

# Optimization-Based Training in ATM

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**Abstract.** Air Traffic Management is responsible for guiding airplanes as efficiently and safely as possible at and between airports. A team of air traffic controllers is required to make good decisions at all times, even under high stress. The complexity of their tasks requires frequent and high-quality training to ensure constant high performance of the team. In this paper, we present work in progress on a novel training tool based on the *Optimization-based Virtual Instructor*. The tool we propose combines mathematical optimization with visualization, and is expected to improve the training quality while reducing the training cost. We discuss the new Virtual Instructor concept and introduce the necessary state-of-the-art advances needed for both visualization and mathematical optimization to make it work. Two early-stage visualization prototypes are presented. The paper concludes with a possible way forward in the development of the Virtual Instructor.

**Keywords:** ATM · Training · Optimization

## 1 Introduction

The increase in air transportation is an important factor for economic growth. However, the current Air Traffic Management (ATM) systems are already approaching their capacity limits and need to be reformed to meet the demands of further growth, sustainability, increased safety, predictability, and efficiency [1]. Coping with these challenges requires not only new automation tools and enhanced procedures, but also a rethinking of Air Traffic Controller (ATCO) training [2].

The real-time simulation (RTS) of work scenarios is considered a cost-effective method of training new and experienced ATCOs to safely manage the efficient flow of aircrafts [3]. One of the great advantages of RTS, compared with other learning aids, is the ability to freeze and replay scenarios directly, enabling instructors to provide timely feedback related to a given traffic situation, as well as on the quality of the decisions made by the trainee [4]. However, there are several disadvantages of RTS: it requires the full attention of an instructor and it disrupts the trainees, making it difficult for them to progress and positively reinforce their learned skills [2]. This can have negative impacts on the achieved learning quality and can consequently affect the operative productivity in Air Traffic Control (ATC) rooms. To overcome this, a self-assessment training tool has been developed that enables ATCOs to review their workflow and

performance at the individual and team level [5]. The results show visual feedback consisting of workflow graphs and radar replays can generate valuable insights that enable self/peer assessments during ATC training. However, the users of the tool expressed a need for the inclusion of a presentation of better (optimal) solutions/decisions that could be used to improve self-learning or group discussions.

In combinatorial complex environments like ATM, it is very unlikely to find optimal solutions/decisions manually. As the many possible decisions and objectives should be considered simultaneously mathematical optimization excels. We believe a training tool based on visualization along with discrete optimization models and algorithms will improve ATCO training. We envisage such a tool will help ATCOs gain an understanding of the effects of their decisions on team performance when using an optimization-based algorithm as a *virtual instructor*.

This paper presents our ongoing development of such a tool. Section 2 describes the related work done in the area of visualization, learning, and optimization. Section 3 presents our optimization-based virtual instructor, and Sect. 4 concludes and proposes future work.

## 2 Related Work

To develop a training tool capable of presenting an optimal solution, we must draw from the related work in the areas of visualization, learning, and optimization. This section briefly presents the related work and our research questions.

### 2.1 Visualization and Learning

Whereas traditionally, the term visualization was used to mean ‘constructing a visual image in the mind’, it now means ‘a graphical representation of data or concepts’ [9]. Visualization has been used to present the data, support reasoning, and make predictions. With the development of the technology and advancements of our abilities to interact with information, the need to understand the benefits of different presentation forms for human cognition has arisen. Scaife and Rogers proposed a framework to investigate the cognitive value of external graphical presentations, such as maps, diagrams, drawings, and graphs [10]. The main cognitive benefits of using such presentations are externalizing to reduce memory load, computational offloading, annotating, and cognitive tracking. Externalization to reduce memory load includes personal reminders and calendars. Computational offloading includes using a pen and paper for calculations. Annotations and cognitive tracking include modifying representations to reflect changes, such as reordering or crossing tasks off a to-do list [11].

