Can holistic optimization improve airport air traffic management performance?

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***Abstract*—There is a need to cope with the expected growth in air traffic while simultaneously meeting demands for increased safety, predictability, and efficiency in air traffic management (ATM) systems. This paper explores the potential effects of a holistic optimization approach on performance of air traffic management systems. We developed and evaluated a tool for optimizing the decision-making process of airport ATM based on holistic optimization, i.e., optimization where each decision is based on all possible airplane movements at the airport. This paper describes the results of a case study investigating the usefulness of this optimization approach. Our results indicate that active operational use of holistic decisions based on optimization tools might reduce taxi time and improve punctuality. Such tools can improve decision making in air traffic control (ATC) towers and contribute to the improvement of the overall ATC process.**

***Index Terms*—Air Traffic Control, Optimization**

I. Introduction

Air transportation is an important factor in the economic growth of the European Union; however, the current system is already approaching its capacity and cost limits, and therefore needs to be reformed to meet the demands of further sustainable development [1]. According to the European Commission, airspace congestion and the delays caused by it cost airlines between €1.3 and €1.9 billion a year [2]. Several research initiatives have been launched to address air traffic management (ATM) challenges. The Single European Sky ATM Research (SESAR) program—a joint effort of the European Commission, EUROCONTROL, air navigation service providers, and the manufacturing industry—aims to define, develop, and deploy what is needed to increase ATM performance and build Europe's intelligent air transport system.

Similarly, in the United States, the Next Generation Air Transportation System (NextGen) is the Federal Aviation Administration–led modernization of United States' air transportation system to make flying even safer, more efficient, and more predictable.

Reducing gridlock, both in the sky and at airports, is one way in which to improve the efficiency of the air transport system. However, according to Anderson and Milutinovic, [3, 4] recent improvements to en-route capabilities have caused a shift in air transport systems, meaning bottlenecks at the airport are now the primary concern.

As such, research on mathematical optimization methods to support decisions near and at the airport is of great interest. Marín and Salmerón [5, 6] were the first to demonstrate a taxi planning optimization tool, which minimized the overall taxi time at the Madrid–Barajas airport based on a space-time multi-commodity network with capacity constraints. Stiverson and Rathinam [7], Rathinam et al. [8] and Wood et al. [9] addressed the runway-queue management problem of the Dallas/Fort Worth using fast search heuristics based on *k*-exchange neighborhoods whereas Avella at al. [10] describe an effective exact MIP for the same problem.

Erzberger et al. [11, 12] proposed an arrival-sequencing algorithm integrated with separation management and weather avoidance within the wider advanced airspace concept. Anderson and Milutinovic [4] applied mixed-integer linear programs to taxi scheduling, taking uncertainty into account. Ravidas et al. [13] addressed the two-runway scheduling problem using generalized dynamic programming.

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However, none of these publications considers the entirety of the problem of air traffic control (ATC) decisions at the airport. Marín and Salmerón [5] and Anderson and Milutinovic [4] focused on the surface routing of airport traffic, while Stiverson and Rathinam [7] and Ravidas et al. [13] focused mainly on the scheduling of runway operations. Erzberger et al. [11] and Avella et al. [10] did not take surface routing and departure management into account. Mathematical optimization methods have yet to be applied to the whole airport. The contribution of this paper is therefore the application of our optimization algorithm to the whole airport decision problem. An additional contribution of our research is a comparison of the results of our algorithm with the performance of human air traffic controllers (ATCOs) using the same data; such an analysis has not yet been performed in the context of the cited literature.

The objective of this paper is to investigate the usefulness of a holistic optimization approach for ATM at an airport using a realistic case study. *Holistic* here has multiple meanings. First, we address the entire traffic control problem, which includes 1) routing, sequencing, and scheduling airplanes on the surface, and 2) sequencing and scheduling airplanes on the runway. Second, our approach goes beyond the natural decomposition process performed by ATCOs, by considering the entire problem in space and time. Indeed, each controller takes care of only a small part of the airport (i.e., his/her area of responsibility) and controls a few airplanes at a time (i.e., the next ones in his/her area/sector). In our case study, we focus on the second point by comparing the performance of our methodology with that of human operators.

