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Decision support system in tactical air traffic flow management for air traffic flow controllers

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A B S T R A C T

A distributed decision support system for tactical air traffic flow management is developed for the First Integrated Center of Air Defense and Air Traffic Control (CINDACTA I) in Brasilia. The paper specifies the role of CINDACTA I, looking at the problems of air traffic flow management in Brazil and describing an initial evaluation of the decision support system. The decision process involves a meta-level control approach and reinforcement-learning algorithms that allow air traffic flow controllers and supervisors to acquire knowledge and get assistance to enhance their decision-making. The paper also develops simulations involving egalitarian and prioritization distribution of flight flows for the Sao Paulo Terminal Area.

1. Introduction

Brazilian air transportation suffered from a number of crises in the early 2000s and a lingering problem is to improve the air traffic control system. In particular, the air traffic flow management (ATFM) decisions are based on pragmatic experience rather any formal model. Linked to this, the inability to quantitatively evaluate the impact of actions in one specific sector on the traffic flows of adjacent sectors makes it impossible to assess the usefulness of alternative actions. A Distributed Decision Support System Applied to Tactical Air Traffic Flow Management (SISCONFLUX) is being developed to assist air traffic controllers at the First Integrated Center of Air Defense and Air Traffic Control – CINDACTA I, in Brasilia, in order to overcome some of these problems. The paper looks at the role of CINDACTA I within the actual problems of air traffic flow management in Brazil.

2. Tackling ATFM problems

2.1. Operational procedures in Brazil

In 1990, the Brazilian Airspace Control System (SISCEAB) was instituted, to integrate flight protection, telecommunications of Ministry of Aeronautics (STMA), search and rescue and air defense and air traffic control (SISDACTA).[1] Established under *Command of Aeronautics Instruction 100-22 (ICA 100-22, 2007)*, control agencies are responsible for the identification of risks of congestion and/or saturation of control sectors and, thus, for adopting restrictive measures for air traffic flow to prevent violation of safety limits. This Instruction defines the restrictive measures to control flights including waiting on the ground, enroute orbiting, reduction of speed, alternative routes, enroute delay, and delay during landing and waiting at intermediate aerodromes.

2.2. Diagnosis and specification of the role of CINDACTA I

Brazilian airspace is divided with four Flight Information Regions (FIR), of which on, FIR-BS (Brasilia), is made up of three sub-regions: Brasilia, Rio de Janeiro and Sao Paulo, consisting of 12 control sectors. CINDACTA I is responsible for the air traffic flow management within the FIR-BS, and controls about 50% of the flow of regular flights in Brazil (Centro de Gerenciamento da Navegação Aérea, 2005). In this center, every sub-region with their related sectors, are managed by a supervisor, who is responsible for making

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[1] SISCEAB is controlled by the Command of Aeronautics, through the Department of Airspace Control that manages Brazilian airspace through its multiple regional agencies, such as CINDACTAs (Crespo et al., in press).

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decisions regarding special situations. Each sector is monitored by a controller and an assistant.

CINDACTA I, together with the Area Control Center of Brasilia (ACC-BS), and the approach control centers (APP), carries out air traffic control within its area of jurisdiction but does not have a specific system for the tactical management and synchronization of traffic flow, especially where disruptions occur due to abnormal meteorological conditions, aeronautical incidents, or accidents. The failure of standard traffic control tools, as well these external factors, can result in saturation of control sectors with 14 or more aircraft in a sector. When there is saturation, supervisors have the responsibility to evaluate the situation, along with the forecast entry of aircraft into sectors, and to approve restrictive measures suggested by the operator. These decisions made by controllers and supervisors are based on their experience without the support of computational decision tools. It is also impossible to perform quantitative evaluations of the measures adopted in a specific sector on the traffic flow of adjacent sectors. Thus, there is no adequate forecast of the impact any individual measure has on the FIR-BS as a whole.

2.3. ATFM using computation methods

ATFM involves synchronization in real time (Stoltz and Guerreau, 2002). Computational approaches for doing this face difficulties in the efficiency of the computational systems, and in the need for stability and security. The majority of the systems are centered architecture,[2] although Wolfe et al. (2007), and others, offer solutions embracing a distribution of actions. Aeronautical information exchange (meteorological data, airspace situations, and congestion forecasts) is important for improving air flow performance (International Air Transport Association, 2003a). Although, aircraft and airports are equipped with instruments that allow monitoring and fast transfer of information, whether the aircraft are on the ground or in flight (International Air Transport Association, 2003b), intuition and experience are the main tools of controllers when deciding on adjustments of trajectories, delays in takeoffs and landings, adjustment to schedules, etc. It is also important for flight trajectories to be monitored to determine if a pair of aircraft will infringe on minimum separation distances, and, if this happens, the action to be taken. Pressures on flight controllers tend to increase with the increments of information they receive, generating a rising load of stress and reasoning difficulties potentially resulting in sub-optimal decisions (Bonzano et al., 1996).