Research has been conducted on understanding the effects of multiple representations. In his Design, Function, Task (DeFT) framework, Ainsworth integrates research in learning, the cognitive science of representation, and constructivist theories of education. He argues that effectiveness of multiple (external) representations can be best understood by considering the characteristics of representations, the role of representations in learning, and the cognitive tasks of learners when interacting with

representations [12]. Furthermore, it has been argued that studies evaluating information visualization should focus on the following three aspects, namely users, tasks, and tools (visual representations) [13].

Research has also been done on how visualization techniques can support the teaching and learning of optimization algorithms [14]. To enhance the learning of the Golden Section method, a tool was developed that visualizes the process of bracketing the optimal solution, the iterative reduction of the interval size, and the effectiveness of using the Golden Section ratio. The results indicate the usefulness of such tools.

## 2.2 Optimization

In optimization, the problem faced by the decision maker is modelled mathematically with the use of constraints, variables, and objectives. When this is done, an algorithm then evaluate a large amount of plausible solutions to the problem to identify the optimal or near-optimal solution. In the context of this paper, a solution describes the decisions that could be implemented.

In more detail, the mathematical model consists of a set of variables, and for each variable, a set of possible values the variable can take. These variables are connected through a set of constraints that restrict which value the variables can take. In general, a feasible solution is the simultaneous assignment of a value to every variable in such a way that no constraints are violated. An objective function is then used to determine the optimal solutions (or good ones) by evaluating the quality of feasible solutions. This objective function consists of a set of decision variables with associated weights of importance (e.g., the importance of route length compared to time used). The feasible solutions are then evaluated through the objective function, and those with the best objective function score are considered the best solution.

Mathematical optimization is used in our daily lives, for example: when asking our GPS navigation system to find the shortest (or fastest) route from point A to point B. Calculating optimal routes manually is a combinatorial, complex, and time-consuming task, while mathematical optimization techniques in our navigation systems often provide the optimal route in mille-seconds.

The ATCO is faced with what mathematicians classify as a hard combinatorial problem where it would be too time-consuming for an ATCO to evaluate all the possible combinations of airplane routes manually. However, while the controller can often find feasible combinations of routes manually (due to the large amount of solutions), it is highly unlikely they would be efficient considering the sheer number of existing combinations—it's a combinatorial problem, where the amount of combinations to investigate increases exponentially with the problem size.

For example, an ATCO assigning existing fixed routes to airplanes from the gate to the runway would have 720 combinations to evaluate when dealing with only six planes and six routes. While some of these combinations (plans) might violate some given constraints (e.g., maximum speed, crossing restricted area, etc.), others do not and are thereby feasible plans. To find the optimal plan, all feasible plans must be evaluated against each other on properties that characterize a good plan (e.g., min. delay, min. distance, preferences, etc.). While six airplanes and six routes is a small

**Table 1.** Route assignment, a combinatorial problem

Number of airplanes	Number of routes	Number of combinations
6	6	720
12	12	479001600
25	25	15511210043330985984000000
50	50	3.0414093e+64

problem, as the problem grows in size, the combinations grow exponentially (see Table 1). Note that a realistic ATC problem is much more complex.

It is in these types of combinatorial problems where optimization algorithms excel over humans by quickly searching through a large number of combinations and identifying efficient or optimal ones by evaluating each possible solution against others with respect to several (and often conflicting) criteria that characterize a good solution.

The literature on optimized air traffic control for an airport is quite wide, and we refer the reader to recent surveys [6, 7]. Relevant recent progress has been on optimizing different routing phases (surface, departure, and arrival phases) simultaneously and only need on average 15 s (on a laptop) to find the optimal solution. In [8], the authors explain the application and results of the optimization model and algorithms that decide the trajectories of all airplanes in time and space at the Hamburg airport. Afterwards, these optimal trajectories produced by the algorithm were compared with the trajectories made by the controllers during training for three simulation runs. The algorithm and the controllers were given exactly the same input from the simulator to ensure as fair a comparison as possible; the algorithm and controllers considered the same safety rules (runway separations, airplane turning restrictions, etc.) with the objectives of “minimizing total taxi time” and “maximizing punctuality”. The results showed optimization-based decision support can provide significant improvements to total taxi time and punctuality, while still maintaining the same level of safety. The improvement potential for the controllers against the algorithm on taxi time was on average 30 %, while punctuality can be improved by 60 %. In addition, without explicitly modelling it, the maximum number of airplanes simultaneously moving on the taxiway can be reduced by 45 %, which would imply a decreased risk of collisions.

