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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 with an incomplete information background. Third, a Bayesian negotiation algorithm is constructed, within which the Harsanyi transformation is introduced to transform the formation coalition problem under incomplete information to a Bayesian-equivalent coalition problem under imperfect information. Experiments indicate that the model and algorithm proposed are fast convergent and can promise robust and equitable formation economies among fleets. Besides, the agent based on BDI model is more reactive to negotiation events and the prediction accuracy can therefore be assured.**

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 CO_2 emissions, increasing concerns for energy demand and environment crisis[1]. In 2009, the European Union urged its member states to cut down CO_2 emissions to half of the 2005 level by 2050[2]. The aviation sector will inevitably to take strategies to run down its share of CO_2 emissions. Flying in formation like migrating birds saving energy, which might be 71% according to Lissaman and Shollenberger[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 the commercial aviation community[4-11].

Formation coalition can be interpreted as when, where and with who flights are planned to join and break away from a formation, with the objective of maximizing overall fuel saving. However, formation paths shall be created in advance to evaluate the fuel economy of a specific formation coalition schedule. Therefore, the formation coalition problem and the formation path planning problem are highly correlated and NP-hard[10]. Ribichini formulated the problem as three related sub-problems, presented a multi-agent coalition algorithm and solved it via the greedy method[11]. Kent built a mixed integer programming model for large-scale formation coalition and solved it based on simulated annealing[12]. Later, he incorporated wind impacts into the model[13]. Xu developed a bi-level formation flight path planning framework in which heterogeneous aircraft drag models are involved. 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[14,15]. Xu and Meng presented a mathematical model of the formation path planning problem along with related geometric deductions[16]. MENG, Xu and Zhao developed a Multi-agent System (MAS) model addressing the commercial formation coalition problem under incomplete information [17].

This thesis is organized as follows: Section 1 introduces present research achievement of formation flight in commercial aviation community. Section 2 builds the basic MAS framework to fit well the agent-based computation.

Section 3 realizes 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 agent based formation coalition model and negotiation algorithm. Conclusions and suggestions for future work in Section 5.

MATHEMATICAL FORMULATION

A. Problem Formulation

In our previous work, the formation flight coalition problem was formulated as an WGSMT construction problem[16]. The formation path can be represented by a WGSMT tree[10,12,16,18], $Y(D,R,B,A,W)$, spanning the departure set, $D=\{d_i|i=1,2,\ldots,m\}$, and the arrival set, $A=\{a_j|j=1,2,\ldots,n\}$ (FIGURE 1). The rendezvous point set, $R=\{r_i|i=1,2,\ldots,m\text{-}1\}$, and the breakaway point set, $B=\{b_j|i=1,2,\ldots,n\text{-}1\}$, are Steiner point sets. 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.

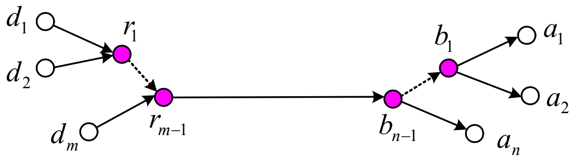


FIGURE 1 WGSMT formation flight path. White circles are origin nodes and pink circles are Steiner nodes.

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 $\Upsilon(k)=\{(o_i(k),\ g_i(k),\ q_i(k)),\ i=1, 2,\ldots,n(k))\}$ until $\Upsilon(k)$ converges. In $\Upsilon(k)$, $o_i(k)$ is i's current position, $g_i(k)$ is i's goal-reachable position, $q_i\ (k)$ 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**[10] is introduced to represent the fuel economy of formation flight as

$$D^{\text{ff}}(o_i(k),g_i(k))=w_i(k)D(o_i(k),g_i(k)) \qquad (1)$$

where $D^{\text{ff}}(o_i(k),g_i(k))$ is the equivalent range from $o_i(k)$ to $g_i(k)$ and can be shortened by $D_k^{\text{ff}}(o_i,g_i)$; $w_i(k)=1/\varepsilon_i(q_i(k))$ and $\varepsilon_i(k)$ is the relative range defined by the ratio of the fuel mileage flying in a formation relative to that flying solo. With the assumption that all formation flights fly at the maximum Lift/Drag point, $\varepsilon_i(k)$ can be formulated as

$$\varepsilon_i(q_i(k))=2q_i(k)/(q_i(k)+1)\,. \qquad (7)$$

Therefore, the **equivalent range** can be explained as the endurance flying solo while burning the same amount of fuel flying in formation.