In this context emerges the ground holding problem (GHP), the resolution of which requires synchronization between adjacent sectors, analyzing a set of landings and takeoffs expected within an area of supervision, in such a way that the optimal flow is found between these sectors (Mukherjee, 2004; Ball et al., 2003). Linear programming is useful for the optimization problems when the objective function and the restrictions are linear. Dynamic programming, however, can be useful for combinatory optimization, where a problem can be decomposed into sub-problems, and can help solve sub-problems that are extended increments of the solution to the problem as a whole. More recently, distributed models based on multi-agent techniques (Heymann et al., 2003; Dib et al., 2007) have been developed that focus on the exchange of messages to negotiate a global balance among pilots, controllers and other participants in the system. Multi-agent architecture, implementation approaches and software prototype for air traffic control within airport airspace, capable of automatic detection of potential violations of safety policies by individual aircraft and corresponding incident management (Gorodetsky et al., 2008), have also been suggested.[3]

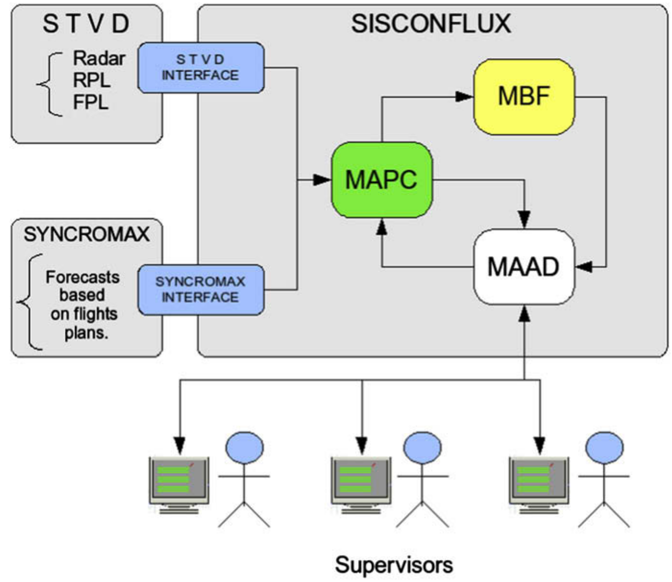

Fig. 1. The architecture of SISCONFLUX.

3. The architecture of SISCONFLUX

The approach adopted here involves a modular system capable of helping both air traffic flow controllers and supervisors to determine the most effective restrictive flow control decisions under certain constraints.

3.1. The architecture of the system

SISCONFLUX was designed to suggest flow measures prioritizing flights, routes or airports prioritized. Actions are based on directions emanated from agencies responsible for the management of traffic flow in Brazilian airspace. The architecture of the system encompasses a modular conformation (Fig. 1), by means of the development of specific modules and interfaces for preexisting modules' aggregation. Therefore, the processing required for the generation of suggestions to air traffic controllers and supervisors is distributed by system modules. SISCONFLUX is a support subsystem to an automated traffic flow management system (SYNCROMAX) that offers an overview of actual and projected air traffic situations, providing flow managers with detailed information to support the implementation of a broad range of measures (Staniscia and Dalmolim Filho, 2008).

3.2. Module of monitoring and scenario forecast – MAPC

MAPC provides the system (Fig. 2), in real time, with expected traffic flows in various sectors using air traffic movement information processed in the FIR-BS, together with information available at the flight plan center of CINDACTA I. A scenario is defined considering information of repetitive flight plans (RPLs), provided by the air navigation management center (CGNA), as well as eventual flight plans that are presented at least of 45 min prior to takeoff, and processed by the flight treatment system in 20 min for

[2] See Weigang et al. (1997), Nguyen-Duc et al. (2003) Dell'Olmo and Lulli (2003), Zhang et al. (2005) and Liu et al. (2006).

[3] Another multi-agent simulation of Collaborative ATFM has been by NASA (Wolfe et al., 2007), where several simple strategies for the airline operations center agents to select routes are evaluated.

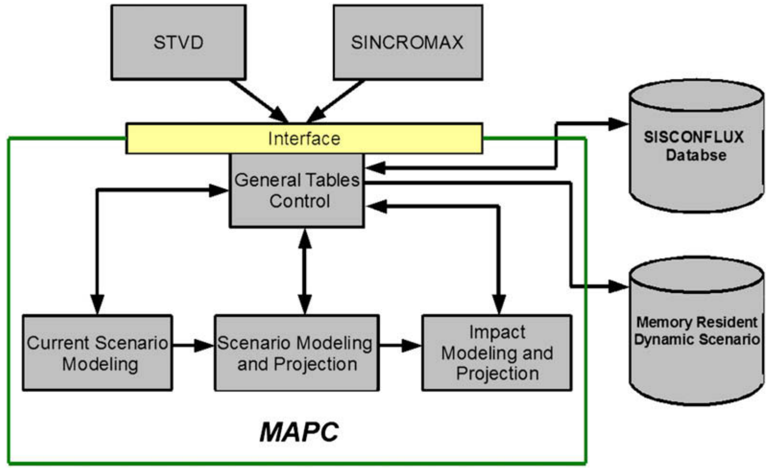

Fig. 2. Module of monitoring and scenario forecast.

