

**PRINCIPLED NEGOTIATION BETWEEN INTELLIGENT AGENTS:  
A MODEL FOR AIR TRAFFIC MANAGEMENT**

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**ABSTRACT**

The worldwide aircraft/airspace system (AAS) is faced with a large increase in air traffic in the coming decades, yet many flights already experience delays. The AAS is comprised of many different *agents*, such as aircraft, airlines, and traffic control units. Technology development will make all the agents in the AAS more intelligent; hence, there will be an increasing overlap of the *declarative functions* of the agents. This paper describes the basis for an *Intelligent Aircraft/Airspace System* (IAAS) that provides improved system performance, redundancy, and safety by utilizing the overlapping capabilities of the agents. *Principled Negotiation* between agents allows all the agents in the system to benefit from multiple independent declarative analyses of the same situation. *Multi-attribute utility theory* and *decision trees* are used as the basis for analyzing the behavior of different types of agents. Intelligent agents are modeled as *rule-based expert systems* whose *side-effects* are the procedural and reflexive functions of the agent. Principled negotiation also is a side-effect of the expert system's declarative functions. A hierarchical organization of agents in the IAAS is proposed to facilitate negotiation and to maintain clear lines of authority.

**INTRODUCTION**

Demand for air transport will continue to grow well into the next century. The annual revenue passenger miles (RPM) flown worldwide is predicted to double by 2005, an annual growth rate of over 5% [1]. By the year 2025, the RPMs flown could be triple today's levels. This will place large demands on the aircraft/airspace system (AAS) which in much of the world is experiencing congestion, delays, and operating restrictions [2,3,4].

An AAS is composed of *agents*, such as aircraft, airlines, airport operators, and various types of air traffic management units (Fig. 1). An agent is an entity that can make decisions based on the data it has available, and whose actions affect the system. Each Air Route Traffic Control Center (ARTCC), Terminal Radar Approach Control (TRACON) facility, or airport tower is responsible for flights within a volume of airspace. The

airspace of a facility is subdivided into sectors. Teams of controllers communicate instructions and information to the aircraft in their sectors to ensure flight safety. The actions of the different controller teams are coordinated by handover procedures, which prescribe the transfer of aircraft between sectors in a control facility, and Letters of Agreement, which cover the transfer of aircraft from the airspace of one facility to the next [5].

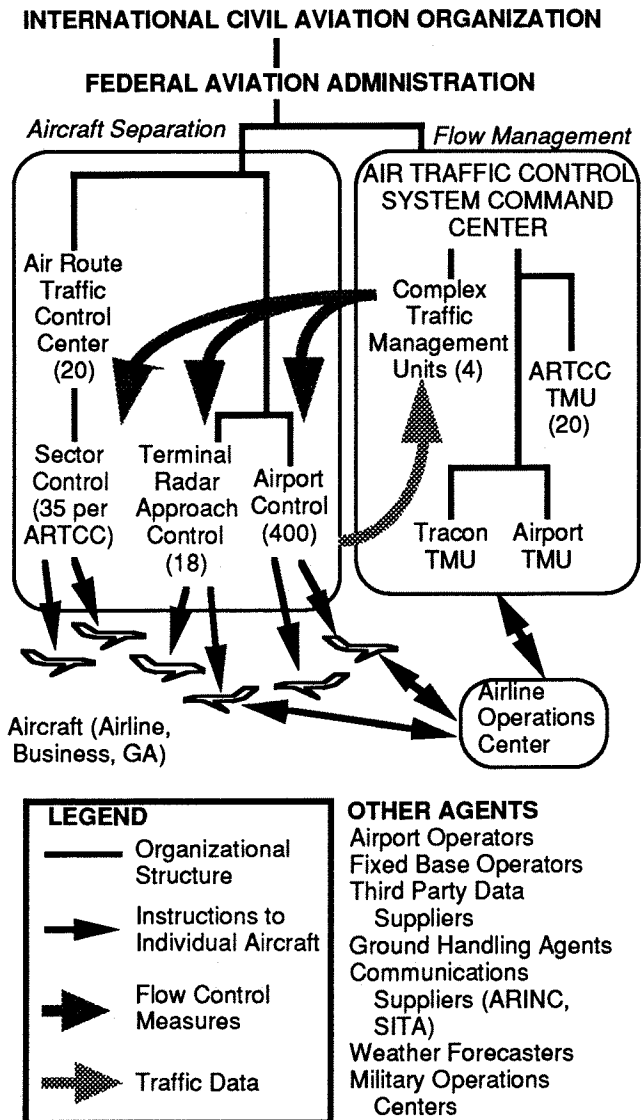


Figure 1. The US Aircraft/Airspace System.

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To prevent excessive controller workload when there is heavy traffic or severe weather, the flow management organization, consisting of the Air Traffic Control System Command Center (ATCSCC) and the traffic management units (TMUs) in each ARTCC, can impose operating restrictions. These are implemented by the controllers in the sectors, TRACONS, and airport towers. Ground Delay Programs and en-route metering are two examples of the operating restrictions imposed. Aircraft experience delays departing and en-route as a result of these restrictions [6].

By the year 2025, advances in communication, computation, data gathering, and forecasting will make all the agents of the AAS far more capable than they are today, even though aircraft performance envelopes and airport design are likely to remain broadly unchanged. Aircraft will have access to large amounts of traffic and weather data, and their on-board systems will be able to analyze the overall traffic situation, something that only air traffic management units can do now. Improved and overlapping capabilities offer the potential for vastly improved system performance, dissimilar redundancy, and graceful degradation of system performance when failures occur, improving operational efficiency and safety. Automatic Dependent Surveillance (ADS) is an example of improved aircraft equipment providing benefits for traffic management units [7,8,9]. Overlapping capabilities also can cause conflicts. Problems of this type have been encountered with the Traffic Alert and Collision Avoidance System (TCAS), such as pilots responding to alerts when controllers have already issued corrective actions [10].

The aim of this research is to define an *Intelligent Aircraft/Airspace System (IAAS)* that makes use of these enhanced agent capabilities to ensure that the demand for air traffic is met, with fewer restrictions, fewer delays, and improved safety compared to today. Without cooperation between agents, overlapping capabilities cannot be utilized. A framework for examining how collections of intelligent agents will cooperate is needed.