To this end, we developed and evaluated a software tool for optimizing the decision-making process at an airport in a holistic way and applied it to the whole airport decision problem at Hamburg airport. In previous work, [14-16] we proposed a productivity improvement process, called Zero Failure Management at Maximum Productivity in Safety Critical Control Rooms (ZeFMaP), to increase the performance within control rooms. Our results showed that ZeFMaP could indeed help improve productivity in the context of tower control rooms. In [12] we describe in full detail the mathematical background for the optimization algorithm applied in our case study, and briefly report the major computational results. In this paper, we focus on the impact of such holistic optimization on the overall decision process and performance of air traffic control at the airport. To better understand how the algorithm can support ATCOs in their work, we analyzed the ATCOs self reported descriptions of the current decision-making process.

II. Holistic Optimization Algorithm

Our holistic optimization algorithm does not look at each airplane trajectory separately but rather at all possible airplane trajectories together, to determine the globally optimal decision at each point in time for each airplane. Note that trajectories are not only defined through airplane (i.e., spatial) movements on the surface at the airport and on the runway but also through the timing associated with these movements (i.e., temporal). A solution for all considered airplanes is called a *plan*.

We are defining airplane movements based on the airport graph, which provides a schematic representation of the airport. Constraints decide whether a plan or a combination of trajectories is feasible. In addition to single business trajectory constraints (turning restrictions on the taxiway and speed limitations), there are constraints relating to pairs of trajectories (separation constraints). Our model obeys the same safety rules (runway separations, airplane turning restrictions, etc.) as those that ATCOs are instructed to follow during training. The objective used by the algorithm is to choose the best possible plan. Possible defined goals include minimizing total taxi time and maximizing punctuality.

Note that in our exercise, ATCOs received in advance a list of arrival times and desired departure times. In the simulations, airplanes landed precisely at the communicated arrival times, and no deviations occurred. Accordingly, our model received deterministic arrival times as the input. In contrast, the departure times were determined by ATCOs' decisions and thus were the output of our algorithm. As mentioned, one of the goals was to minimize deviations from the desired departure times (i.e., to maximize punctuality).

Following is a schematic representation of our algorithm (for all details, see [17]):

1. For every arrival flight on the planning horizon, find the shortest route from a (feasible) runway exit to the assigned parking position.
2. For every departure flight on the planning horizon, find the shortest route from the parking position to a feasible runway entry.
3. For each flight *f*, compute the minimum taxi time by assuming that *f* runs the assigned route without stops.
4. For each departure flight, compute the minimum show-up time (i.e., when the flight can start rolling on the runway). This depends on the minimum taxi time and on the minimum off-block time.
5. Considering the input landing times for arrivals and the minimum show-up times for departures, compute an optimal sequencing of arrivals and departures on the runway (if necessary, dropping a minimum number of departures).
6. According to the sequencing determined in point 5, compute a conflict-free schedule for all flights taxiing to and from the runway.

Point 1 and 2 are solved using a specialized version of the shortest path algorithm on a transition graph, derived from the airport graph to represent only feasible movements. Point 3 and 4 are computed by simple arithmetic. Point 5 is solved by integer programming. We associated a time-indexed formulation and solved the model using a commercial solver (Cplex). Point 6 is carried out by 1) constructing a discrete event simulation graph, 2) solving potential conflicts by establishing suitable precedence constraints and adding corresponding arcs, and 3) computing a longest path tree on the resulting acyclic directed graph. In addition, a graphical user interface was implemented to allow for visual inspection of the produced trajectories to ensure that no unsafe or impossible airplane movements were calculated by the algorithm [17].

III. Case Study

The data we needed for evaluating the effects of the holistic optimization on the main indicators of the SESAR key performance areas (KPAs) were collected in a set of real-time simulation exercises. During these exercises, ATCOs were subjected to realistic work scenarios using an air traffic simulator. In this section, we briefly describe these simulation exercises and clarify which types of data were collected. The details can be found in [18]. The airport is typically divided into multiple areas of responsibility. Each ATCO oversees a single area. One of the main reasons for this division is to organize the work in such way that each controller can cope with the workload arising from controlling airplanes. Activities making up this workload include communicating with pilots and other ATCOs, scanning the radar and the outside window view to check that everything is going as planned, and deciding when and how to guide the airplane safely. A disadvantage of this division of responsibility is that it makes it inherently difficult for ATCOs to coordinate their local decisions with other ATCOs. Our hypothesis is that this leads to higher taxi-times and lower punctuality than necessary. Therefore, this case study's goal is to assess the potential benefits of an optimization-based decision support system that does not take divisions of responsibility into account while evaluating possible decisions and providing more coordinated decisions.