At k=0, $\Upsilon(k)=\{f_i(k)=(o_i(k),g_i(k),\ q_i(k))|i=1,2,\ldots,n(k),\ o_i(k)\in D,\ g_i(k)\in A,\ q_i(k)\in N\}$.

At each k>0, any fleet i needs to select a partner j from $\Upsilon(k)$ to form a formation to maximize both sides' utility based on the strategies both agents' take:

$$\max_{j\in\Upsilon(k)}\left[\pi_i\left(1-\pi_j\right)q_i(k)e_i^{ij}(k)+\left(1-\pi_i\right)\pi_j(k)q_j(k)e_j^{ij}(k)\right] \qquad (8)$$

where

$$e_i^{ij}(k)=u_i^{ij}(k)\big/D(o_i,g_i)$$

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

$$u_j^{ij}(k)=D(o_j,g_j)-\left[D_k^{\text{ff}}(o_j,r_{ij})+D_k^{\text{ff}}(r_{ij},b_{ij})+D_k^{\text{ff}}(b_{ij},g_j)\right]$$

is fleet i's utility in formation <i, j>. $\pi_i\in[0,1]$ denotes fleet i's strategy of selecting a partner where 0 indicates i is definitely uncooperative, and 1 indicates i is definitely cooperative. $r_{ij}(k)$ and $b_{ij}(k)$ each separately denotes the rendezvous point and breakaway point 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

$$u_i^{ij}(k)\ge e_iD_k(o_i,g_i) \qquad (9)$$

$$u_j^{ij}(k)\ge e_iD_k(o_j,g_j) \qquad (10)$$

where $0\le e<1$ is the minimum expected utility factor of fleet i and fleet j. Let

$$e_i^{ij}(k)=u_i^{ij}(k)/D_k(o_i,g_i)$$

and

$$e_j^{ij}(k)=u_j^{ij}(k)/D_k(o_j,g_j)$$

which represent i's utility fraction and j's utility fraction in formation <i, j>, then constraint (9) and (10) can be rewritten as $e_i^{ij}(k)\ge e_i$ and $e_j^{ij}(k)\ge e_j$.

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

$$q_i(k) \le q_{\max} \tag{11}$$

$$q_j(k) \le q_{\max} \tag{12}$$

To be noted that only the prior distributions of π_i and e_i are private information which endows the formation coalition process with the incomplete information background. Therefore there exists a risk of failing to reaching 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.

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 two fleets i and j who have formed a formation $< i, j >$ at k-1,

$$f = < i, j > \tag{13}$$

$$\left(o_f(k), g_f(k), q_f(k)\right) = \left(r_{ij}(k-1), b_{ij}(k-1), q_i(k-1) + q_j(k-1)\right) \tag{14}$$

$$\Upsilon(k) = \Upsilon(k) \bigcup \left\{\left(o_f(k), g_f(k), q_f(k)\right)\right\} \tag{15}$$

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

$$f = i \tag{16}$$

$$\left(o_f(k), g_f(k), q_f(k)\right) = \left(o_i(k-1), g_i(k-1), q_i(k-1)\right) \tag{17}$$

$$\Upsilon(k) = \Upsilon(k) \bigcup \left\{\left(o_f(k), g_f(k), q_f(k)\right)\right\} \tag{18}$$

When the sequence {$\Upsilon(1)$, $\Upsilon(2)$,……, $\Upsilon(k)$} converges due to any one of the two constraints, we then have one or more formation paths represented by WGSMT trees.