### BEHAVIOR OF AN INTELLIGENT AGENT

To model the behavior of a collection of Intelligent Agents, we need to understand the decision-making and control processes of each agent. A cognitive model of decision-making and control in an Intelligent Agent is proposed in [11]. A human's actions are the result of a hierarchy of thought processes. Conscious thought is the *Declarative* processing of knowledge or beliefs, exhibited as awareness and focus. Pre-conscious thought is pre-attentive Declarative processing. Subjects are pre-consciously selected for conscious processing, and concepts and frameworks for investigation are developed, guided by intuition. Sub-conscious thought is *Procedural* processing of knowledge and beliefs not dependent on conscious focus. Examples are communication, skill learning, and knowledge acquisition. *Reflexive* behavior

is an instantaneous response to stimuli; no conscious or unconscious thought is involved. Reflexive actions are forceful, elementary, and directed toward simple goals. Many of a human's reflexive actions are responses to stimuli threatening health (batting an eyelid when something contacts an eyelash) or balance (constant contraction and relaxation of muscles to maintain posture).

We can use Declarative, Procedural, and Reflexive functions to describe the behavior of any Intelligent Agent operating within the AAS. Traffic Management Agents (TrMAs) and Aircraft are two types of AAS agent (Fig. 2). (The term Traffic Management Agent describes all ground-based agents with responsibility for aircraft operations safety and supporting systems.) There is great similarity between the Declarative functions of these two agents and of all agents in the IAAS. All agents identify scenarios, assess the situation, and then make decisions based on that assessment. All the agents operate in the same environment, but they have different interests and priorities when choosing how to respond to particular situations.

TRAFFIC MANAGEMENT AGENT	AIRCRAFT AGENT
<u>Declarative Functions</u> Traffic Monitoring and prediction Conflict detection and prediction Constraint Monitoring Hazard Detection Weather monitoring and prediction Assessment of pilot requests Trajectory assignment	<u>Declarative Functions</u> System monitoring Goal planning Scenario identification Choice of operating mode Conflict resolution
<u>Procedural Functions</u> Conflict resolution Trajectory adaptation Flow control Communications	<u>Procedural Functions</u> Adaptation Guidance and Navigation Estimation and Control Crew Coordination Communication
<u>Reflexive Functions</u> Display Update State vector processing Aircraft handover Flight information processing	<u>Reflexive Functions</u> Measurement Actuation Inner-loop regulation

Figure 2. Function hierarchy for two agents.

### Definitions and Assumptions

The following definitions and assumptions are used in the discussion of agent interaction in the IAAS.

- **Assumption 1:** *An IAAS is a non-deterministic, mixed-event, dynamic system, with N agents.* It follows that no agent can have perfect knowledge of the system. Equation 1 gives a general expression for the dynamics of the system:

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{w}(t), t) \quad (1)$$

The state,  $\mathbf{x}(t)$ , and control,  $\mathbf{u}(t)$ , include continuous, discrete, binary, and mixed variables. The disturbance inputs,  $\mathbf{w}(t)$ , are the environmental variables (wind speeds, visibility, etc.).  $\mathbf{x}(t)$  describes the state of all  $N$  agents in the set of all airborne and ground-based agents,  $A$ :

$$A = \{a_i; i = 1, \dots, N\} \quad (2)$$

• **Definition 1:** A plan is a sequence of actions that an  $M$ -member subset of the set of agents  $A$  takes over a given time interval:

$$\begin{aligned} \mathbf{u}_{A_M}(t_1, t_2) &= \{\mathbf{u}_{a_m}(t_1, t_2); m = 1, \dots, M\} \\ A_M &\subseteq A \end{aligned} \quad (3)$$

• **Definition 2:** An action plan is the sequence of actions that a single agent will perform as part of the overall plan:

$$\mathbf{u}_{a_j}(t_1, t_2) \in \mathbf{u}_{A_M} \quad (4)$$

Any plan is a collection of individual action plans. An aircraft's action plan may be entirely defined by mapping a trajectory into control inputs. Other agents' action plans may consist of discrete events. For example, an airport tower may choose to change runway configuration at a particular time.

• **Definition 3:** An option is a proposed alternative to an existing plan:

$$\begin{aligned} \tilde{\mathbf{u}}_{A_K}(t_1, t_2) &= \{\tilde{\mathbf{u}}_{a_k}(t_1, t_2); k = 1, \dots, K\} \\ A_K &\subseteq A \end{aligned} \quad (5)$$

Options are indicated with tildes. An option put forward by one agent may suggest actions to be taken by other agents.

• **Assumption 2:** An agent has interests that can be translated into constraints on its action plan. It tries to satisfy constraints while maximizing utility functions through its choice of actions:

$$\begin{aligned} I_{a_i} &\Leftrightarrow \max U_{a_i}(\tilde{\mathbf{x}}, \tilde{\mathbf{u}}, \mathbf{w}, t) \\ &\text{subject to } \mathbf{c}_{a_i}(\tilde{\mathbf{x}}, \tilde{\mathbf{u}}, \mathbf{w}, t) \leq 0 \end{aligned} \quad (6)$$

In the IAAS there are  $N$  sets of interests  $I_{a_i}$ .  $\tilde{\mathbf{x}}$  are the predicted trajectories resulting from  $\tilde{\mathbf{u}}$  control inputs. A constraint vector  $\mathbf{c}_{a_i}$  results from bounds imposed by a superior agent, the expected behavior of other agents, and the performance limits of the agent. The size of  $\mathbf{c}_{a_i}$  is different for each agent. An example of an imposed constraint would be an airline informing an aircraft of a change of destination due to a decision to relocate a bank

of flights. Minimum separation criteria are constraints resulting from the behavior of other agents. Physical limits would result from an aircraft's performance envelope. A typical utility function would be the profit generated by a flight.

• **Assumption 3:** Agents only propose options that satisfy their constraints and have increased utility. That is, we assume that agents behave rationally and with self-interests in mind.

### Principled Negotiation

The agents in an IAAS do not act alone, so their action plans may conflict. Two airlines may want flights to depart from the same runway at the same time, or the trajectories of two aircraft may cause them to pass too closely. However, each agent is intelligent: given relevant data, an agent can reason about both the probable decisions and possible interests of other agents in the system. Not only does this allow each agent to change its own action plan to avoid conflicts, but it also can examine whether there are changes to the action plans of *other agents* that might benefit one or more other agents as well as itself. The system must solve  $N$  problems of the form of (6) without any single agent having complete knowledge of  $A_M \subseteq A$ . Agents must have procedures to communicate and discuss these plans in order to effectively coordinate actions.