To test this hypothesis as fairly as possible, ATCOs and the algorithm were given the same input. Moreover, before our simulations, the ATCOs were told that there would be no external disturbances (i.e., ideal weather, flights ready as planned at the gate and landing as planned, no sudden stopping of airplanes at the airport, etc.). The only disturbances that would be in the system were the ones introduced by other ATCOs (e.g., late transfer of responsibility requests from one controller to another or not giving a clearance). ATCOs were also told that they could take advantage of the absence of external disturbances and of the fact that pilots would react (almost) immediately (and without the need for voice communication) to what they put into the system. Having the simulation set up this way allowed for a controlled measuring of the difference between local, less coordinated decision making and more holistic, coordinated decision making. In addition, the possible hindsight advantage of the algorithm over the ATCOs of knowing all disturbances is in this way removed.

A. Participants

The simulation exercises involved five ATCOs from Eurocontrol and Frequentis. Four of them had much experience working as ATCOs, whereas the last one (who was working in the least demanding position) and had solid experience in using and testing the systems we used in the study. Three of the five participants had earlier experience with the simulator and the simulated environment, as they had participated in a similar two-day study conducted several months prior to this one. To ensure that the participants were familiar with the working procedures at the airport used in the study and with the simulator, its environment, and the experimental procedure itself, we provided extensive training for all the participants. Several weeks prior to the simulation, the participants were asked to familiarize themselves with the training material describing the working procedures that were to be followed during the simulation. One week before the simulation, a telephone session was held that included a walkthrough of all the procedures. The participants had an opportunity to ask any questions they had regarding the material, and all unclear issues were discussed. In addition, the first day of the study was devoted to training, including a walkthrough session, two training runs, and discussions. During these training runs, the participants had the opportunity not only to become completely familiar with the tasks and the environment but also to improve their performance as a team. They discussed situations with the potential for performance improvement and, together, found better detailed procedures to be followed during the study.

B. Materials

The participants were subjected to realistic work scenarios using the NAVSIM air traffic simulator [19]. The simulator was set up to replicate the tower environment at Hamburg airport in terms of runway configuration, traffic scenarios, and controller equipment. The traffic scenarios were based on real traffic data from Hamburg airport, taken from the peak hours on a specified set of dates. This traffic data was adapted to some extent, in order to provide the required traffic loads. Each of the five ATCOs had a working position configured for his or her particular role, equipped with a radar screen, an electronic flight strip tool, and an auxiliary screen used for arrival/departure management (see Figure 1). The simulation did not involve simulated pilots or participating pilots; hence, the ATCOs did not have to handle voice communication with pilots. Instead, the simulation was held as if there were a controller–pilot data link connection to the aircraft facilitated by means of the electronic flight strip tool. Instrument meteorological conditions were used, with a wind component of 10 kts from 270°. The participants followed a tower working procedure. Training materials were produced to familiarize the participants with these working procedures.

Figure 1. The controller working positions included a radar screen, a flight strip tool, and an arrival/departure manager. The radar screen was a modified version of the Navsim air traffic simulator, stripped down to the graphical user interface for the display of the simulated radar image. The electronic flight strips tool "SmartStrips" was supplied by Frequentis AG; this was used to display the state of the simulated aircraft and for communication with the simulated pilots. The auxiliary screen was a generic implementation of an arrival/departure management tool, providing the controller with increased time awareness.

C. Procedures

As described previously, we organized training before the simulation. The simulation session spanned two days. It consisted of two training runs and three measured runs that were used for analysis, each lasting approximately one hour. At the beginning of each run, it was explained to the participants how much traffic they would need to handle during the run, and they were reminded that they should follow the following priorities during the simulation:

- Priority 1 – Safety: Minimize the number of safety violations during the simulation.
- Priority 2 – Punctuality: Make flights depart the runway as close to the calculated takeoff time as possible.
- Priority 3 – Efficiency: Minimize taxi time and taxi distance.

The participants were then seated at their respective positions in the simulation room (Figure 2), and the simulation was initiated.