B. Formation coalition rules

Two formation coalition rules are considered in our framework:

- Cooperative rule(Fig. 3). If i and j rendezvous into <i, j> at $r_{ij}(k)$ and break away from <i, j> at $b_{ij}(k)$, where $r_{ij}(k)$and $b_{ij}(k)$ are the two WGSMT points of {$o_i(k)$, $o_j(k)$, $g_i(k)$, $g_j(k)$}, then the next state vector of <i, j>, ($o_{ij}(k+1)$, $g_{ij}(k+1)$), shall be replaced by ($r_{ij}(k)$, $b_{ij}(k)$). The cooperative rule is fair to both sides because the rendezvous and breakaway points are based by on geometric law. Each side shares the utility corresponding to its fleet size. Cooperative is denoted as "C".
- Semi-cooperative rule (Fig. 4). If j leave $o_j(k)$ for $o_i(k)$ to join <i, j> and break away from <i, j> at point $g_i(k)$, then the next state vector of <i, j>, ($o_{ij}(k+1)$, $g_{ij}(k+1)$), should be replaced by ($o_i(k)$, $g_i(k)$). In this case, i gains more than it would while j gains less than it would based on the cooperative rule. Semi-cooperative is denoted as "SC".

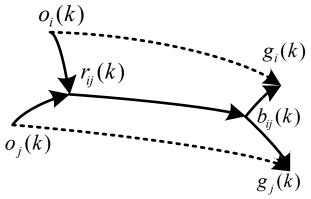


Fig. 2 Cooperative rule

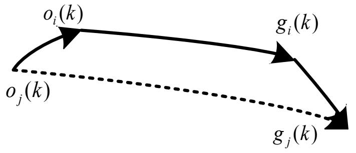


Fig. 3 Semi-cooperative rule

AGENT-BASED FORMATION COALITION MODEL

A. Agent model based on BDI

Our previous research constructs a MAS coalition model to address the commercial formation scheduling problem under incomplete information. In our framework, a formation is terms as a *coalition*, a flight or more flights with the same origin-destination (OD) are termed as a *fleet*. Formation coalition negotiations are always initiated by powerful airlines with dominating positions due to their fleet sizes and dominating OD locations in route network. Those with low dominated positions have either the right to decide whether to agree upon forming a cooperative coalition or to initiate a negotiation to form a semi-cooperative coalition. The social position of a fleet is termed as the social *reputation*. 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. However, our previous work only provides a basic agent-based framework for coalition while it is not competent to realize agent's reasoning process of making decisions. The agent-based formation coalition model developed in this thesis will also use a BDI architecture which provides a more realistic way to capture agent's mental state of deliberating the rational negotiation set and selecting an intended partner. BDI model, probably the most successful agent model in history, was proposed by Rao and Georgef[20] and developed into a number of models[21-24]. In BDI architecture, the agent executes a cycle of observation of the environment, update of beliefs, deliberation of over intentions, and execution of an intended plan. Each of the agent's possible worlds are generated by its beliefs and deliberated by its desires. Finally, some reasonable desires must be chosen as intentions and must be any consistent subset of its desires and beliefs. The agent must choose to one goal.

In our framework, an agent with asymmetric roles is modeled based on BDI model are realized as:

Properties (SetAccess=Protected)

agentid; % Agent's identification number
o; % Origin state, agent's current position
g; % Goal state, agent's current goal position
q; % Resource an agent owns, fleet size in this thesis
c; %Social class, determined by agent's social reputation and determining agent's behaviors and authorities
e; % Utility factor, representing agent's utility in a coalition game
leader; %Pointing to agent's leader, representing agent's role in a coalition
cooperator; % Pointing to agent's cooperator, representing agent's role in a coalition
follower; % Pointing to agent's follower, representing agent's role in a coalition
message; % The message box for communicating among agents
quit_flag; %The flag to indicate an agent's active state.

Properties (SetAccess=Private)

$p_{e,\min}$; %The membership of the minimum expected utility factor belonging to $e_{\min}$
$p_{e,\max}$; %The membership of the minimum expected utility factor belonging to $e_{\max}$
$p_{\pi,\mathrm{nc}}$; %The membership of strategy type belonging to uncooperative
$p_{\pi,\mathrm{c}}$; %The membership of strategy type belonging to cooperative
$\boldsymbol{p}^*_{e,\min}$; %The expectation of other agents' utility type belonging to $e_{\min}$
$\boldsymbol{p}^*_{e,\max}$; %The expectation of other agents' utility type belonging to $e_{\max}$
$\boldsymbol{p}^*_{\pi,\mathrm{nc}}$; % The expectation of other agents' strategy type belonging to uncooperative
$\boldsymbol{p}^*_{\pi,\mathrm{c}}$; %The expectation of other agents' strategy type belonging to cooperative