The main reason for the performance difference between ATCOs and the algorithm is the capability of the algorithm to make more globally coordinated decisions than the ATCO team. Each individual controller is only responsible for a part of the airport. This compartmentalization of responsibility within the ATCO team is needed to manually cope with the complexity of the task. However, its downside it that it removes the globally view of the problem and most likely also some globally efficient solutions are removed. One really god solutions for one ATC might create havoc ATC down the line. Optimization techniques do not have this disadvantage.

### 2.3 Research Questions

The research conducted in the areas of visualization and learning forms a solid basis for our understanding of the effects of different presentation forms on learning. However,

there is a lack of knowledge on how to present pedagogically alternative solutions in complex domains, such as ATM. According to our knowledge, there is a large research gap when it comes to optimization used for learning.

This leads us to the following research questions:

- **RQ1:** How can we visually present alternative (optimal) decisions and impact of these decisions in order to improve learning?
- **RQ2:** If and how optimal solutions proposed by the mathematical optimization can improve learning? How can we identify the most beneficial and learnable changes to the decisions made by the controller given the optimal solution?

### 3 Virtual Instructor

To enhance learning in the ATM context, we envisage a tool called the *virtual instructor*, which will enable trainees to replay their decisions, present the impact of these decisions on system performance, and present the alternative solutions in a pedagogical way. This section describes the requirements for such a tool.

An important concept in the ATM context is *situation awareness (SA)*. SA is ‘the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future’ [8]. Work has been done on the development of design guidelines for SA [9]. In the context of air traffic control, SA usually means the picture, a mental representation of the situation the controllers have on which they base their decisions. A training tool for ATCOs should aim to increase situation awareness.

The above-described frameworks [10–13] identify the main components that should be understood when using visualization in learning. Designing an efficient learning tool for ATCOs should build on:

- A good understanding of users. This includes different levels of expertise in their job, such as general ATCO experience, as well as experience with a particular airport, proficiency with the tools they are using, and cognitive abilities, such as spatial ability and associative memory. Standard tests like *Kit of Factor-Referenced Cognitive tests*<sup>1</sup> can be used.
- A good understanding of the tasks conducted in a learning situation with no instructor.
- A good understanding of potential cognitive benefits of different presentations. The above-described benefits, design objectives, and design heuristics [11, 12] can be used.
- Identifying the learning benefits of different information, presentation forms, and their combinations.

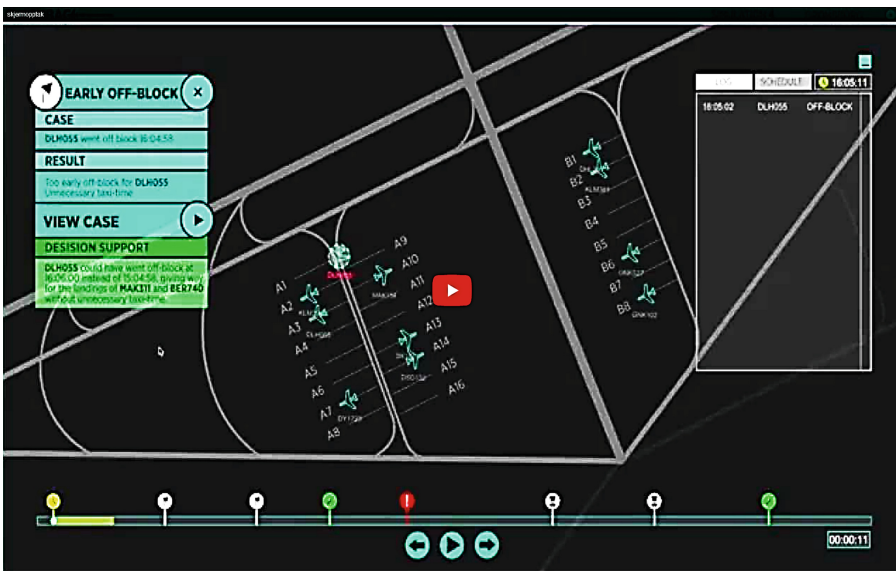
We started by identifying two possible scenarios. In the first scenario, the trainees replay their actions, receive feedback from the system at different decision points based