The traffic scenarios used during the simulation runs differed in terms of traffic load. The first training run involved a scenario with a traffic load of 30 aircraft, while the second training run made use of a scenario with a traffic load of 60 aircraft. The measured runs had the following characteristics:

- Measured run 1: A traffic load of 45 aircraft, running at normal speed
- Measured run 2: A traffic load of 60 aircraft, running at normal speed
- Measured run 3: A traffic load of 45 aircraft, running at approximately 1.5 times normal speed

After the last run, the participants were interviewed individually and asked to fill in a post-run questionnaire. At the end of the simulation session, the participants were encouraged to reflect on their own individual experience, performance, and decision-making during the simulation runs.

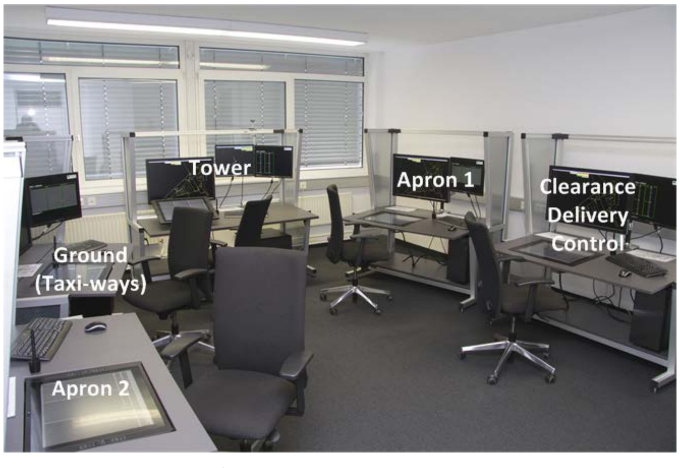

Figure 2. Control room of the Hamburg airport human-in-the-loop simulation exercise. Each controller workstation is labeled with the controller's function in the experiment.

D. Measures

The necessary input data were mainly collected by means of the logging functionality of the simulator. The logging focused on the actions performed by the ATCOs during the simulation runs and on the movements of aircraft (taxiway segments), including their timestamps. The complete list of logged variables is given below:

- Commands with timestamps
- Total number of aircraft handled per exercise
- Taxi time from gate to runway (departures), including details on all taxiway segments
- Taxi time from runway to gate (arrivals), including details on all taxiway segments
- Taxi distance from gate to runway (departure)
- Taxi distance from runway to gate (arrivals)
- Punctuality for departing flights

To supplement these objective measures, a number of subjective data collection methods were utilized, including interviews, questionnaires, and note-taking. Video and audio recording, along with screen-capture recording, were also used to document each run. These data sources were used to verify and explain the findings from the log files.

IV. Results and Discussion

We first analyzed all the decisions made by the ATCOs during the measured runs and compared them with the decisions suggested by the optimization tool. We then calculated the effects of the optimization on the relevant KPAs. Based on the optimal trajectories, the global optimal taxi time and punctuality could be calculated and compared with the outcomes of the ATCOs' manual decisions.

During each scenario, the ATCOs were obliged to follow all safety rules at the airport that was simulated and to prioritize safety, punctuality, and efficiency (in that order). Following the experiment, the optimization algorithm was subjected to the same work scenarios as the ATCOs were presented with, and given the same set of safety rules and priorities. Because the safety rules were known to the algorithm and treated as hard constraints, the proposed trajectories are at least as safe as the manual solutions provided by the ATCOs. A visual check was conducted to ensure that the optimization algorithm adhered with the predefined safety rules.

Based on the data collected in the experiment, we evaluated the decision quality of ATCOs in terms of punctuality and taxi time and compared this with the decision quality achieved when using optimization technology. The comparison was conducted through a pair-wise one-tail t-test where both average taxi time and average punctuality was compared for each of the three scenarios. Our hypothesis was that the decisions made by the optimization technology would result in a significantly improved (i.e., lower) average taxi time and a significantly improved average punctuality when compared with the decisions made by ATCOs.

Table 1: T-test comparison of ATCOs vs. algorithm.

Run 1	**paired t-test (p-value)**	**controllers (s)**	**algorithm (s)**	**∆(%)**
Avg. taxi time	0.000001	283.02	183.516	-35.2
Avg. punctuality	0.010514	243.32	80.59	-66.9
Run 2				
Avg. taxi time	0.000000	299.15	199.32	-33.4
Avg. punctuality	0.000290	190.17	80.44	-57.7
Run 3				
Avg. taxi time	0.00001	298.93	199.79	-33.2
Avg. punctuality	0.00506	144.30	59.74	-58.6

The results of the comparison show that the optimization technology performed significantly better than did the ATCOs both with respect to taxi time and punctuality. The decrease in average taxi time was between 33% and 36%, while punctuality improved by 57% to 67%. The p-values calculated from the runs were all significantly lower than 0.05, meaning that the results are significant. The results for each run are presented in Table 1.