Events

fail; %Agent's proposal being rejected
omit; %Received a proposal from an agent not included in BeliefSet

Methods(SetAccess=Protected)

Agent; %Creating an agent object
BeliefSet; %The possible utilities agent
DesireSet; %Deliberating the best partner with the Bayesian rationality
SendMessage; % Sending a message to the best agent with the Bayesian rationality
HandleMessage; %Handling messages received.
EventListener; % Revising the beliefs according the outcome of certain triggered events
UpdateOrganization; %Updating the organization when formed a coalition successfully

Some terminologies in the model are explained in a plain simply way.

- Social classes: *elite, everyman.*

In the beginning of each *k*, 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 low 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.

- 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 a *leader* role, or arbitrated by the arbiter if both have the same level of reputation. The other assumes a *cooperator* role.

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

- Behaviors: *recruit*, *enlist*, *follow*, *accommodate*.

Agents possess different authorities associated with their social class levels. Agents of the same classes are not allowed to form coalitions in our framework for fear of the precocious convergence of MAS. Therefore negotiations are only conducted between elites and everymen. An elite has the authority to *recruit* an everyman to form a cooperative coalition, or to *accommodate* an everyman to form a semi-cooperative coalition. An everyman has the authority to *enlist* an elite to form a cooperative coalition, or to *follow* an elite to form a semi-cooperative coalition.

- Communication among agents

Messages are managed via mailbox mechanism. The arbitrator manages a public mail box where each agent has a private room, identified by its identification code, to be used for receiving messages only by itself and sending messages by other agents.

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

Although an 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. In this case the minimum utility factor each would accept and the strategy each takes are private beliefs[25]. Thus, the formation coalition problem can be formulated as a cooperative dynamic coalition game under incomplete information. The Harsanyi transformation builds the fundamental framework for playing games with incomplete information[26-28]. By using the Harsanyi transformation, the original game with incomplete information can be transformed to the Bayesian-equivalent game with imperfect information. The imperfect information an agent keeps is described by its subjective confidence of other agents' utility and strategy types, as based on each player's expectations.

Consider a formation coalition problem G:(I,J,$\mathbf{E}$,$\mathbf{\Pi}$,R), with m elites and n everymen, where $I=\{i=1, 2,\ldots,m\}$ is the elite set and $J=\{j=1,2,\ldots,n\}$ is the everyman set. $\mathbf{E}=[0, 1]$ is the range space of the minimum expected utility factor. $\mathbf{\Pi}=[0, 1]$ is the range space of the strategy type. R is the set of social rules applied in formation coalition process.

The key to the Harsanyi transformation is that each agent assigns and revises the subjective confidence of other agent's unknown information based on its negotiation events occurring to it in each previous negotiation game. When this task is completed, the agent can then assess the utility splits in all possible coalitions and thereafter deliberates its negotiation sets based on the Bayesian approach.

In our framework, agent initially believes that any other agent's unknown information obeys a basic probability profile $\mathbf{P}=(\mathbf{p}_{\mathbf{E}},\mathbf{p}_{\mathbf{\Pi}})^{\mathrm{T}}=[(p_{\mathbf{E}}^0,p_{\mathbf{E}}^1),(p_{\mathbf{\Pi}}^0,p_{\mathbf{\Pi}}^1)]^{\mathrm{T}}$ of e and π satisfying $p_{\mathbf{E}}^0+p_{\mathbf{E}}^1=1$ and $p_{\mathbf{\Pi}}^0+p_{\mathbf{\Pi}}^1=1$. For any $i\in I$, let the profile of its utility type be $\mathbf{p}_i^e=(p_i^0,p_i^1)$ and that of its strategy type be $\mathbf{p}_i^\pi=(p_i^0,p_i^1)$. Let $J\,|\,i=\{(e_{j|i}^*,\pi_{j|i}^*)\,|\,j\in J\}$ be j's unknown information vector set that i keeps in mind as $\mathbf{P}_{J|i}^*=\left\{(\mathbf{p}_{j|i}^{e*},\mathbf{p}_{j|i}^{\pi*})^{\mathrm{T}}\,|\,j\in J\right\}$ in i's own expectations, where $\mathbf{p}_{j|i}^{e*}=(p_{j|i}^{0*},p_{j|i}^{1*})$ and $\mathbf{p}_{j|i}^{\pi*}=(p_{j|i}^{0*},p_{j|i}^{1*})$. At k=0, $\mathbf{P}_{J|i}^*=\mathbf{P}$. In conjunction with the negotiation process, i revises $\mathbf{P}_{J|i}^*$ by observing each previous negotiation outcome.