*Principled Negotiation* [12] was developed as a method that negotiators could use to reach better agreements than could be obtained using traditional confrontational tactics. The underlying idea is that in most situations there are options that will benefit all the parties in negotiation. A favorable agreement is more likely to be reached if a negotiator proposes *options for mutual gain* and if all the parties *assess the options using objective criteria* (Fig. 3).

The overlapping of declarative functions of agents in an IAAS gives rise to many situations where negotiation could occur. Every part of an aircraft's flight from gate to gate would be negotiable. Traffic management agents would be able to approve many of the proposals, as the proposing agent would try to ensure that the options provided *mutual gain*. An airline might suggest that a lightly loaded aircraft take-off from a stub runway or carry out an intersection departure rather than use the main runway, reducing the delay to the flight and increasing the airport's throughput. Aircraft would propose modified trajectories that improved the overall traffic situation or increased safety margins, as well as reducing fuel usage.

Limited negotiations already occur in today's AAS. Pilots can propose course and altitude changes to controllers. When ground delay programs are run, airlines can propose flight cancellations to the flow management authority, allowing substitution of flights into the newly available slots, reducing total delays. The IAAS concept

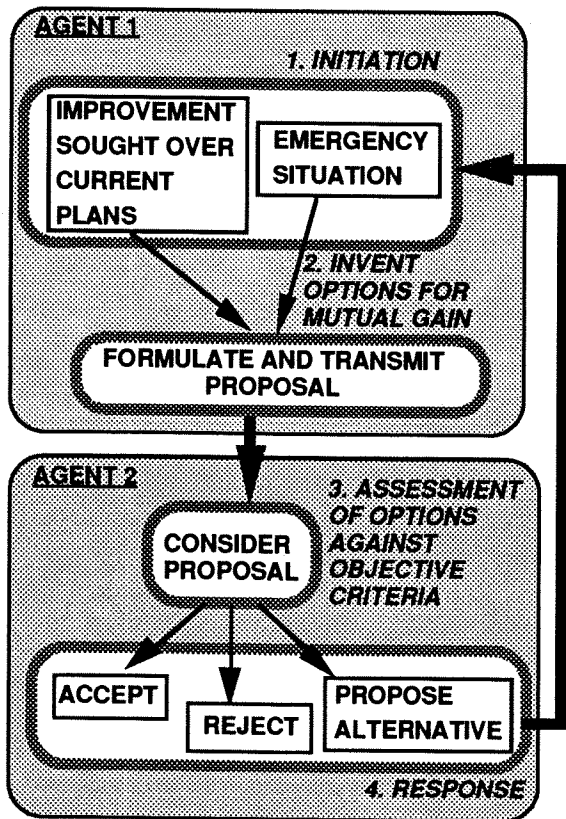


Figure 3. The Principled Negotiation process.

encourages widespread negotiations. If more agents are applying their data, processing power, and analytical approaches to any particular situation, the chances of improving the system's performance in the view of most agents will be increased. At the same time, the chance of contention between agents also rises.

It is important to agree on *objective criteria* for assessing options [12]. If agreement can be reached about the criteria, then it is much more likely that the assessment of any particular option will be rational, so overall agreement is easier. However, agents are concerned with different subsets of all the flights that make up the dynamics of an IAAS. An airline is concerned mainly about the flights of its own aircraft, while a traffic management agent must be concerned about all the flights in its area. Hence, the criteria for assessing an option will not be shared, even if both agents use identical measures.

Agents need knowledge of other agents' criteria to propose options for mutual gain that have a high probability of acceptance. Use of objective criteria makes an agent's negotiating behavior more predictable, helping other agents to propose mutually beneficial options. *Subordinate* agents are more likely to regard imposed decisions as fair if *superior* agents use objective criteria that can be inspected.

Agents use different methods for assessing options, and they display different negotiating behavior.

Some agents display *maximizing* behavior in negotiating situations, while others display *satisficing* behavior. A *maximizer* tries to ensure that any agreed-upon option provides increased utility compared to the existing plan; when given a choice, it chooses the option with the maximum utility. A *satisficer* is an agent that assesses options presented to it by subordinate agents; it accepts an option if certain criteria are satisfied. A TrMA examines a proposed trajectory change to check that no separation criteria are violated and that no hazards are encountered, but it does not try to maximize a quantity like throughput unless traffic is particularly heavy. As the situation is dynamic, both the utility functions of maximizers and the satisfactory sets of satisficers change over time.

### Representation of Negotiation Situations

Visualization of the possibilities arising from a negotiation situation is aided by diagrammatic representation of the constraints and the utility function of each agent. Each point represents an action plan. The constraints  $c_{a_i}$  on the action plans for a single maximizing agent  $a_i$  define a *feasible set* (Fig. 4). The utility  $U_{a_i}$  of the options within the feasible set is represented by contours of equal utility.

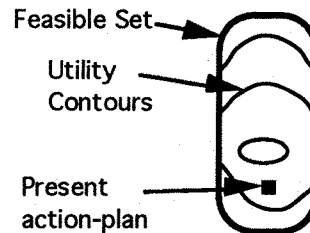


Figure 4. Representation of the constraints and utility function of a maximizing agent.

The feasible set, utility contours, and action plan are dynamic. The action plan represents the *intended* actions of the agent at a point in time. Deviations can be caused by changes in environmental conditions or by performance limitations of the agent. The feasible set and utility contours vary as the agent's state changes or as the agent receives new data.

A typical negotiation situation in the IAAS involves a maximizing agent proposing an option to a superior satisficing agent. The proposing agent has to ensure that any proposed option lies in the satisfactory set of the satisficer; otherwise it will not be approved (Fig. 5). The boundary of the satisfactory set of the satisficer also is dynamic. The satisfactory set of a TrMA depends on the prevailing and predicted traffic and weather conditions. Other factors, such as the equipment fit of the aircraft and the runway configuration, also affect the bounds.

