USING ARTIFICIAL INTELLIGENCE TO SUPPORT TRAFFIC FLOW MANAGMENT PROBLEM RESOLUTION

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Abstract

The Federal Aviation Administration (FAA) is in the process of defining and documenting the operations concept and architecture for the future Traffic Flow Management (TFM) system. The challenge of future TFM is to organize complex air traffic flows through busy areas in the National Airspace System (NAS), manage the volume of traffic into and out of congested airport areas, and minimize delay-related problems in the advent of continued growth of air traffic and its complexity.

The goal of this project was simply to determine if artificial intelligence (AI) techniques can be applied in a useful way to TFM problem resolution. This paper describes a particular class of decision making that relies on past experiences, and how this applies to the TFM domain. We have adopted a case-based reasoning (CBR) approach (Kolodner 1991) to recognize "similar" problems and to guide TFM decision making by looking at and reasoning about past situations. This paper describes how the eventual users of such a tool, the TFM specialists, feel about this CBR methodology. Finally, this paper provides a mechanism for documenting the many lessons that we learned over the course of this project.

1.0 Introduction

Many TFM problems that occur in the NAS repeat in a similar manner on a fairly regular basis. Much of the information that describes these problems has been recorded on a daily basis. By using this historic data, problem patterns (or cases) can be recognized and stored in a case library along with the actions that were taken to resolve the problems. TFM problems are generally created whenever the normal capacity of the system components (sectors, airports, runways, etc.) is reduced and cannot meet existing demand (such as flight schedules). External events (weather or equipment failures, for instance) often cause this imbalance of demand and capacity. For example, if a thunderstorm is directly over an airport, that airport may close until the storm has moved a safe distance away. This backs up arrival demand due to the decrease in capacity at the airport, and causes an imbalance.

The FAA currently has 20 Air Route Traffic Control Centers (ARTCCs) in the conterminous United States (CONUS), responsible for varying volumes of airspace. Figure 1 is an illustration of the various ARTCCs that cover the United States and highlights the New York ARTCC (ZNY), which will be focused on throughout this paper. Any TFM problem that cannot be handled internally to an ARTCC, or that is of interest to other parties nationally (including the airlines), is coordinated through the Air Traffic Control System Command Center (ATCSCC). The ATCSCC provides a system-wide perspective for all TFM actions. This project concentrates on problems that have nationwide impacts and thus are of interest to the specialists in the ATCSCC.

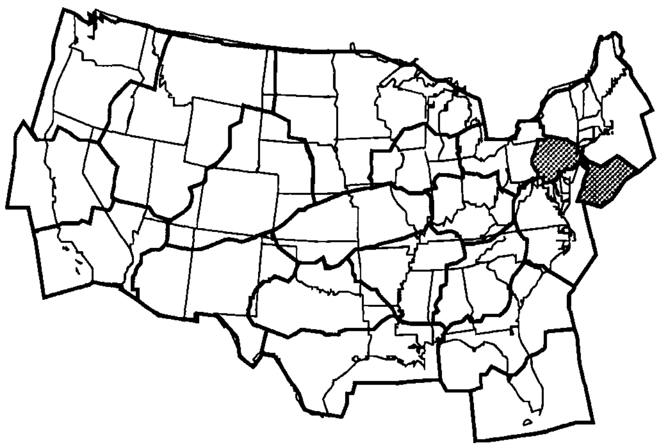

Figure 1. ARTCCs in the Conterminous United States (ZNY is highlighted)

A major factor in the specialist's process of decision making is operational experience. FAA personnel typically rotate on two- to three-year tours of duty in various facilities, with only a few individuals staying permanently in one location. Through these changes in duty and normal retirement cycles, valuable job experience is wasted because currently there is no way of formally capturing it. This experience is critical when dealing with problems that often occur on a day-to-day basis. This project suggests a methodology for capturing a specialist's experiences in resolving TFM problems as cases. These cases are then available to all the specialists who may encounter a similar problem.