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

- A is interpreted as "the membership grade of e_j belonging to 0 was overestimated by δ_e and that belonging to 1 was underestimated by δ_e with the confidence level $p_i^{e,\mathrm{fail}}$".
- B is interpreted as "the membership grade of π_j belonging to *non-cooperative* was underestimated by δ_π and that belonging to *cooperative* was overestimated by δ_π with the confidence level $p_i^{\pi,\mathrm{fail}}$".

Because $\{\mathrm{AB},\mathrm{A\overline{B}},\mathrm{\overline{A}B},\mathrm{\overline{AB}}\}$ constitutes a partition of the complete cause set of a *fail* event, agent i can revise its expectation of the probability distribution of j's unknown information using (20).

$$\mathbf{P}_{j|i}^*=\left(\begin{array}{l}\left[\mathbf{P}_{j|i}^*+\begin{pmatrix}-\delta_e & \delta_e\\ \delta_\pi & -\delta_\pi\end{pmatrix}\right]p_i^{e,\mathrm{fail}}p_i^{\pi,\mathrm{fail}}+\left[\mathbf{P}_{j|i}^*+\begin{pmatrix}-\delta_e & \delta_e\\ 0 & 0\end{pmatrix}\right]p_i^{e,\mathrm{fail}}\left(1-p_i^{\pi,\mathrm{fail}}\right)+\\ \left[\mathbf{P}_{j|i}^*+\begin{pmatrix}0 & 0\\ \delta_\pi, & -\delta_\pi\end{pmatrix}\right]\left(1-p_i^{e,\mathrm{fail}}\right)p_i^{\pi,\mathrm{fail}}+\mathbf{P}_{j|i}^*\left(1-p_i^{e,\mathrm{fail}}\right)\left(1-p_i^{\pi,\mathrm{fail}}\right)\end{array}\right) \tag{20}$$

If i receives a *follow* proposal from j while j is not in i's negotiation set, there are be two independent causes, C and D, contributing to this event, deemed an *omit*, where:

- C is interpreted as "the membership grade of e_j belonging to 0 was underestimated by δ_e, and that belonging to 1 was overestimated by δ_e with a confidence level $p_i^{e,omit}$".

- D is interpreted as “the membership grade of *j*’s strategy type belonging to *non-cooperative* was overestimated by δ_π , and that belonging to *cooperative* was underestimated by δ_π with a confidence level of $p_i^{\pi,fail}$ ”.

Because $\{\mathrm{CD}, \mathrm{C}\overline{\mathrm{D}}, \overline{\mathrm{C}}\mathrm{D}, \overline{\mathrm{CD}}\}$ constitutes a partition of the complete causes set of an *omit* event, agent *i* can revise its expectation of the probability distribution of *j*’s unknown information using (21).

$$\mathbf{P}_{j|i}^{*} = \left(\begin{array}{l} \left[\mathbf{P}_{j|i}^{*} + \begin{pmatrix} \delta_e & -\delta_e \\ -\delta_\pi & \delta_\pi \end{pmatrix}\right] p_i^{e,\mathrm{omit}} p_i^{\pi,\mathrm{omit}} + \left[\mathbf{P}_{j|i}^{*} + \begin{pmatrix} \delta_e & -\delta_e \\ 0 & 0 \end{pmatrix}\right] p_i^{e,\mathrm{omit}} \left(1 - p_i^{\pi,\mathrm{omit}}\right) + \\ \left[\mathbf{P}_{j|i}^{*} + \begin{pmatrix} 0 & 0 \\ -\delta_\pi, & \delta_\pi \end{pmatrix}\right] \left(1 - p_i^{e,\mathrm{omit}}\right) p_i^{\pi,\mathrm{omit}} + \mathbf{P}_{j|i}^{*} \left(1 - p_i^{e,\mathrm{omit}}\right)\left(1 - p_i^{\pi,\mathrm{omit}}\right) \end{array} \right) \tag{21}$$