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<sup>1</sup> <http://trec.nist.gov/data.html>.

on the consequences of their decisions, and are presented with an alternative (better) solution. For example, one can present the information on the reduction of taxi time achieved by changing the block-off time and present the movements at the airport in that case. In the other scenario, one can guide trainees to make better decisions by using reminders. For example, one can remind ATCOs of the optimal time for a plane to leave the gate.

The preliminary exploration of the above-described scenarios has been done in two student projects. The first one developed and evaluated a post-simulation training tool that presented an animation of the plane movements based on what the trainees did in the previous training session. The tool presents some critical decision points on a timeline, as well as an explanation of the how these decisions can be improved [14]. During the evaluation, several participants pointed out they would prefer an animated presentation of the optimal solution instead of its textual description (Fig 1).



**Fig. 1.** Flashback tool. from [14]. The green box on the left presents an explanation (early off-block in this case). Different decisions that can be improved are presented on the timeline (Color figure online).

The other project focused on informing the controllers when to leave the gate, as well as which route should they take [15]. Visualizing the state of a plane (more than 5 min to off-block: red; less than 5 min: orange; time for off-block: green) and presenting a timer was proposed. These two scenarios will further be detailed to provide a list of tasks the trainees perform when learning with the help of an optimization tool.

To identify the learning benefits of different information, presentations forms, and their combinations, a set of measures capturing the learning effect in this context must be proposed. Presenting to ATCOs an alternative way of doing their job is not only a

question of presentation form, but also a question of the selection of data to be presented. Whereas traditional studies on the usefulness of visualization in learning compare the effects of two different ways of presenting the same information (e.g., comparing an animated and static condition like in [16]), we must also identify the information that will be presented. We assume some solutions generated by an optimization algorithm are more difficult to explain and less intuitive than others.

The virtual instructor would need to suggest the most optimal sequence of changes, starting from the decisions made by the controller. How do we identify this sequence was the subject of research question 2 (Sect. 2.3). Furthermore, for this, we use optimization techniques. A change is defined as a set of decisions that must be modified to move from one solution to another. Two different types of objectives determine whether one change is better than another. The first objective is maximizing performance improvement. In our case, we would like to make changes that improve aspects, such as total taxi time and punctuality. The second objective is more related to the learnability of the changes themselves. Are the proposed changes easily understood by the trainee so that in the future, he or she would take the more performant decision? How this learnability can be measured and formalized is still a subject for future work. However, one can imagine the learnability of the changes depends on multiple factors, such as:

1. The number of decisions that are different from the original decisions;
2. How far into the decision tree the proposed changes propagate;
3. How complex the actions are to perform to implement in practice the change.

We assume a suitable learnability distance measure can be defined based on the above and possibly other factors. The larger the learnability distance between two solutions, the more difficult it would be to learn the changes to move from one solution to another. Hence, the second objective boils down to minimizing this distance from the initial solution when selecting changes to improve the first objective. The two objectives will often be conflicting and a suitable balance between them must be achieved. Furthermore, we want to avoid changing a solution such that it becomes unfeasible, i.e., two airplanes crash. In Fig. 2, the optimization problem to find the optimal sequence of changes is illustrated. In summary, the algorithm must find the best possible solution (in terms of the first objective), which can be reached by applying a sequence of changes from the starting solution. The sequence of changes should result in the lowest possible learnability distance from the starting solution.