a military or non-regular civil flight. The combined FPLs and RPLs, and information of air movements within the FIR-BS, make up the database for scenario management. Such information can be extracted from the system of data treatment and visualization (STVD) in operation at CINDACTA I. MAPC is generated using accelerated simulations based on air traffic flow analysis, and provides information about future demands on airspace and national aerodromes for agencies responsible for ATFM, allowing them to identify an air traffic control sector's capacity for a given period, on a given day (Gonzaga da Silva, 2001).

3.3. Interface with STVD system

The STVD is an air traffic control system that processes information from radar that is part of the air defense and traffic control systems and provides air traffic controllers with pictures of air traffic within the FIR-BS. The system also processes all information of air movements with real time forecast in the FIR-BS by combining the flight plans available. The interface with STVD enables the extraction of information for composing the scenario that is processed by MAPC (Fig. 3).[4] The information processed by SISCONFLUX is made available on two subsystems: flight plans and radar information processing. The interface is developed using parameters specified for the subsystem of communication and support, which contains a communication layer.

3.4. Module of flow balancing – MBF and Module for evaluation and decision support – MAAD

Both modules will be described in the following items 4 and 5.

4. Module of flow balancing – MBF

The MBF interacts with the MAPC, while receiving the information from MAAD concerning modifications to the current scenario that are not the result of air movements or restrictive control measures. Once projections relating to traffic flows in the FIR-BS are made, MBF proceeds to analyze movement distributions in progress, as well as the planned flows in the various control sectors. When the projected values in the scenario get close to the congestion limits (80% of the sector's capacity) or saturation, the module will initiate traffic flow balancing and project a new scenario.

4.1. Balancing methodology

A graph is defined as $G=(V, E)$ comprising the group of sectors that form FIR-BS. There is a multi-flow that corresponds to the combination of directional flows. Unlike Zhang et al. (2005), the edges correspond to sectors and a path in the graph is related to a possible route. Each edge has a capacity and the vertexes represent the transition points between sectors. To illustrate, consider Fig. 4 as a partial cutting of FIR-BS with only three terminals with the set of paths between the sectors in the figure composes a multi-flow as shown in Fig. 5. The routes connecting T_1, T_2 and T_3 are: T_1 S05 S06 T_2; T_1 S05 S04 S01 T_3; T_2 S06 S05 T_1; T_2 S06 S03 S02 S01 T_3; T_3 S01 S04 S05 T_1; and T_3 S01 S02 S03 S06 T_2. One can identify three flows in Fig. 6: from T_1 to T_2 and T_3, from T_2 to T_1 and T_3 and from T_3 to T_2 and T_1. Suppose that f is the number of flows combined in the multi-flow, where in the example $f=3$. Fig. 5 represents the flow from T_2 to T_1 and T_3 and similar graphs for all relevant flows can be obtained in the same way. It is possible to build from these a graph that combines all flows into a multi-flow, associating an origin to a destination.

Taking C_{ij} as the capacity of sector i and flow j, but with legislation limiting the capacity of each sector to M, and forecast traffic in i of U_i, then the balance of residual workload is $L_i = M - U_i$, where

$$\sum_{j=1}^{f} C_{i,j} \leq L_i \quad \text{for all sector } i$$

with f being the flows associated with the multi-flow. The objective is to attain the most efficient use of the flow, so that solutions can be found for

$$\sum_{j=1}^{f} C_{i,j} = L_i$$

Taking $k_{i,j}$ as the fraction of flow j associated with sector i, the equation can be written as

$$\sum_{j=1}^{f} K_{i,j} L_i = L_i \quad \text{for all sector } i$$

[4] The system of treatment and visualization of data is composed of subsystems developed on a CPU platform 333 MHz UltraSPARC-II, with the operational system Solaris 2.6.

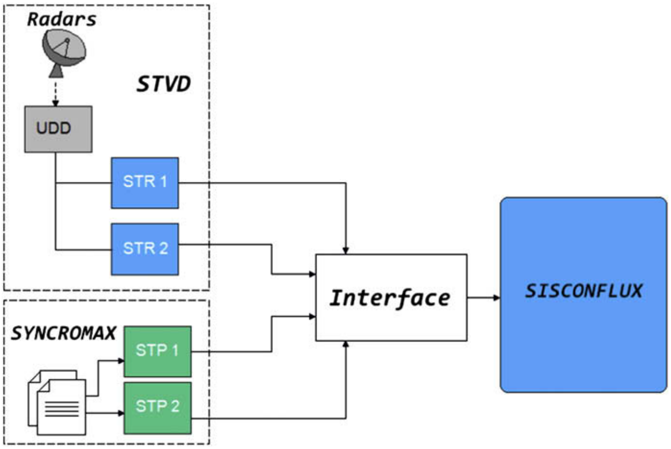

Fig. 3. Interface of SISCONFLUX with STVD.