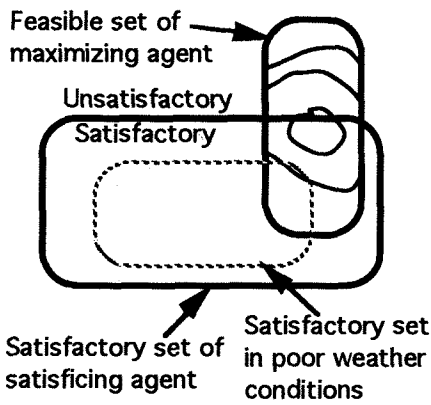


Figure 5. Overlap of the satisfactory set of a satisficer and the feasible set of a maximizer.

The maximizing agent usually does not know the satisfactory set bounds of the superior agent. Negotiation allows the maximizer to obtain information about the satisfactory set. If the satisficer rejects a proposal, the maximizer gains information about a portion of the boundary of the satisfactory set. The maximizer gains more information if the superior agent supplies reasons for the rejection. For the TrMA-aircraft example, this reason could be a conflicting aircraft. The two aircraft could negotiate with each other to search for options that have higher utility for both agents and that are acceptable to the TrMA (Fig. 6).

Aircraft must ensure adequate separation from other traffic. Separation may be specified in terms of time or distance. Different separation criteria are represented by the shaded circles in Fig. 6. In case (a) it is possible for both aircraft to fly optimal action plans and meet those separation standards. Although this is not possible in case (b), aircraft A can still propose an option to aircraft B that would improve its utility and allow aircraft A to fly closer to its optimal action plan. Negotiation allows agents to infer information about other agents' utility functions. In some cases agents could provide information that affects

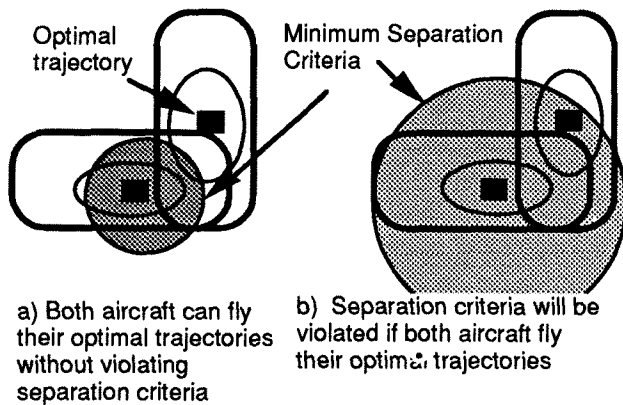


Figure 6. Feasible sets and separation criteria for two aircraft.

the utility function contours of another aircraft. In case (b) aircraft B may receive improved weather data from aircraft A, leading to a different optimal action plan for aircraft B.

### Inventing Options for Mutual Gain

The aircraft/airspace system is characterized by a large number of feasible options available to all agents at all times. In some cases the option space is discrete (e.g., flight arrival and departure order for a specific runway). In other cases, it is continuous (e.g., the possible trajectories for an aircraft). Today it is the human controllers and pilots, aided by computer systems, who invent options. A pilot can use the flight management system to calculate the cost of various routings. The Automated En-Route Air Traffic Control system (AERA) will allow sector controllers to see the effects of strategies they might use before they issue instructions to pilots [13].

*A\* search* finds the optimal path through a network of decision nodes [14]. It is a branch-and-bound search that minimizes a lower-bound estimate of the cost of the remaining path. At each node the algorithm expands the path that has the lowest total of cost-so-far and estimated cost-to-go. All paths that reach a particular node except the lowest cost path to that node are pruned.

A network representation of the choices is straightforward if the option space is discrete. If the option-space is continuous, *heuristic* rules can be applied to generate a network. To illustrate this technique, consider an aircraft flying on a busy jet route (Fig. 7). Aircraft A has just entered the sector and is cleared to fly at FL310 to the end of the jet route (400km). It has received information on the wind-profile for the jet route. The aircraft would like to find trajectories that allow it to reach the end of the jet route with reduced fuel consumption in the planned time of 30 minutes.

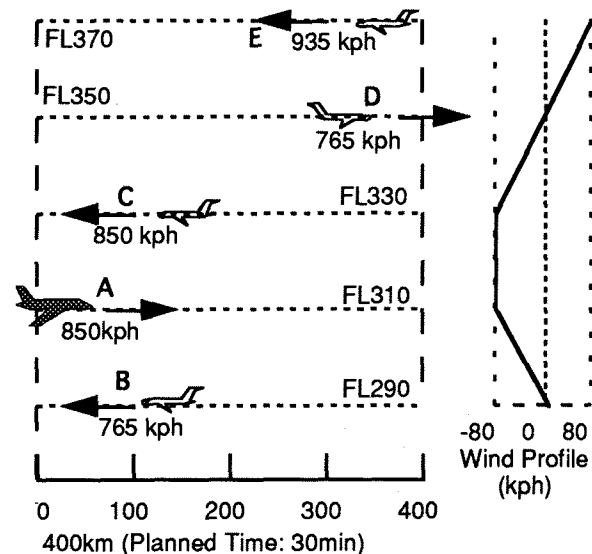


Figure 7. An example traffic scenario.

There are an infinite of number of trajectories that the aircraft could fly, bounded only by its performance envelope, but we can apply several rules. Aircraft must fly at the flight levels indicated unless they are climbing or descending. Paths that involve both descents and ascents also are pruned for reasons of pilot workload and passenger comfort. Only altitude changes that occur within 10 minutes are considered, as options will be re-examined at that time. The option space can be discretized further by setting climb rates at 1000ft/min, assuming constant air velocity, and initiating climbs only at 2 minute intervals. The network generated applying these rules to the scenario contains 48 possible trajectories. The heuristic rules can be adapted to generate more or fewer options in accordance with the computational capacity of the system used. The network can be reduced further if the aircraft has knowledge of the surrounding situation. Figure 8 shows the remaining network if the aircraft is aware of the two closest aircraft (B and C) and has to satisfy a 5 n.m. separation criteria.

The A\* algorithm searches the network for the optimal path, which the aircraft can then propose to the TrMA. In this case a number of the paths would be rejected by the TrMA because of the traffic at FL350. If the aircraft had this information the network could have been pruned further. The utility function of the aircraft could be defined as the fuel saved compared to the existing trajectory. The aircraft also might include the deviation from the planned 30 minutes for the traversal of the sector.