Similarly, we can easily get $\mathbf{P}_{i|j}^{*}$. The original coalition problem, **G,** can then be transformed into G^{*}:(I,J,$\mathbf{E}^{*}$,$\mathbf{\Pi}^{*}$,R), within which each agent plays with a virtual agent of a different class who conducts a lottery in accordance with its expectation of the probability of *j*’s unknown information[26],[27]. In the coalition game G*, *i* calculates its negotiation set using Bayesian rationality via the following rule:

If both $e_i^{ij} \geq e_i$ *and* $e_j^{ij} \geq e_{j|i}^{*}$ *hold*, *then j is i*'s *rational negotiation partner* where

$$e_{j|i}^{*} = \mathbf{P}_{j|i}^{*} \begin{pmatrix} 0 & 1 \end{pmatrix}^{\mathrm{T}} \tag{22}$$

However, *i* does not know if *j* will accept the proposal because it does not know *j*'s strategy type and utility type exactly. In this case, it assesses the utility factor split in coalition <*i*, *j*> based on its own strategy type and its expectation of *j* 's strategy type using formula (23).

$$e_i^{ij,*} = p_i^0 p_{j|i}^{1*} e_i^{ij} + p_i^1 p_{j|i}^{0*} e_j^{ij} \tag{23}$$

e_i^{ij} and e_j^{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 by maximizing $e_i^{ij,*}$.

C. Agent-based framework for formation coalition

An agent’s BDI calculating and updating process is depicted in Figure 2 while the MAS evolving process is depicted in Figure 3.