that results in

$$\sum_{j=1}^{f} K_{i,j} = 1 \quad \text{for all sector } i \text{ and flow } f$$

which is always true because of the definition of $k_{i,j}$. The challenge is to determine $k_{i,j}$ so that the multi-flow has a balanced distribution. The distribution of $k_{i,j}$ can be obtained either by supervisors defining flow quotas with the help of stored data embodies previous experiences or by querying previous actions, seeking the most suitable decision for the current situation. The information is fed into the MAAD module. Maximization of the internal flow, f, implies smaller flows because the 4th sum is constant and equal to unity. Thus maximization of the multi-flow does not imply maximization of all its components. Often there is a need to prioritize a specific flow, say to relieve a particular airport, and so $k_{i,j}$ is adjusted to favor the flows of aircraft leaving it and to the detriment of others.

Based on the graphing technique, the maximum flow is found in the combination of flows comprising the multi-flow. The flow measure is based on the minimum cut, which corresponds to maximum flow. The sum of flows in the combined graph (Fig. 6) equals the flow in the multi-flow. The Edmonds–Karp algorithm is used for flow adjustments because of its simplicity and relative efficiency. The model considering a maximum of 12 sectors performs well for an algorithm complexity of O($V \times E^2$).

The flow adjustment algorithm does not consider variations in flow over time (Crespo et al., in press). The model here

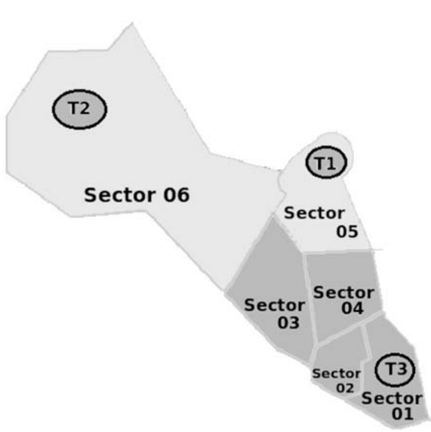

Fig. 4. Part of FIR-BS.

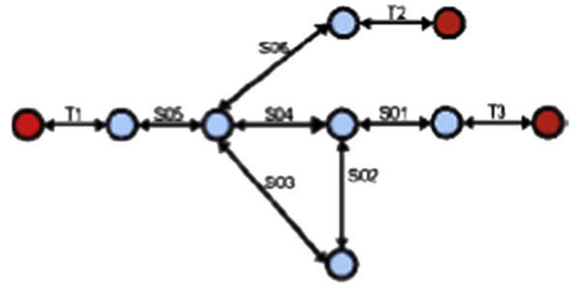

Fig. 5. Multi-flow of the part of FIR-BS.

establishes a heuristic that redistributes capacities based on each sector's mean time occupation. The problem with time analysis involving air traffic is that aircraft are discrete entities that can produce inefficient use of sectors if there is a delay between the departure and the effective occupation of the sector. When reducing departure frequency to solve a saturation problem in sector i, that will, say, be saturated in 20 min, some of the intermediate sectors $i-1$, $i-2\ldots$ working with departure frequencies lower than i can admit traffic. This is more pronounced when these sectors are at the intersection of several paths. Moreover, there is the need to adjust flows after departures because saturation involves aircraft that have already taken off. In this case, flow restrictions controlling the internal flow among sectors are important and thus MFB involves a time analysis using queuing techniques and heuristics for each sector.

If the mean time needed to cross sectors are equal, algorithm are not needed for time effects, flow would be approximately continuous and the space model associated with scenario forecasts is sufficient for ground holding adjustments. Unfortunately, there are variations in sectors sizes, in aircraft speeds and in the time needed to cross sectors. A solution is to use excessive processing time that defines a balance using a mean time $m'_{s_i} \leq m_{s_i} \leq m''_{s_i}$ to cross sectors with tight limits for all routes, assuming the time the aircraft enters the sector b_{v_j,s_i} is known (v_j is the flight j and s_i the sector i); that flight v_j has a known route; that the exit time or the time the aircraft will take to leave the sector a_{v_j,s_i} can be calculated by$a_{v_j,s_i} = m_{s_i} - b_{v_j,s_i}$; and that the time of entrance in sector i is equal to the time of exiting sector $i-1$ sectors on the same route.