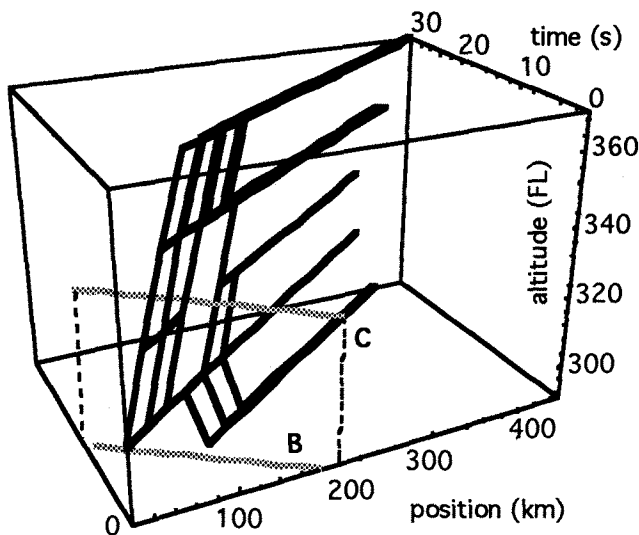


Figure 8. Path network accounting for aircraft B and C.

### Techniques for Assessing Options

Once options have been generated, the agents in the negotiation must assess them. A maximizer checks to see if a proposed option has an increased utility compared to the present plan. The utility of an option may be difficult to quantify, as the agent may be interested in many different attributes of the option. An aircraft agent assessing a trajectory change considers the effect on

arrival time, fuel consumption, safety (separation from other aircraft and other hazards), direct operating costs, and passenger comfort. The relative weight that the maximizer attaches to these attributes also can change. An aircraft that is part of a bank of arrivals puts a higher weight on deviation from planned arrival time than a flight that is not part of the bank. A flight that has suffered a major system failure is far more concerned about safe arrival of the flight than fuel usage.

*Multi-Attribute Utility Theory (MAUT)* [15] provides a way to assess options within complex sets of alternatives. The weight of each attribute changes with the agent's scenario [16]. The utility of the option is given by:

$$U_{a_i}(\tilde{u}_{A_M}) = W_{a_i}(\mathbf{x}) \cdot \mathbf{a}(\tilde{\mathbf{x}}, \tilde{u}_{A_M}, \mathbf{w}, t) \quad (7)$$

where  $U_{a_i}(\tilde{u}_{A_M})$  is the utility of option  $\tilde{u}_{A_M}$  to agent  $a_i$ , and  $\mathbf{a}(\tilde{\mathbf{x}}, \tilde{u}_{A_M}, \mathbf{w}, t)$  is the vector of attribute values for that option.  $W_{a_i}(\mathbf{x}, t)$  is the weighting vector for the agent, and it is a function of the agent's state. Many of the attribute values in  $\mathbf{a}(\tilde{\mathbf{x}}, \tilde{u}_{A_M}, \mathbf{w}, t)$  may be uncertain or may rely on estimated data. The agent may choose to reduce the weighting of uncertain attributes. Alternatively, Monte Carlo evaluation could be used to probabilistically assess the utility of the option [17,18].

Satisficers and maximizers assesses options differently. A satisficer has to decide whether an option is acceptable rather than quantify the option's utility. Satisficers have to handle multiple proposals, so the method of assessment must be quick and accurate. The method also must deal with the uncertainties inherent in the IAAS.

*Decision trees* classify situations by testing the attributes of the situation in a particular sequence. At each node of the tree a different attribute, or combination of attributes, is tested. The result of the test determines the next node reached. When a *leaf* node is reached, the classification (or decision) is returned. The trees are created by inducing rules from a large number of training examples using a suitable algorithm, such as *ID3* [19] or *OCI* [20]. *Pruning* strategies can be employed to prevent the tree from over-fitting noisy data. Uncertainty in the attribute values is handled implicitly during creation of the tree; tests on uncertain attributes are less useful for establishing the class of a situation. If an estimate of the uncertainty (or accuracy) of an attribute measurement is available, then this can be added to the list of attributes and used by the decision tree.

Satisficers may have to make decisions based on their assessment of how accurately agents will follow a

particular plan. The control system for a hybrid aircraft navigation system has a similar problem: to decide what combination of navigation aids should be used when each navigation system will provide imperfect position estimates. The errors obtained are dependent on many factors. An expert system that uses a decision tree has been developed for hybrid navigation systems [21]. The configuration of aircraft navigation sensors was chosen by classifying the probable position accuracy obtained from the various possible sensor combinations. The decision tree examined attributes such as the number of available navigation stations and the trajectory geometry to choose the sensor configuration. The training set for the decision tree was constructed by running a large number of Monte Carlo evaluations of the navigation system performance for many different scenarios. The important factors affecting the performance were identified using analysis of variance (ANOVA), and the ID3 algorithm was then used to construct a decision tree, based on these factors.

### MODEL OF A NEGOTIATING INTELLIGENT AGENT

The declarative functions of intelligent agents (IAs) are well modeled by *expert systems* [11, 22-24]. Goal planning, scenario identification, and operating mode selection require reasoning. Alternatives must be evaluated, and decisions must be made through a process of *deduction*, that is, by inferring answers from general or

domain-specific principles. A *rule-based expert system* uses an *inference engine* to process the knowledge and beliefs contained in its *rule base* and *data base*. The procedural and reflexive functions of the agent, such as communication and estimation, are *side effects* of a rule being queried by the expert system (Fig. 9). As well as providing a model for analysis of collective IA behavior, this structure could be used as the basis for systems that provide intelligent assistance to humans (pilots, controllers, schedulers) or for systems that operate autonomously under human supervision.

The negotiation functions are carried out as side effects of the expert system. The expert system deduces the weighting function, constraints, and heuristics that are used by the systems that generate and assess options.

The functions of an IA can be divided into four *task groups*: emergency tasks, mode specific tasks, negotiation tasks, and routine tasks. The top-level structure of the rule base controlling these task groups is shown in Fig. 10. Rectangular boxes represent *parameters*, and ovals represent *rules*. Parameters contain raw data and other factual information about the domain. The possible *values* of the parameter are shown in the slots. Rules describe the relationship between parameters. The form of the rule is shown by the lines linking the parameters and the rule. AND relationships are indicated by arcs between the lines.