This mathematical optimization problem is not easily solved and to the best of our knowledge, not much relevant research exists. Although used in another context (solving vehicle routing problems), distance-based path relinking is an approach [17] that shows potential for several reasons. Path relinking assumes a good solution exists on the path between a so-called “incumbent” solution and the “guiding” solution [18]. The former would be the manual or initial solution, while the optimal solution is the latter. There exists an exponential number of paths or sequences of changes between these solutions. The resulting path is chosen by making local changes to the solution, and a distance measure is used to ensure it moves further away from the incumbent

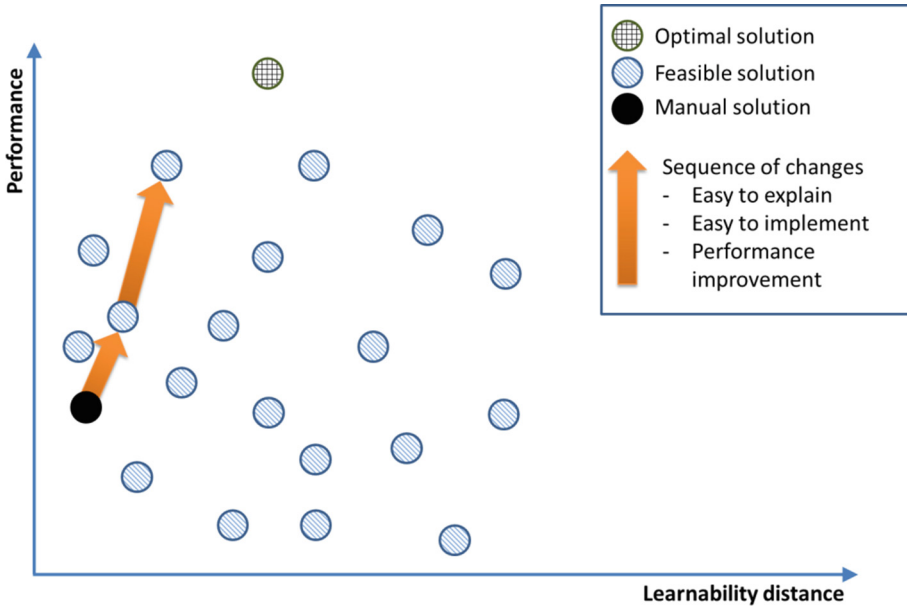


Fig. 2. Finding the optimal sequence of changes

solution. In our case, we would try to stay as close as possible to the incumbent solution. This looks like a promising path to solve such optimization problem but further investigation is needed.

#### 4 Conclusions and Future Work

In this paper, we proposed the development of a novel concept to improve training of decision maker in complex environments. We focused on ATC as a use case and introduced the optimization-based Virtual Instructor. The Virtual Instructor is part of a training tool that can generate challenging scenarios or can replay historic ones. The latter can be used, for example, at team meetings when traffic from the previous day is discussed. The optimization-based Virtual Instructor uses discrete optimization to analyze the decisions made by the trainee and to propose improvements without the need of a physical instructor to be present. The tool is able to run on a standard PC so the training could take place at work, workshops, or at home.

This paper describes relevant concepts from two different research areas, namely HCI and Optimization, to develop such a Virtual Instructor. We argue that it would benefit training to combine and advance the state-of-the-art in visualization for learning and optimization in a learning environment.

As a first step, we give an initial specification and indicate where the state-of-the-art needs to be advanced. The main challenge is to identify the groups of individual’s decisions which can not only significantly improve the team performance, but also be



explained and visualized in a way that enhance learning. Therefore, we identified theoretical frameworks and algorithms that form the basis for exploring benefits of optimization in ATCO training. In addition, we prototyped visualizations based on two usage scenarios of the virtual instructor. We presented the improvement potential of using optimization algorithms. Then we identified factors that affect the learnability of the decisions proposed by the algorithm. Finally, we describe a suitable algorithm that would find a sequence of changes to the controller's decisions that are both learnable and result in a solution closer to the optimal one.

We plan to formalize different learnability distance metrics, to develop different algorithms to suggest learnable solutions, and their visualizations. Explorative studies are needed for investigating the effects of: i) the efficiency and the accuracy of the algorithms, ii) the different learnability distances, iii) the different visualization forms, and their combinations on learning. We are going to conduct several studies with ATCO and ATCO trainees to explore this.

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