For each section, flights are organized in increasing order by the exit time of the sector $Ls_i = a_{v_j,s_i} \geq a_{v_{j-1},s_i} \geq a_{v_{j-2},s_i}\cdots$. A comparison of the time to exit the first element of Ls_i with that to exit the first element in Ls_{i-1} is made. If the time to exit i is below or equal to that of exit $i-1$, the aircraft will leave the sector before the next enters (or at the same time), so the capacity of i can be increased by a unit. Repeating the analysis for other aircraft, if the time to exit i becomes longer than the time to exit $i-1$, capacity does not change because aircraft stay in the sector during the period. Sectors $i-1$

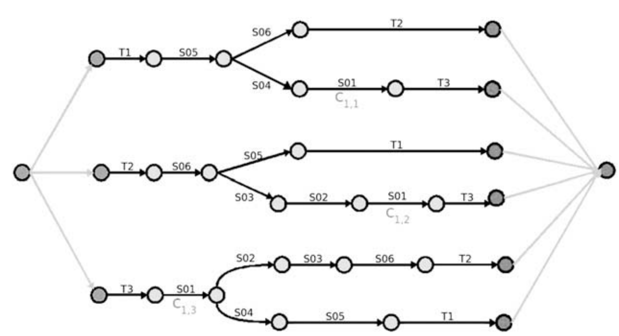

Fig. 6. Joining the flows to generate the complete graph.

and $i-2$ are then processed to obtain their desired capacity. By analyzing these lists, MFB obtains the time to hold en route in case sector i is saturated and the time to exit sector $i-1$ gets very short. It will suggest to MAAD to hold an aircraft en route on list Ls_{i-1} and provide an estimated holding time. The combination of space and time analysis corrects the initial analysis by approaching a dynamic solution using this second estimate.

4.2. The architecture of the MBF

MBF looks for possibilities that result in ideal conditions for air traffic flows that entail maximum fluidity within any capacity restrictions in controlled sectors. It also adjusts capacity so that some flows are prioritized. Supervisors, taking into account technical and operational factors, determine the selection of any constraint if there is saturation. Once decided, MBF submits suggested balance adjustments to MAAD that then evaluates them, informs the operational team about recommended actions and performs the learning procedure allowing the system to store a group of prior decisions and adapt to the environment. After the decisions are submitted to MAAD, the module also stores the scenario forecast associated with the group of actions. These are applied to the real scenario, and the MAPC builds a new scenario, considering the new information. This new scenario is, again, inputted to MFB for reassessing the need for any restrictive actions.

The mapping of the multi-flow into separate flows allows adjustment and prioritization of some flows. Supervisors who observe guidelines known to produce efficient results do prioritization. The most recommended flow restrictions associated with each terminal are converted into frequencies of departures from specific origin points because flight controllers work by limiting the interval between departures from an airport, and not specifically, with flight schedules. Specific schedule adjustments are the responsibility of the aerodrome administrations, once the frequency of departures is supplied.

4.3. The relationship between the sub-modules in MFB

Fig. 7 shows the role of each sub-module of MFB. The subdivisions in the sub-modules distribute system tasks to produce a better structural organization, facilitating overall understanding. The approach used is top down, where, starting from the end of activity, specializations designed for accomplishment of that activity are defined.

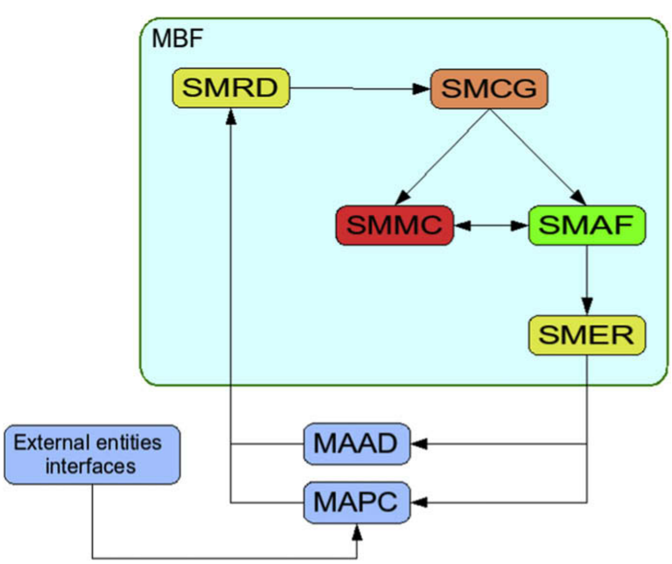

Fig. 7. Architecture of the module of evaluation flow balancing.

- Data persistence involves receiving and/or looking for and formatting data for processing. The search is made through queries to a database of stored information.
- SMCG is the building of the graph associated with the current situation in sectors considering the routes in the Route Table and the associated attributes of the active sectors in each route.
- SMAF computes the distributions of gaps between various flows, adjusting the occupation of a sector according to the average flight time of aircraft en route. It also balances the flow and determines flow restrictions according to the prevailing situation.

5. Module for evaluation and decision support – MAAD

MAAD provides air traffic controllers and supervisors with restrictive traffic flows for scenarios in case of congestion (Alves et al., 2008). The best restrictive action is conditioned by parameters defined by the supervisor and may include the need for prioritization of flights at a certain airport. This information is sent to the MAPC for new scenarios to be developed and to restart the cycle. There are four stages involved.