1.1 SCOPE

This report addresses the application of CBR technology to TFM problem resolution, and how the specialists will accept such a technology. The objectives of this project were to determine if AI could be applied to the TFM domain. There was no intention of performing lengthy analyses to determine exactly "how much better" the specialists' decisions would be using CBR. Our goals were to determine if the specialists would welcome a CBR tool in their decision-making process, thus making it a useful tool. We have done no formal evaluation of the degree to which this affects the quality of their decisions.

2.0 Technical Approach

2.1 Problem Description

When dealing with the dynamics of weather and air traffic operations, no two days are ever exactly the same. Our goal was to generalize some events into similar "type" problems. The example used in our scenario was severe summer thunderstorms in the New York ARTCC called ZNY, which is highlighted in Figure 1. These afternoon storms happen often and are *similar* in nature, but never exactly the same. These repeating problems are exactly what CBR is designed to handle.

The CBR approach is proposed to capture experiences in dealing with these thunderstorm problems. Those experiences are then reviewed to support the decision-making process while resolving a current thunderstorm problem of a similar nature. Through the course of this project, the focus was on problems with *national* traffic implications, as opposed to *local* implications. Problems with national implications are most suitably handled at the ATCSCC, while local problems are dealt with by the local ARTCCs. A problem with national implications is one that involves the cooperation of many ARTCCs to solve it, whereas a local problem can be solved internal to an ARTCC. Many of the concepts covered in this project would be applicable to problems of either scope.

The TFM problem used for our scenario is the situation of severe weather approaching and/or traveling through ZNY, impacting traffic nationwide due to the volume of airplanes and the constraints of the airspace in this area (Figure 2). This severe weather comes most notably in the form of summer afternoon thunderstorms and occurs quite often in the months of June, July, August, and even September. These storms tend to form solid lines of turbulent air or lightning activity and thus render those areas useless to airplanes. The fact that we are using the ZNY area also adds some interesting features to the problem. As seen in Figure 1, ZNY has the smallest volume of airspace in the NAS. However, it also has some of the highest traffic counts of any ARTCC in the NAS (FAA 1993). ZNY has three major airports within its airspace: John F. Kennedy International, LaGuardia, and Newark International. ZNY also contains many other high-traffic airports such as Philadelphia International, Teterboro, White Plains, and Islip. The tight volumes of airspace that aircraft are permitted to travel while in or near ZNY make manipulation of these aircraft very difficult. When coupled with the complexity of the East Coast jet routes, the problem becomes evident. The final constraint on ZNY is the ocean to the east. Only properly equipped aircraft can be routed over the ocean, so for the most part, ocean routes are not an option for the specialists when manipulating flows of aircraft.

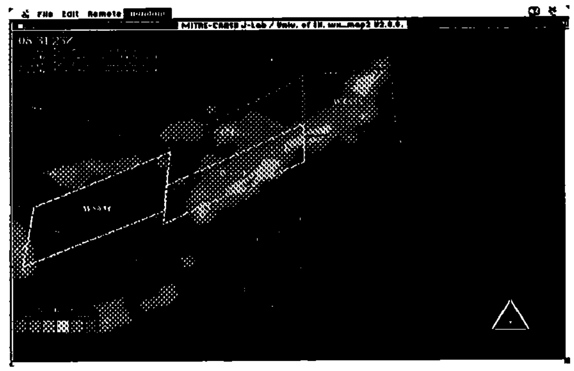

Figure 2. A Line of Thunderstorms Moving Through ZNY and Neighboring Centers

Because these thunderstorm situations occur frequently, ZNY and other ARTCCs have established a Severe Weather Avoidance Program (SWAP). These SWAP routines are a published set of departure routes that are to be implemented when severe weather is impacting the normal departure routes. There are many variations for the specialist to choose from, depending on the conditions. ZNY will notify the ATCSCC and all interested parties when implementing SWAP procedures, thus warning these parties some delays may be forthcoming. The majority of the cases in this prototype were recorded while SWAP was being implemented. Many of the ground-delay programs implemented during these cases were initiated to *support SWAP* procedures, depending on the location of the severe weather.