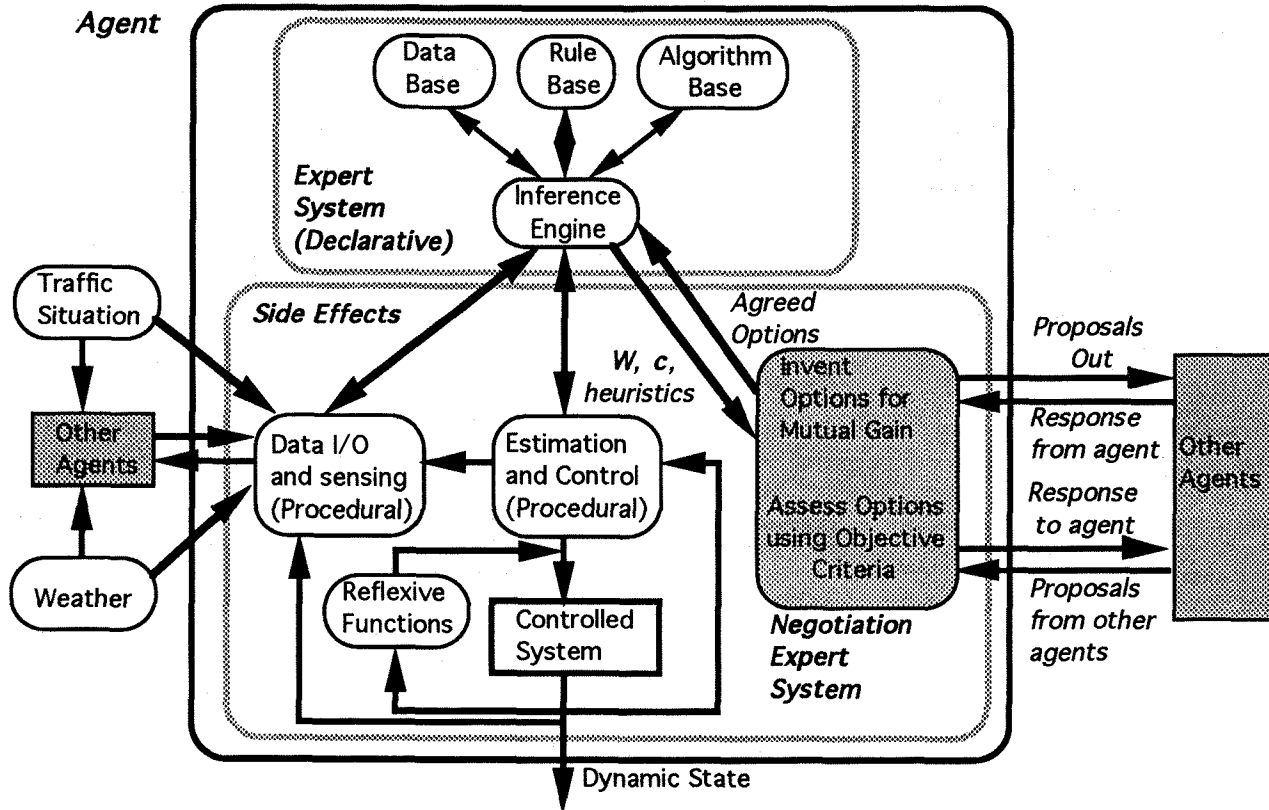


Figure 9. Structure of an Intelligent Agent.

The inference engine traverses the rule base using *backward* and *forward chaining*. If the value of an unknown parameter is desired a goal-directed search (backward chaining) is used. The logical outcome of new data, or a set of premises, is found by a data-driven search (forward chaining). The control cycle is driven by backward chaining to establish the value of a top-level parameter (TOP-LEVEL SEARCH COMPLETED in Fig. 10). This "fires" Rule 1, which is read:

```

IF    the value of parameter EMERGENCY
      TASKS COMPLETED has been determined
AND   the value of parameter MODE SPECIFIC
      TASKS COMPLETED is TRUE
AND   the value of parameter NEGOTIATION
      TASKS COMPLETED has been determined
AND   the value of parameter ROUTINE TASKS
      COMPLETED is TRUE
THEN  set the value of parameter TOP-LEVEL
      SEARCH COMPLETED to TRUE
  
```

EMERGENCY TASKS COMPLETED will be set to TRUE only if the actions that are required in an emergency situation have been executed. The value of this parameter may be TRUE or FALSE; the agent is not in an emergency situation at all times. The use of the

shaded box indicates that the search should continue (i.e., the control cycle continues) once the value of EMERGENCY TASKS COMPLETED has been determined, whether this is TRUE or FALSE.

Mode specific tasks are the functions that are executed only if the agent is in a particular state. For example, an action such as TAXI INSTRUCTIONS LOADED would be required only when an aircraft was on the ground or on approach; it would not be executed during departure or en-route phases.

The routine tasks are undertaken whatever the mode of an agent. A TrMA will update radar displays, fuse raw data, and update data bases on each control cycle.

The skeletal rule base for an expert system that would handle negotiations autonomously is shown in Fig. 11. It is applicable to any IAAS agent. Subroutines for generating and assessing options, described earlier, are executed when rules N4, N12, and N13 are fired. The rule base is separated into two sections; the rules for assessing options received by the agent, and rules for the agent to generate options.