5.1. Meta-level control

Meta-level control is the ability of complex agents operating in open environments to sequence domain and deliberative actions to optimize expected performance. Raja and Lesser (2004, 2007) add an additional layer of meta-control that acts over the component of control in the system to help the decision process. Reinforcement learning also allows agents to acquire knowledge from experience to enhance decision-making. Meta-level control is a process of deciding between dropping the goal and not do any analysis; delaying goal analysis; reasoning about the amount of effort to go into goal analysis; and determining the context of the goal analysis – e.g. whether to analyze it as one goal or multiple goals within a single agent's perspective, or as single or multiple goals in the context of a facilitating agents' goals.

Meta-level control is useful in situations where options for goal analysis are expensive – when costs detrimentally affect agents' performances and when the cost of goal analysis is significantly more expensive than meta-level control actions. It is also useful where a choice has to be made about the type of goal analysis and the options for goal analysis have different costs and produce results with significantly different utilities.

5.2. Reinforcement learning

Reinforcement learning is learning what to do and how to map situations to actions so as to maximize a numerical reward signal (Sutton and Barto, 1998). The learner is not told which actions to take, as in most forms of machine learning, but rather must discover which yield the most reward by trying them. Actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards. These two characteristics (trial-and-error search and delayed reward) are the two most important distinguishing features of reinforcement learning. One of the challenges that arise in reinforcement learning and not in other kinds of learning is the tradeoff between exploration and exploitation.

To obtain a lot of reward, a learning agent must prefer actions that it has tried in the past and found to be effective in producing reward. But to discover which actions these are it has to select actions that it has not tried before. The agent has to exploit what it already knows to obtain reward, but it also has to explore to make better action selections in the future. The dilemma is that neither exploitation nor exploration can be pursued exclusively without failing at the task.

For control problems such as ATFM, the learning agents can be left to learn in a simulated environment and eventually they will come up with good controlling policies. An advantage of using reinforcement learning for control problems is that an agent can be retrained easily to cope with environment changes, and trained continuously while the system is online (Sutton and Barto, 1998). The typical model of reinforcement learning is the Markov Decision Process (Russel and Norvig, 2003) that considers two main conditions:

- The Markov Property – Situation in which the probability of transition of a state s for a next state s' depends only on state s and of the action adopted in s. This means that the current state supplies enough information to the learning system to decide which action must be taken.
- Markov Decision Process – a process in which a set of states ***S***, *s* Î ***S***, *a* Î set of *A*(*s*) actions, *T* set of transitions between states associates with the actions and a set of probabilities *P* on the joint ***S*** that represents a modeling of the transitions between the states.

5.3. Architecture of MAAD

MAAD (Fig. 8) is developed as a meta-level control layer that receives messages in a more appropriate sequence, sets appointments to certain messages and decides on the priority sequence of messages (Alves et al., 2008). It consists of two main modules: a module for decision and control (MDC) and a module for reinforcement learning (MRL). MDC uses a set of parameters to link each message and generates a series of other parameters reflecting the probability of important messages arriving in the entrance list. The utility of the messages is used for setting appointments in the agenda list, during the execution of the message.

To enable message exchange in a distributed system, it is necessary to establish a hierarchy reflecting the features of that system. System attributes are attached to a message from the meta-level controller. The destination of a message is also processed by a meta-controller within the multi-agent system. He receives the message and analyzes the attributes. The manager at meta-level control can decide between setting appointments in the message for later retrieval, transferring the message in the system, or discarding it.

5.4. Decision and control approach

The decision process is carried through by MDC and supported by a knowledge base defined as a part of MRL. A heuristic is used initially in MRL, where for each state of the environment, an action is suggested in accordance based on previous analysis. However, if dealing with a random environment, a best action is not always initially suggested. Thus the options are modified to help the agent know the environment better.

MDC is developed for controlling the state changes, managing the entrance and the exit of messages and carrying the communication among the various agents. And MRL uses reinforcement learning for better decision-making. Six parameters are used to define a state: p_1 is priority of the message that arrives; p_2 is the existing stated period so that the messages can be processed; p_3 is good utility of the set of appointment of the messages; p_4 is the stated period of execution of the messages that are set appointments; p_5 is probability of a arrived message with high priority; and p_6 is the reason of flow of the messages in MAAD.