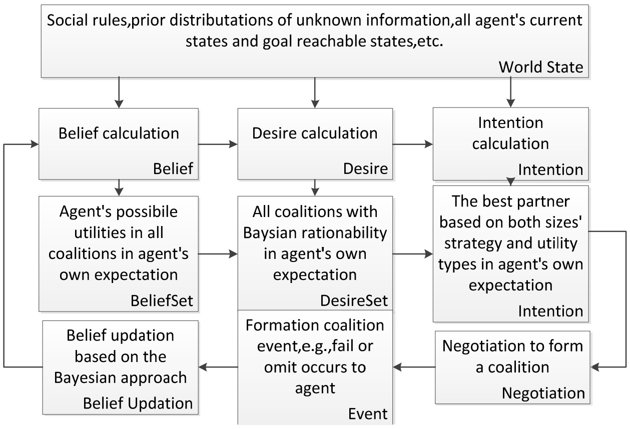


Fig. 4 Agent BDI calculating and updating process

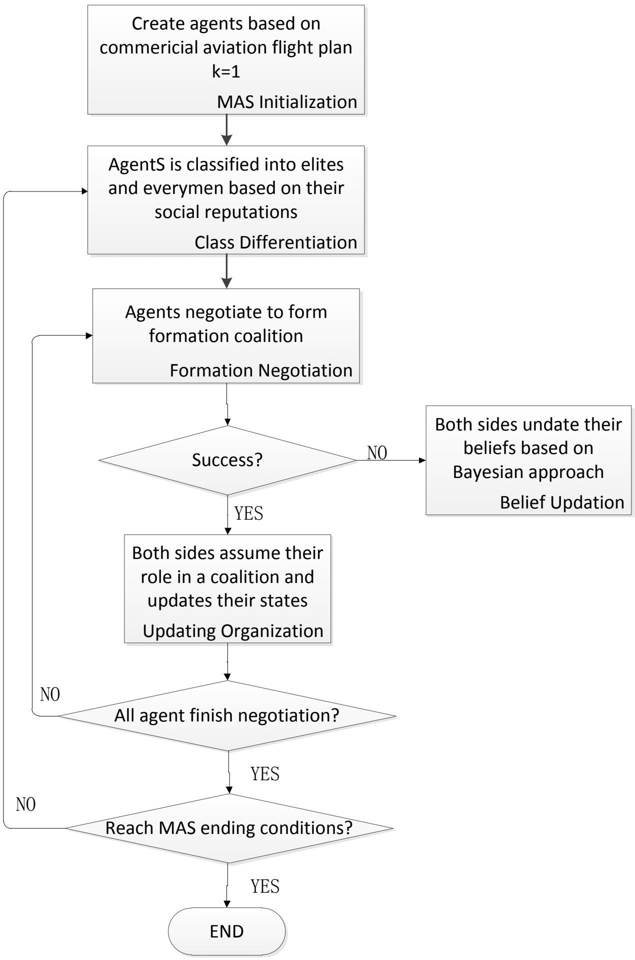


Fig. 5 MAS evolving process

EXPERIMENTS AND RESULTS

Experiments are conducted on Matlab 2012b. Object oriented techniques were utilized to realize agent model. Three groups of metrics were chosen as metrics to make comparisons between the origin version of MAS cooperative coalition algorithm and the improved BDI based formation coalition model.

A. Data preparation

See[17], 100 intercontinental flights were selected to validate the proposed BDI agent-based formation coalition model against the previous model we proposed. Uniform rejection sampling method[29] was used to produce a series of normal random numbers representing agents' minimum expected utility factors and strategies. These pseudo-random numbers were subsequently transformed into the utility factor profile and the strategy profile based on their lower and upper boundaries. Other simulation parameters can be seen in TABLE 1.

TABLE I SIMULATION PARAMETERS

Parameters	**Settings**
$q_{\max}$	10
$\{p_i^{e,fail}, p_i^{\pi,fail}\}$	{0.7,0.7}
$\{p_i^{e,omit}, p_i^{\pi,omit}\}$	{0.3,0.3}
$[e^0, e^1]$	[0,0.2]
$\mathbf{P_E}$	(0.5,0.5)
μ_e	0.1
σ_e	0.033
[non-cooperative, cooperative]	[0,1]
$\mathbf{P_\Pi}$	(0.5,0.5)
μ_π	0.5
σ_π	0.067
χ_0	0.5
δ_e	0.1
δ_π	0.1
δ_χ	0.1

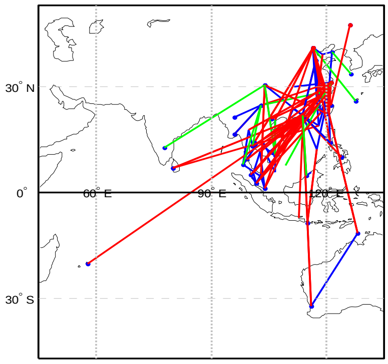
B. Comparisons

- The performance of algorithm

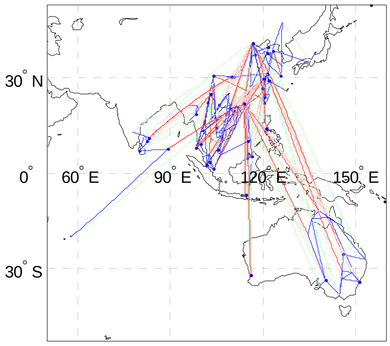
Agent system based on the previous MAS cooperative coalition model converges at 59th generation. 100 candidate agents finally converge into 36 formations as well as 15 solo flights. Agent system based on the BDI-based formation coalition model converges after 5 generations with 100 agents finally converging into 54 coalitions along without solo flights. A dramatic improvement in convergence rate was achieved. It can be attributed to the elimination of the coalition gap between agents of same class which permits those agents showing great similarities in geometrical aspects take their priority to form coalitions with promising utilities.