We chose this scenario because of its many facets that affect the decision-making process. ZNY is constrained by the neighboring ocean and the congested airspace. Also, due to ZNY's traffic patterns, a problem in this area can escalate very quickly into a problem that affects the flow of traffic in the entire country. The specialists challenged us to develop a prototype that could help them in this area. They felt that a useful tool in this particular scenario had to be useful in other areas as well. This scenario offers difficult decisions for even the most experienced specialist, and thus was chosen as the perfect environment to prove the benefits of a CBR tool.

2.2 Problem Analysis: The CBR Approach

Although the weather patterns may not change much, the complexity of traffic patterns will increase in the future with the ever-increasing demand of more flights. Thus, this application will evolve and our case library will provide the framework for a learning paradigm.

We feel CBR has many advantages over rule-based reasoning (RBR), but also admit that CBR must be complemented with other systems such as RBR to build successful applications, including our application. There are some arguments that CBR systems are cheaper to build than RBR systems because the experts can describe *experiences* more easily than specific *rules* to the system designer (Cognitive Systems Inc. 1993). CBR can easily incorporate experiences of multiple experts because it allows for contradictory cases, whereas rules do not; this facilitates system maintenance. CBR systems like ours, evolve over time. The system can easily *learn* as new cases are encountered and added to the case library. This allows for more specific searches and a more useful system. RBR systems find it very difficult to dynamically add new situations. A final advantage, if not the largest, is that CBR systems justify solutions with actual cases from the past, as humans do.

The TFM domain is very dynamic and difficult to formalize. Even for an experienced specialist, rules to solve the problem appear to be complicated and hard to explicate. Often, rules are too numerous to write, possibly leading to delays in rule processing. RBR systems are suitable for those domains where rules are readily available and are relatively stable with time. Within the FAA there are efforts to research RBR approaches in the TFM domain. While it is possible that rules can be explicated and then used to model certain aspects of the domain, RBR alone may not be appropriate for the entire domain. In the literature, a mixed paradigm approach, that is, a combination of CBR and RBR methods has been found effective for several applications (Golding & Rosembloom 1991) (Skalak & Rissland 1990). This work supports the notion that neither CBR nor RBR alone will be the better paradigm for a decision-support tool; instead a combination of these two fields (and possibly others) is best.

2.3 Knowledge Engineering (KE)

The experts in this domain are the TFM specialists who work in the ATCSCC and the TFM Coordinators who work in the Traffic Management Units (TMUs) of the ARTCCs. Over 50 specialists, including both supervisors and staff, with varying levels of experience and backgrounds participated in our KE activities. While we were studying the details of their job, we solicited ideas on useful capabilities in a CBR tool as well. Approximately 200 hours were spent in the ATCSCC and another 50 in ZNY.

Once we had confidence in our understanding of the TFM operations, we shifted the focus to gathering specifics needed for the prototype. During this period, we concentrated the KE sessions on a few specialists, who were chosen based on their experiences with the ZNY airspace and dealing with thunderstorm-related problems. Many heuristics, or rules of thumb, were revealed and codified in the prototype. For example, a step in evaluating how a previous resolution performed would be to check the amount of airborne holding that occurred during the program. A rule of thumb states that "if the airborne holding delays were less than 15 minutes during a program, the program performed well." That is one indicator of many that must be evaluated.

The process of refining the attributes that define these problems was an iterative one. When a consensus was reached among the specialists, the attribute would be added to the case representation. This continued throughout the project.

The specialists were very encouraged by the goals we were trying to accomplish, and thus were very enthusiastic about helping us. The specialists in both the ATCSCC and ZNY have been an integral part of designing this prototype and have truly been included since the very beginning. The first of three prototype demonstrations was reviewed by a specialist, and his comments were incorporated into the further prototypes.