Each parameter is valued as high, average or low. When a state has one or more of parameters not valued, such as 00_2, it will not be studied. Here, six valid states are assumed to be dealt with by MDC. For example, the state $(100111011101)_2$, in binary terms, would present the values for each parameter of $p_1 = 10$, $p_2 = 01$, $p_3 = 11$, $p_4 = 01$, $p_5 = 11$, $p_6 = 01$, corresponding to the state in decimal form of 2525.

$$\underbrace{11}_{P_1}\quad\underbrace{11}_{P_2}\quad\underbrace{01}_{P_3}\quad\underbrace{01}_{P_4}\quad\underbrace{10}_{P_5}\quad\underbrace{11}_{P_6}$$

where $(11)_2$ is high, $(10)_2$ is medium, $(01)_2$ is low and $(00)_2$ is undefined. Given a state of the environment for MDC, it can be transferred to MRL and then an action can be suggested. The selected action is executed and then reinforcement is adopted to allow learning about the impact of the action. If the agent only considers reinforcement learning, the general process will be slow. In the example, adaptation to select randomly between

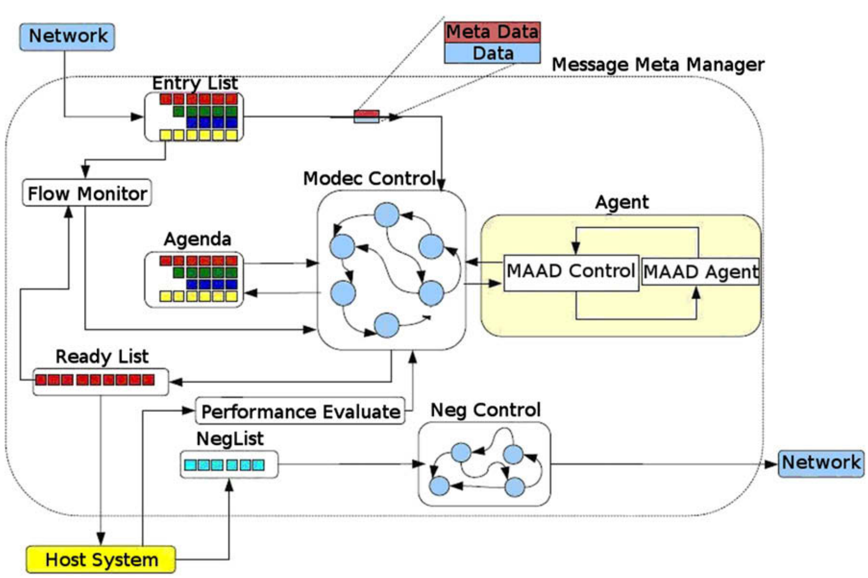

Fig. 8. Architecture of MAAD.

Table 1
Distribution of the slack between the flows of the net for the prioritization of flow with its origin in Sao Paulo.

Flow	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11	S12	S13	S14
TMA_AM	0	0	0.25	0	0	0.2	0.25	0.25	0	0.1	0	0	0	0
TMA_AN	0	0	0	0.1	0.1	0.2	0	0	0	0	0	0	0	0
TMA_BH	0.1	0	0	0	0	0	0.25	0.25	0.3	0.1	0.1	0.3	0	0.25
TMA_BS	0.2	0	0.25	0.1	0.1	0.2	0.25	0.25	0.4	0.1	0.1	0	0	0.25
TMA_CW	0	0.5	0.25	0.1	0.1	0.2	0.25	0	0	0.1	0.1	0	0	0.25
TMA_CY	0	0	0	0	0.1	0.2	0	0	0	0	0	0	0	0
TMA_RE	0.2	0.5	0	0.1	0	0	0	0.25	0	0.1	0.1	0.4	0	0
TMA_RJ	0	0	0	0	0	0	0	0	0.3	0	0.1	0	0.5	0.25
TMA_SP	0.5	0	0	0.5	0.5	0	0	0	0	0.5	0.5	0	0	0
TMA_VT	0	0	0	0	0	0	0	0	0	0	0	0.3	0.5	0
TMA_YS	0	0	0.25	0.1	0.1	0	0	0	0	0	0	0	0	0

exploitation and exploring may be influenced by the performance of the agent in the environment and factors external to it. To evaluate the performance of the current state of the system five parameters are considered to obtain AvD:

$$\mathrm{AvD} = \frac{(3 \times \mathrm{SDS} + 2 \times \mathrm{RF} + \mathrm{SEL} + \mathrm{SAL} + \mathrm{SPL})}{8}$$

where SDS is the situation of the host system that MAAD serves and has a factor 3 weighting in the general evaluation, due to the necessity of increasing the host system influence on the MAAD performance evaluation; SDS is reason of the flow (RF) measures the flow of the messages in MAAD and has a factor 2 weighting, due to the necessity to show more efficiency of the communication of the messages in MAAD; situation of the entrance lists (SELs) measures the queue of entrance messages, and can be changed when the system is more congested or less congested; situation of the agenda (SA): measures the agenda of messages, and changes when the agenda is more congested or less congested; and situation of the ready list (SPL) measures the processed messages in the queue, and can be changed with different levels of congested.