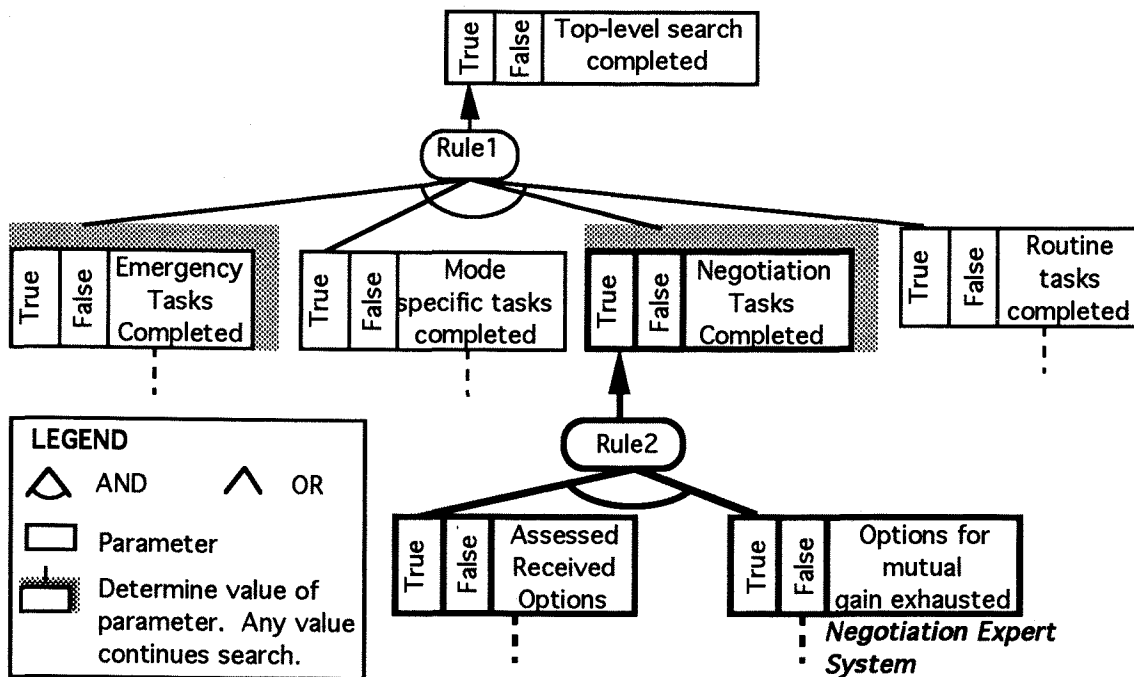


Figure 10. Top level rule-base for an Intelligent Agent.



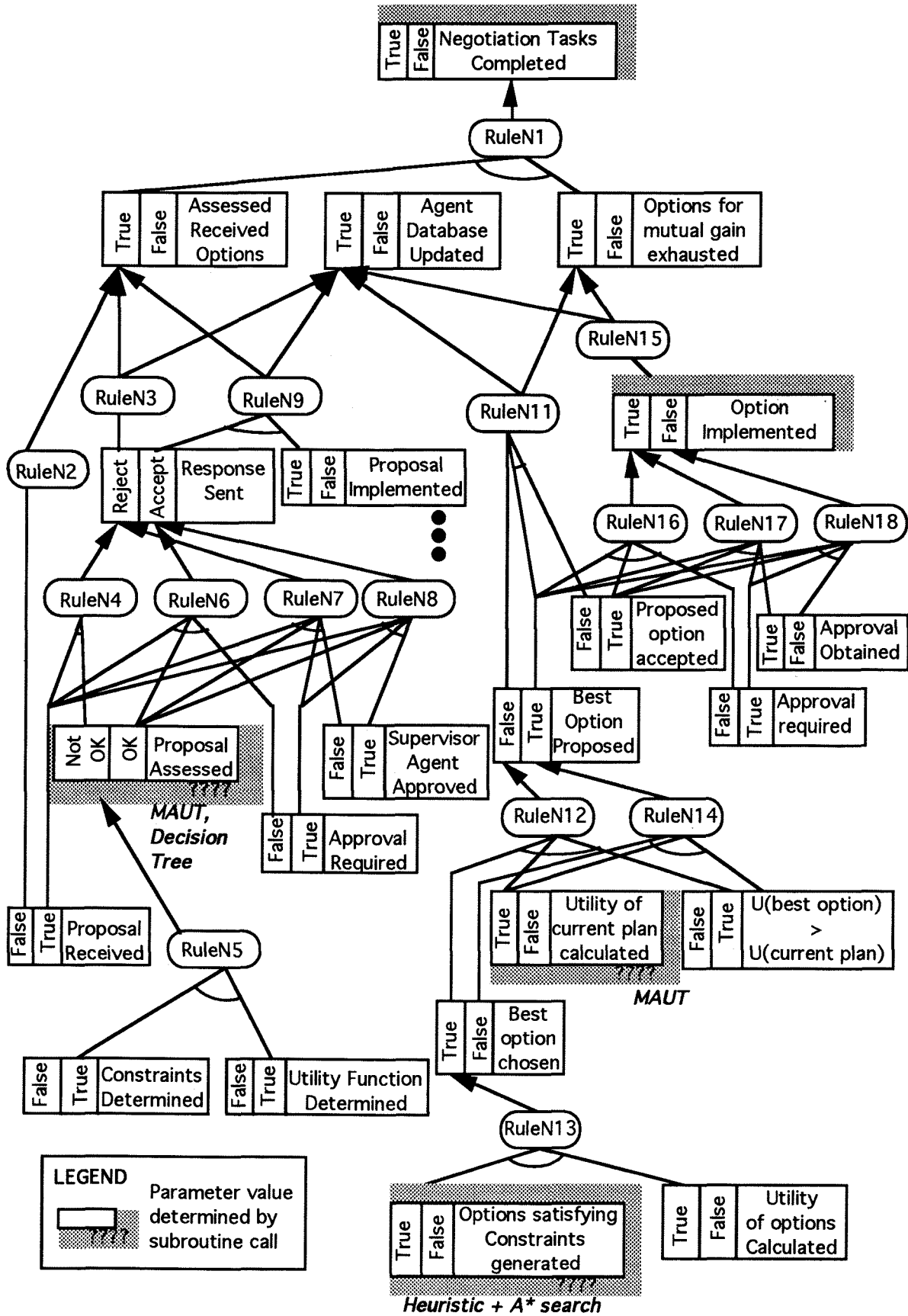


Figure 11. Rule base for a negotiation expert system.

## ORGANIZATION OF AGENTS IN AN INTELLIGENT AIRCRAFT/AIRSPACE SYSTEM

The lines of communication in the Intelligent Aircraft/Airspace System must facilitate effective negotiations and provide clear lines of authority. This can be provided by a hierarchical arrangement of traffic management agents (Fig. 12).

An agent initiating negotiations with the TrMA system will communicate initially with a sector, airport, or TRACON TrMA. An aircraft negotiating a trajectory change contacts the TrMA in whose airspace the trajectory first differs from the existing plan. This often will not be the TrMA for the airspace in which the aircraft is currently located. A trajectory change usually will affect all the downstream TrMAs, too. In this case, once the initial TrMA has approved the trajectory change in its airspace, it must pass the negotiations to the superior agent (Area TrMA) in the hierarchy. A long-haul flight may be passed up to regional level or higher. All TrMAs access the same central flight data base (CFDB), so an Area agent has access to the same information as do all its Sectors TrMAs, and it has a wider perspective. The superior agent will then communicate directly with the aircraft, accepting or rejecting the proposal, providing data, or supplying alternative options. Similarly, an Area TrMA that detects a possible conflict between aircraft in two different sectors would handle negotiations with those aircraft. If the conflict involved two aircraft in the same sector, the sector TrMA would handle negotiations.