2.3.1 Case Representation. Determining appropriate case granularities for the problem at hand, that is, at what level of detail the case must be represented, consumed a great deal of effort. KE sessions were of considerable help in this matter. The following four attributes are the primary discriminators that the specialists specified for preliminary indexing of the case library:

- Density of thunderstorm
- Jet routes affected
- Major airports involved
- Type of problem

These attributes relate to probable effects due to predicted weather. A TFM specialist uses these key features to retrieve situations from the past in his own mind and would use these in the tool to get an initial sampling of similar previous problems. The following secondary attributes are filled in as information becomes available:

- Day of the week
- Duration
- Push
- Demand
- Arrival rates
- Runway configuration

The primary and secondary attributes are used in indexing cases. The first level signifies effects due to the weather, while the second represents mostly effects due to the traffic in addition to weather. However, a case consists of other attributes besides those in the two categories. A typical example of a case is shown in Table 1. These attributes provide additional information to the user about a case and are not necessarily used in indexing cases. For example, the attributes *resolution-arrivals* and *resolution-departures* describe solutions or resolution methods. The case outcome is represented by the attribute called *resolution performance*. However, current understanding of the system is not sufficient to model this attribute appropriately. Therefore, we

Table 1. A Typical Example of a Case

	Field Name	Field Value
S	arrival rate for program	48
S	arrival rates during program	60, 49, 37, 28
	ARTCCs included in pgm	ALL
	date	9/3/93 19:00:00
S	day of the week	Friday
S	demand during program	60, 52, 24, 14
P	density of thunderstorms	solid line
	departure rates during pgrm	24, 28, 28, 37
S	duration of problem	4
P	jet routes affected	64, 60, 6, 75, 80
P	major airport involved	JFK
	max depart. delay during pgm	210
	other pgms affecting this area	SWAP, ground stops
	resolution performance	average
	resolution-arrivals	1500-implement pgm w/48 rate
	resolution-departures	2000-West gates closed, reroute
S	runway configuration	arr-22L, depart-22L
	time of day (Z)	evening
P	type of problem	enroute
	weather description	line of tstms from Jamestown
S	where is push coming from?	Oceanic
	winds at airport	14

P = primary attributes
S = Possible secondary attributes

have used qualitative indicators like good, average, and bad as values for the resolution performance attribute. A great deal of effort has been spent in other projects trying to determine the best performance metrics. When conclusive results are obtained from these projects, we can easily insert the results into our case representation.

2.3.2 Case Retrieval. Currently there are 100 cases in the TFM case library. At this time, the nearest neighbor method of retrieval appears to be the most suitable due to the limited number of cases and lack of a specific outcome attribute. In this method, attributes are appropriately weighted according to their relative importance, and a scoring scheme is used to index cases. The relative weights were assigned after the specialists indicated the level of importance they assigned to each attribute. Thus, the primary attributes, as we have referred to them, have higher weights than any other attribute, followed by the secondary attributes. The weights of all the attributes can be adjusted before each search depending on what the specialist is looking for. For the most part, we were searching for close matches to the primary attributes, with another level of similarity assigned to matching some of the secondary attributes. The relative weights (where 8 = very important) we used to measure importance for retrieval were as follows:

- Density of thunderstorm (weight = 8)
- Jet routes affected (weight = 8)
- Major airport involved (weight = 8)
- Type of problem (weight = 8)
- Day of the week (weight = 4)
- Other programs affecting this area (weight = 1)

In our prototype, a case is described by a set of features or attributes leading to the attribute (or possible outcome) called *resolution performance*. The metrics of determining how well a resolution performed are not very well understood by the TFM community in general. Our prototype uses some simple rules to determine the value of this attribute, but this is only a small subset of the rules that would have to be incorporated into determining that value in an operational environment. Once metrics for determining *resolution performance* are better defined, those results can be incorporated into our tool. At that time, inductive retrieval methods with *resolution performance* as the outcome can be more thoroughly investigated. The main strength of induction is that it can objectively and rigorously analyze cases to determine the best features for distinguishing between outcome values and use those case features to build an index that will be used for case retrievals. Inductive retrievals are efficient because of the hierarchical structure of the tree, and the retrieval time only increases by the log of the number of cases, rather than linearly as with the nearest neighbor retrievals.

3.0 Lessons Learned

Knowledge engineering is easier for CBR systems than for other knowledge-based systems. KE is traditionally a very painstaking task. However, we feel that the KE process in CBR reduces the time and cost compared to that of RBR systems. The "experts" are more at ease describing experiences and situations as opposed to exact rules. CBR also captures negative or contradictory cases with no additional effort. It is relatively easy to use the same case library to arrive at different outcomes simply by changing the index structure to suit specific needs. For example, if Specialist A felt differently about what attributes were important to match than Specialist B, Specialist A could change the indexing weights but still use the same case library to determine solutions that he/she is comfortable with. In the current TFM system, this is acceptable because there are many different ways of accomplishing the desired results.