Moreover, seven calculated time of takeoff (CTOT) windows were broken by the ATCOs, while this was not necessary, as proven by the algorithm. In addition, 89% of all flights (over all scenarios) were scheduled by the algorithm within an interval (-3; +3) around the CTOT, despite some very late target off-block times. In contrast, the ATCOs scheduled just 63% within this CTOT window, illustrating the human challenge of managing time and space simultaneously.

Each of the simulations included three to four flights scheduled to depart after 17:00, which is a target takeoff time after the end of the simulation. During the experiment, the ATCOs allowed the airplanes to take off before 17:00 out of necessity. In contrast to this, the algorithm planned these airplanes to take off at their exact target takeoff times. This led to a large difference in punctuality for these flights, which could affect the significance of the above results in terms of punctuality. Because the ATCOs did not have the option to schedule flights after 17:00, we decided to remove these flights from the analysis.

Because there were no other disturbances or external influences, other than those from the ATCOs or algorithm themselves, the difference in optimization can be explained by how coordinated the different decisions were. The results show that the algorithm improved the overall result in terms of both punctuality and taxi time by integrating both departure and surface routing management, giving rise to a more holistic evaluation of local decisions.

An important byproduct of this optimization is that it leads to a reduction in the number of airplanes simultaneously moving on the runway and taxiways, which, in turn, decreases the risk of collisions. For example, in Scenario 2, the ATCOs needed to guide up to 11 airplanes at the same time. In contrast, the algorithm almost halved the maximum workload, only guiding up to six airplanes at once (see Figure 3). Similar to the airspace sector workload indicators, the number of moving aircraft being actively monitored by the ATCOs can be seen as an adequate workload indicator. A reduction in the number of airplanes moving simultaneously means that less communication with pilots is necessary. This allows more time for monitoring the safety of the airport. Similar observations can be made for the other two scenarios. Given these results, it is expected that this difference will expand even more when the number of flights handled by the airport increases.

An increased integration of arrival scheduling with departure and surface routing is expected to yield even better overall results. Further investigation showed that the algorithm currently performs better for departures that it does for arrivals. From a practical standpoint, arrivals are less controlled by the receiving airport than they are by the departing airport and actual flight operations. This is especially true in the conducted case study, in which the arrivals landed exactly at their scheduled times. Because of this, the algorithm is configured to prioritize departing flights over arriving flights.

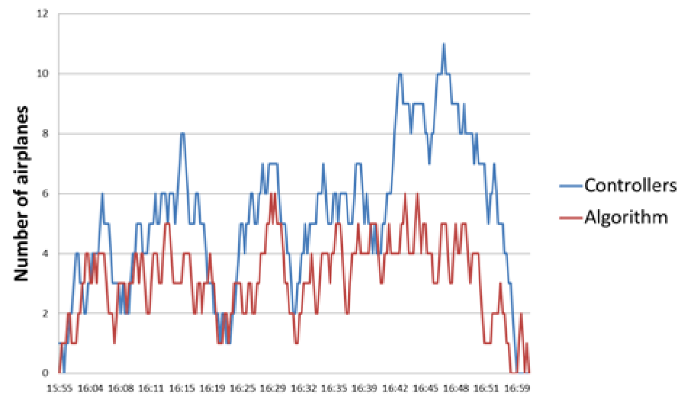

Figure 3. Number of moving airplanes over time in Scenario 2.

If ATCOs could have access to solution proposals generated by the holistic optimization algorithm and the associated tool, it could be an important enabler for airports to reach a higher safety level, due to the following reasons: First, the algorithm works on a mathematical model that inherently adheres to all safety rules (e.g., separation). In contrast, ATCOs, as a group of decision makers, lack the ability to jointly consider time and space with mathematical precision. This is a drawback because ATCOs need to resolve safety issues during execution, when the issues are about to occur. Second, the results have shown that the number of airplanes moving simultaneously can be reduced substantially through the use of optimization technology. Such a reduction might also lead to a decreased risk of collisions.