6. Evaluation of the system and simulation results

The case study involves evaluation of the compatibility between the measures taken for the control of the air flow at CINDACTA I and the actions suggested by the flow balance model (Souza et al., 2008). The data is submitted to the balance module that then suggests some restrictive measures which are normally compared to the ones adopted. The execution of the prototype occurs in a manner that is controlled and supervised. The data is updated by means of a set of simulation sasses, and the output is calculated and analyzed through the use of tables. A set of 15 schedules was separated, in which the possibility flow problems had been detected, by means of the CGNA graphs. The occupation of the sectors is simulated with the classes of persistence, while the dynamics of the aircraft was simulated with the aid of the tables included in the memory.

We take 30th of April of 2008 – a high traffic day within the FIR-BS to apply balancing policies (Souza et al., 2008). The data from CGNA database covers takeoff rates originated at Sao Paulo Terminal (TMA SP). The flow at sector 1 is analyzed to determine a time intervals 10 min before and 10 min after the hour denoted in the table; an interval adopted because it is the average time to exit the sector. The model proves effective in the egalitarian balance but for the prioritized balance an adjustment policy is required. The prioritization of a certain flow will lower other flows, and, so, these policies have to be deployed carefully. Two policies are used for simulation:

- *Policy of egalitarian distribution*. The balance policy in this case is insensitive to any attempt of prioritizing the flows. The division is fair and egalitarian between the flows of the net. In this policy, the slack of the sectors is equally divided between the copies of the sector, and each copy belongs to a distinct flow. The policy is simpler as it does not require the utilization of the table that associates flow × sector × schedule.
- *Policy of distribution with flow prioritization*. The balance policy in this case focuses on the prioritization of the flows. The division occurs in accordance with the time at which a certain has to be prioritized over the other flows of the net, thence the need to use the table of flow × sector × schedule to simulate the updating of the forecasting module (MAPC) and the learning estimated actions in the administrative module (MAAD).

For application in the prioritized distribution model, one utilizes Table 1 for flow prioritization with traffic originating from TMA SP. In sector 1 (S01), the flow from Sao Paulo is prioritized with 50%, and from Brasilia is 20%.

The balance policy with an egalitarian distribution emerges as insensitive to prioritization of flows. The division between the flows of the net is fair and egalitarian. In this policy, the slack of the sectors is divided equally between the copies of a sector, with each copy belonging to a distinct flow. This policy is simpler, since it does not require the utilization of the table that associates flow × sector × schedule, (see Table 2).

The balance policy with a flow prioritization distribution focused on the prioritization of the flows. The division takes place in accordance with the period in which a certain flow is prioritized in the net, thence the need to use the table flow × sector × schedule for the simulation of the updating of the MAPC and the learning estimated actions in the MAAD.

Table 2
Takeoff interval for TMA SP on a day of high use with an egalitarian distribution policy.

Period	Origin	Suggested min. rate	Suggested max. rate	Real rate
13:25	TMA-SP	6.5	7.55	9.6
21:13	TMA-SP	9.2	10	9.6
21:45	TMA-SP	6.5	7.5	19.1
22:08	TMA-SP	6.5	7.5	9.6
22:32	TMA-SP	6.5	7.5	6.4

Table 3
Takeoff interval for TMA SP on a day of high use and a prioritized distribution policy.

Period	Origin	Suggested min. rate	Suggested max. rate	Real rate
13:25	TMA-SP	3.2	3.8	9.6
21:13	TMA-SP	4.3	5.0	9.6
21:45	TMA-SP	4.3	5.0	19.1
22:08	TMA-SP	4.3	5.0	9.6
22:32	TMA-SP	3.2	3.8	6.4

This table is rather long and will not be presented here. It can be pointed out that the table was divided into two other ones: the first table associates flow $\times$ sector $\times$ schedule and indexes one of the coordinates of the second table with the schedule, thus obtaining the occupation percentage associated to the triple (flow $\times$ sector $\times$ schedule), (see Table 3).

The egalitarian distribution model results are close to reality and that during certain periods it improves the results. For instance, in the case of the flow around 21:45 h, the real data shows a separation rate of 19.1 min on the 30th of April, in contrast with the rate indicated by the prototype of 6.5–7.5 min per takeoff in the egalitarian model, with a gain of at least 11.6 min. And the rate of 4.3–5.0 min in the prioritized model, in which the flow originating from Sao Paulo was prioritized, with a gain of at least 14.1 min.

7. Conclusions

The SISCONFLUX constitutes the scope of a strategic project of cooperation between CINDACTA I of Commission for the Implantation of the Airspace Control System – CISCEA of the Brazilian Command of Aeronautics and the University of Brasilia – UnB, with the purpose of developing a system of extreme importance to the operational context of the traffic control agencies to fill an important gap in the national concept of air traffic management. The SISCONFLUX, with applicability directed to the tactical ATFM, can be used along with the Visualization System and Data Processing of the Aerial Navigation Management Center – SYNCROMAX. In this sense, the Brazilian Airspace Control System – SISCEAB will be able to make use of a set of tools capable of fully supporting the traffic flow management in its three levels: strategic, pre-tactical and tactical.

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