The specialists support this type of tool. Given the input scenario described in Section 2.1, and other hypothetical scenarios, the system performed admirably. The previously encountered cases retrieved by the system were very similar to the input cases. The tool allows you to set a threshold of how similar the retrieved cases must be (similarity index of 1–100), but we just assumed anything with a similarity of 70 or above was worth looking at. The resolutions to these problems were, in fact, very similar to what the specialist was hypothesizing for a resolution to the input case. Some specifics of the retrieved cases, which were useful in developing a resolution to the input case, were pointed out by the system much to the specialist's delight. The primary attributes used for indexing were sufficient for the users to retrieve meaningful cases. Also appreciated was the fact that the system retrieves similar cases that performed "poor," as well as those that performed "good." The specialists felt this was useful for determining which strategies should be avoided given certain conditions. The case information overall was deemed to be very useful for supporting decision making.

This tool is helpful to inexperienced, as well as experienced, specialists. The inexperienced specialist can be helped by having the tool describe the entire situation, not just the solution. This gives the specialist a feeling for all the conditions present at the time of the decision. The specialists thought our cases did this very well. The experienced specialists do not really need help with the routine problems. However, they felt this tool would be very helpful in SWAP situations or for very complex weather problems that not everyone has encountered routinely. The information generated by the cases was also deemed sufficient to accomplish this. In our specific example, the knowledge incorporated into the system from former ZNY specialists was much more detailed and thus helpful to the specialist who is not familiar with the intricacies of ZNY airspace, regardless of years of experience. Other lessons learned (but detail left out due to space requirements) are:

- Not all data for defining TFM problems and resolutions is available electronically.
- Describing the resolution performance itself is a difficult task.
- Some details can be generalized, and must be.
- A CBR tool is well suited for training.
- CBR can be useful in the TFM domain.

4.0 Conclusions

The goal of this project was simple: determine if AI can be useful in TFM problem resolution. Through the support of the eventual users (the specialists) of this prototype, we have determined that AI, and CBR specifically, can be helpful in a decision-support role for TFM problem resolution, both at the national ATCSCC and the local ARTCCs. This project did not perform formal analyses of whether using this tool provides *better* decisions; it did illustrate what features of CBR the specialists found most useful.

The specialists are eager to investigate tools that will assist them, but are very selective in their support of the numerous tools proposed to them. The specialists appreciated that this CBR tool provides suggestions of how things were handled in the past, as opposed to direct solutions. They liked the ability to be able to access a common "experience-base" of veteran's procedures, as well as innovative ideas from the less experienced specialists. Finally, they appreciated the idea of being able to support their own decisions by using portions of previous solutions that worked well, or improving portions that did not work well. It was important to the specialists to be able to view the previous cases that performed well, and just as important, the cases that did not perform well.

We have described a CBR approach to help resolve a particular class of TFM problems. A proof-of-concept CBR prototype was developed using ReMind (Cognitive Systems, Inc.) to demonstrate the effectiveness of this approach, as well as the validity of our problem description. The attributes that we have settled on for describing TFM problems provide a robust definition. It is our opinion that only minor modifications would be needed to use this representation to describe all TFM problems.

It is also clearly evident that CBR must be supported by other techniques to be completely useful. In this prototype, we combined a simple rule-base with the CBR system to achieve our results. As the system becomes closer to an operational tool, the rule-bases will need to be more comprehensive. Another limitation that needs to be resolved, before the tool will be accepted operationally, is the process of collecting data for the cases. This process will need to be automated considerably and depends on all the necessary data becoming available electronically.

Another goal of this project has been achieved by creating the user interest in this prototype and in CBR technology. While the CBR system is in the early stage of development, a number of interesting research possibilities exist. Using previous experiences is a straightforward concept that the users can easily understand. This, combined with their involvement from the very early stages of this project, has led to strong support in helping this work proceed.

Acknowledgments

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