The average duration of a complete optimization run, without a "warm" start and for which all flights from each scenario are considered, is 15 s on a laptop with an Intel i7 central processing unit (CPU), four cores, and 4 GB of random-access memory (RAM). This was the first implementation of the algorithm. From previous experiences, we learned that further implementation and design efforts of the algorithm will probably lead to shorter running times and improved decision quality.

We also analyzed the interviews we conducted to understand what the participants themselves thought about their own performance and the realism of the study. It should be noted that four of the ATCOs have extensive experience not only as ATCOs but also as ATCO instructors and advisors; as such, they were able to recall and explain in detail their decisions and the cognitive processes behind them. Their general impression was that they performed well. They gave several examples of instances in which they improved their performance as a team by changing sequencing after discussing it during the training sessions. When asked about the realism of the study, the participants said that they were working as they would in a real working situation, both individually and as a team; that they were familiar with the traffic, the airport, and the used tools; and that they experienced no difficulties during the exercise.

One of the simplifications made in the study was the lack of pseudo-pilots. The participants reported that this improved their performance, as they spent no time on communicating with pilots. Furthermore, it reduced their cognitive workload, as they had no need to postpone communications with one pilot while talking with another pilot.

Another simplification that improved their performance compared to real-life circumstances was that speed of the arriving aircrafts, was much more predictable. Normally, the variations in arrival speed and the behavior of the pilots during the last four minutes before landing are quite large, increasing the ATCOs' workload. One controller mentioned that they missed the possibility of looking out the window, as normally, the ATCOs know that there is a small delay on the radar and instead look out the window. If a controller sees that an aircraft has passed the crossing of the runway, he/she would immediately launch the takeoff clearance. However, in this study, as there were no delays in the simulator, this was not needed.

A controller working at the tower (TWR) position described situations in which the performance of the ATCOs could be improved in some control centers. If a landing aircraft is within three nautical miles of the airport, one should not depart the next one. This rule should always be followed and will sometimes decrease efficiency. When one has a slow aircraft on approach and has a quick departing flight, some ATCOs take speed into account and stretch the rule (as one did in this experiment), thus improving performance. Others, however, always take a conservative approach and follow the given rule.

ATCOs are trained (although one interviewee called it "an instinct") not to hold up aircraft lined up on the runway just because it is too early to depart. Instead, one should get rid of the aircraft that are on runway because holding traffic on the runway is always a risk. Descriptions of the decision-making process reported in interviews indicate that ATCOs both used simplifications made in the experiment and stretched the given rules to improve their performance.

V. Limitations of this Case Study

A main threat to the validity of a study is the effect of having a subject population that is not representative of the population to which the study aims to be applied. It can be expected that the ATCOs from the Hamburg airport would perform better than the participants in the study due to their local working experience.

To minimize this threat, care was taken to recruit participants that had many years ATC working and/or training experience and to provide them with extensive training, as described in Section III. A. In the interviews that followed the study, all the participants reported that they had good knowledge of the Hamburg airport infrastructure and working process after the training. They also described that they used the training sessions to improve their performance as a team. They discussed situations that needed better coordination and agreed on improvements.

Another threat to validity is related to the ability to generalize from the tasks the participants conducted. In our study, we used a real-time simulation in which ATCOs were situated in a realistic tower environment, performing ATC tasks in realistic traffic scenarios. The process applied to solve the tasks replicates the process used at the Hamburg tower. To reflect the Hamburg tower setting as closely as possible and to ensure that the setting was representative of today's practices, the environment was set up to make use of electronic strips for coordinating the work of the different controller roles. However, there were some simplifications. There were no pilot (i.e., pseudo-pilot) positions in the exercise. The participants reported that this improved their performance, as they spent no time on communicating with pilots, the pilots (simulated by the system) always followed their orders immediately, and the speed of the arriving aircrafts was much more predictable. However, the controller missed the possibility to look through the window.

A potential shortcoming of this set up could be that the algorithm had a hindsight advantage by knowing the actual disturbances that happened in the simulation and taking this into account in its calculations. To remedy this threat, the ATCOs were instructed that there would be no external disturbances and that they could take advantage of this. In the interviews, all ATCOs described that knowing this improved their performance on taxi time and punctuality.

