
<td>0.5</td>
<td>The initial class differentiation pressure</td>
</tr>
<tr>
<td>(\delta_e)</td>
<td>0.1</td>
<td>The Bayesian updating step size for utility profile</td>
</tr>
<tr>
<td>(\delta_{\Pi})</td>
<td>0.1</td>
<td>The Bayesian updating step size for strategy profile</td>
</tr>
<tr>
<td>(\delta_{\Pi})</td>
<td>0.1</td>
<td>The step size for class differentiation pressure</td>
</tr>
</tbody>
</table>

B. Comparisons

1) MAS convergence

Agent system based on the MAS cooperative coalition model converges at 10th generation. 100 candidate fleets form into 36 formations as well as 15 solo flights. Agent system based on the BDI-based formation coalition model converges at 4th generation. 100 agents converge into 54 coalitions and without solo flights.
The improvement in convergence rate could be attributed to the elimination of the coalition gap between agents of same class which allows those agents showing great similarities in geometrical aspects to take their priority to form coalitions with promising utilities.

2) The structure of formation paths (see Fig. 6)

Formation paths based on the BDI-based formation coalition model show a more strict hierarchical structure, than those based on the MAS cooperative coalition model. The average formation size is about 5.15 with a standard variation 1.55. The average formation size based on the MAS cooperative coalition model is 3.73 with a standard variation 2.11. The results indicate that a larger formation size and better structural equity could be achieved by using the BDI-based formation coalition model.

3) The formation flight economy

The average utility factor based on the BDI-based formation coalition model varies from 13.8% to 14.2% with a standard variation 5.7%. By comparison, the average utility factor based on the MAS cooperative coalition model varies from 10% to 45% with a standard variation greater than 20%. The improved model thus can promise a robust utility achievement and a fair utility split among agents.

4) The Bayesian estimation performance

Another aspect of the BDI-based formation coalition model against the MAS cooperative coalition model is the accuracy of the other agent’s unknown information prediction. Fig. 7, Fig 8, Fig 9 and Fig 10 show comparisons of agents’ Bayesian estimation performance when MAS converges. The color-coded marks on the back-diagonal lines of each graph represent agents’ true utility and strategy types. The off-diagonal marks represent agents’ Bayesian estimations of other agents’ utility and strategy types. A large color intensity discrepancy between off-diagonal marks and back-diagonal marks illustrates a higher Bayesian estimation error. A dense off-diagonal mark distribution tells a frequent occurring of fail or omits events, which can also be explained as a worse accuracy of agents deliberating a partner. Apparently, MAS based on BDI-based formation coalition model shows a fast convergent speed and a more accurate Bayesian estimation than that based on MAS cooperative model.
CONCLUSIONS

The thesis builds a basic MAS framework for solving commercial formation flight coalition problems with incomplete information in decentralized environment. As an improvement to the MAS cooperative coalition model in [21], this study redefines the problem to fit well agent-based computation. A BDI-based formation coalition model with asymmetric roles and social class differentiation mechanism is developed to capture airlines’ behavioral and structural characteristics in formation coalition process. The model ensures the formation coalition process being carried out hierarchically and therefore an equitable fuel economy split among fleets being achieved. A faster convergent speed, a more accurate Bayesian estimation of other agent’s unknown information, and therefore a better fuel efficiency are achieved compared to MAS cooperative model.

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