- The structure of formation paths (see FIGURE 6)

Formation paths based on the BDI-based formation coalition model show a more distinct WGSMT structure, which can also be explained as a more strict hierarchical structure, than those based on the MAS cooperative coalition model. The average formation size is about 4.55 with a standard variation 1.39. The average formation size based on the MAS cooperative coalition model is 5.1 with a standard variation 3.7. The results indicate that a better structural equity can be achieved by using the BDI -based formation coalition model.



a) MAS cooperative coalition model



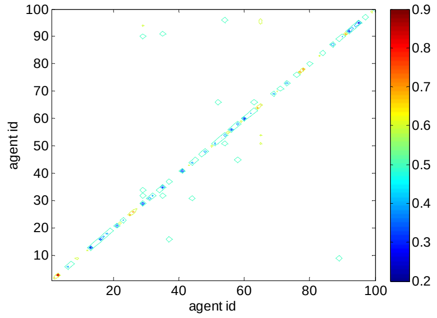
(b) BDI-based formation coalition model

FIGURE 6 Formation flight paths. The green arcs represent fleets not joining a formation, the blue arcs represent rendezvous and breakaway legs, the red arcs represent formation legs.

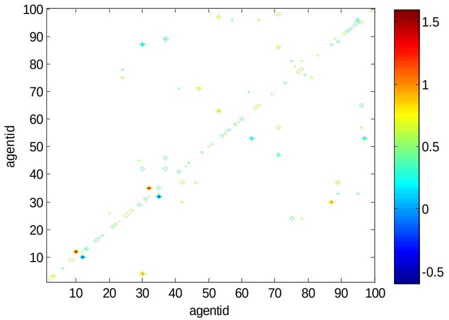
- The economy efficiency (see Figure 7 and Figure 8)

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% among fleets. 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% among fleets. Besides, the results based on the BDI-based formation coalition model take more realistic and strict prerequisites than those based on the MAS cooperative coalition model. The improved model thus can promise a robust utility achievement and a fair utility split among agents.

Another aspect of the BDI-based formation coalition model against the MAS cooperative coalition model is the convergence and accuracy of the other agent's unknown information prediction. The comparisons in Figure 7 and Figure 8 show that the convergence rate of prediction based on the BDI-based formation model is much faster than that based on the MAS cooperative coalition model with a rather similar prediction accuracy between them. Besides, agents in the BDI-based formation coalition model are more active in Bayesian updating based on omit and fail events, taking agents' expectations of other agents' utility type belonging to e^h and agents' expectations of other agents' strategy type belonging to cooperative as examples.

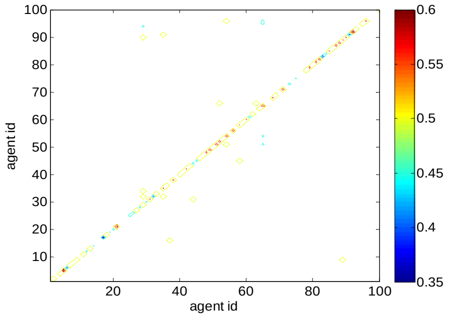


(a) MAS cooperative coalition model (*k*=59)

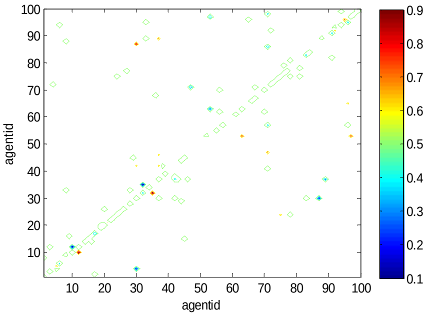


(b) BDI-based formation coalition model (*k*=5)

FIGURE 7 Agents' expectations of other agents' utility type belonging to e^h



(a) MAS cooperative coalition model (*k*=59)



(b) BDI-based formation coalition model (*k*=5)

FIGURE 8 gents' expectations of other agents' strategy type belonging to cooperative

CONCLUSIONS

The thesis creates a basic framework for solving commercial formation flight coalition problems with incomplete information in decentralized environment. As an improvement to the MAS cooperative coalition model in [17], this study redefines the problem and builds the basic MAS framework to fit well the agent-based computation. A BDI agent-based formation coalition model is realized to capture airlines' social, behavioral and structural characteristics in formation coalition process and demonstrates a fast convergence rate, a promised prediction accuracy and, most important, a robust fuel efficiency and equity among flights.

The model and algorithm might have more applications in decentralized environment, e.g., air traffic flow management (ATFM) and Automatic Self-Assurance Separation (ASAS) techniques, etc.

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