The main difference between this structure and today's AAS is the combination of flow management and aircraft separation functions in a single hierarchy. The

aim of flow management is to prevent the number of flights from exceeding the safe throughput capacity of any airport or volume of airspace at any point in time. The IAAS achieves this by requiring the departure airport, arrival airport, and the higher TrMA (the TrMA that contains all the sectors through which the aircraft will fly) to "sign-off" on the planned trajectory at the time of flight plan filing. The trajectory is specified in more detail than in today's flight plans. The IAAS flight plan contains Out-Of-On-In (OOOI) times for the aircraft and a four-dimensional specification of the flight path.

From the moment an airline starts planning a flight, it provides data on the flight to the CFDB. As the day of the flight nears, the airline can provide increasingly accurate projections of OOOI times, aircraft type (and its equipment), and preferred trajectory. At the same time, TrMAs can make increasingly accurate predictions of the weather and traffic situations, probable runway configurations, throughput given the weather conditions, etc. If any TrMA predicts excessive traffic, it initiates negotiation with the airlines to reduce or reschedule movements to achievable levels. The early provision of accurate data and accurate forecasting should allow negotiated agreements to be reached well before flight time. Compared to today's flow management techniques, airlines should be able to plan for reduced capacity days, rather than hours, in advance.

The IAAS allows negotiation between agents other than TrMAs; airlines can negotiate on flight cancellations to match runway throughput, and aircraft can negotiate solutions to conflicts. However, if no negotiated solution is reached sufficiently quickly, the TrMA imposes solutions on the other agents.

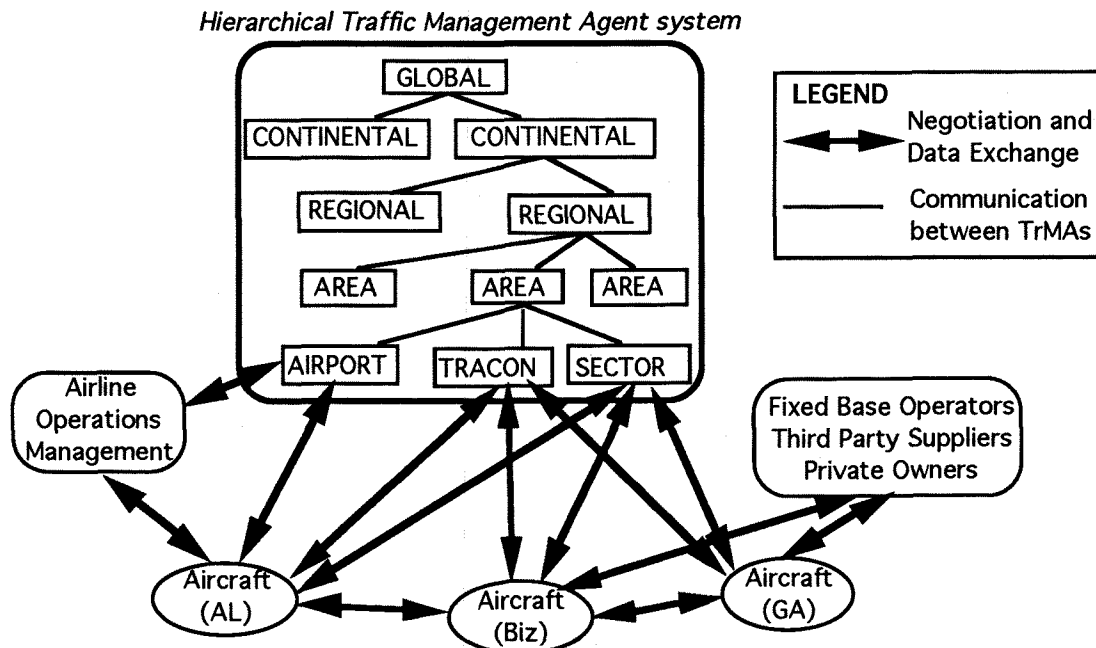


Figure 12. The structure of the IAAS.

Flights are subject to many causes of variability, such as slow passenger loading or changing wind speeds. No aircraft will ever precisely follow the trajectory filed in the flight plan, though advanced estimation and control techniques can minimize this error. To prevent the need for renegotiation at any deviation from flight plan, the TrMAs specify trajectory bounds when approving a flight plan. The aircraft needs to renegotiate its trajectory only if it is not able to stay within the bounds, or if it wants to fly outside those bounds. The bounds are changed by the TrMAs as the weather and traffic situation develops. Bounds on flights through heavily used airspace and into busy airports will be tighter. The uncertainty of a flight's position at any future time increases with the look-ahead time. TrMAs use *probabilistic reasoning* when assigning bounds. There always is a possibility that conflict situations will arise given uncertain trajectories. Excessively tight bounds would, however, restrict airspace capacity. The TrMAs therefore set bounds aiming to keep the probability of conflict arising below an acceptable level. As a flight progresses, the uncertainty in the TrMAs' predictions of the weather and traffic around the flight will reduce. In most cases, the TrMAs will be able to ease the bounds on a flight. Tightening will be required only in those cases where conflict situations are predicted given the present bounds on the aircraft.

## CONCLUSIONS

The operation of an Intelligent Aircraft/Airspace System has been described. An IAAS would use principled negotiation as the basic form of interaction between agents, allowing them to make best use of all their capabilities, particularly their declarative functions. An expert system framework has been presented that captures the declarative, procedural, and reflexive functions of intelligent agents. Subroutines for inventing and assessing options, outlined in this paper, are called as side effects of declarative decision-making functions. The framework can be used as a model for analysis of the behavior of groups of interacting intelligent agents. It provides a basis for designing intelligent systems that provide assistance to humans or that operate autonomously.

## ACKNOWLEDGMENT

This work has been supported by the Federal Aviation Administration under FAA Grant No. 92-G-0011.

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