Finally, due to data limitations, the algorithm used a constant speed conservatively set at 7.5 m/s, whereas it is often 10.0 m/s. Thus, the taxi times of the algorithm were somewhat higher than they would be in a real-world setting

VI. Conclusions and Future Work

The holistic optimization tool we proposed makes decisions based on its global view of the airport, while each individual controller makes decisions for his/her limited area of responsibility, with little coordination with other ATCOs. Therefore, the tool performs better than ATCOs in terms of optimal taxi time and punctuality. This is primarily related to the optimization technology's ability to calculate enormous numbers of variables that affect the decision space, outputting optimized decisions in a matter of seconds. Based on this, we regard holistic optimization technology as a promising aid to support decision making in ATC towers, and in turn the overall ATC process.

Our results show that the holistic optimization algorithm can reduce taxi time and improve punctuality, while still maintaining the same level of safety. Identified improvements might also affect KPAs beyond the ones investigated this study. Improvements in average taxi time and punctuality can increase airport capacity. Further, reducing the taxi time contributes to fuel efficiency.

Currently, the power of optimization technology is not used to its full extent. Future work includes making the optimization model even more complete with respect to detailed real-world constraints. Large-scale simulations are needed to support this. We need to incorporate the ability to maintain stable solutions in a dynamic environment. We also want to extend our model to fully include arrival management. Finally, this optimization technology can also be developed to become part of a learning tool for ATCOs, providing them with a comparison basis between their decisions and the optimal ones.

Interaction between the optimization tools and ATCOs should also be investigated. By introducing heuristic optimization, we actually open up new ways of utilizing human performance. Additionally, some of the dedicated variables or parameters in the heuristic algorithm can be tuned by input from human experience, analysis, and judgment. And, in turn, a human operator can improve manual performance when using an automated decision support tool. Introducing optimization tools creates a need for new empirical studies on the interplay among tools, ATCOs, and organizations.

For future work, we can also consider uncertainty in the input to the algorithm, such as taxi speeds, pilot reaction times, and arrival times, in two different ways: first, by exploiting robust and stochastic optimization models; and second, by exploiting our optimization algorithm to re-optimize in real time whenever large enough deviations from the current plan occur. In addition, our algorithm can be expanded to decide not only the departure times but also the arrival times. In this way, the arrival and departure sequence on the runway could be further optimized with regard to punctuality and taxi times.

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References

1. EU, *Commision of the European Communities: European Transport Policy for 2010; Time to Decide* 2001: Brussels.
2. EU. *Transport - Single European Sky* 2009; Available from: http://ec.europa.eu/transport/air/single_european_sky/single_european_sky_en.htm
3. Anderson, R. and D. Milutinovic. *Optimization of taxiway traversal at congested airports*. in *10th AIAA Aviation Technology, Integration, and Operations (ATIO)* 2010.
4. Anderson, R. and D. Milutinovic, *An approach to optimization of airport taxiway scheduling and traversal under uncertainty.* Proc IMechE Part G: J Aerospace Engineering, 2012. **227**(2): p. 273–284.
5. Marín, A. and J. Salmerón, *Taxi planner optimization: a management tool.* Proc. IMechE Vol. 222 Part G: J. Aerospace Engineering, 2008: p. 1055-1066.
6. Marín, A.G., *Airport taxi planning: Lagrangian decomposition.* J. Adv. Transp., 2013. **47**: p. 461–474.
7. Stiverson, P. and S. Rathinam, *Heuristics for a runway-queue management problem.* Proc. IMechE Vol. 225, Part G: J. Aerospace Engineering, 2010: p. 481-499.
8. Rathinam, S., J. Montoya, and Y. Jung. *An optimization model for reducing aircraft taxi times at the Dallas Fort Worth International Airport*. in *Proc. 26th International Congress of the Aeronautical Sciences (ICAS)*. 2008. Anchorage, Alaska, USA: Optimage Ltd.
9. Wood, Z., et al. *A simulator for modeling aircraft surface operations at airports*. in *Proc. AIAA Modeling and Simulation Technologies Conference*. 2009. Chicago, Illinois: AIAA.
10. Avella, P., et al., *Time-indexed formulations for the Runway Scheduling Problem.* Transportation Science, 2017. **51**(4): p. 1196-209.
11. Erzberger, H., T.A. Lauderdale, and Y.-C. Chu, *Automated conflict resolution, arrival management, and weather avoidance for air traffic management.* Proc. IMechE Vol. 226 Part G: J. Aerospace Engineering, 2011: p. 930-949.
12. Erzberger, H., et al. , *Algorithms for control of arrival and departure traffic in terminal airspace*. Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering 2016. **23**(9): p. 1762-1779.
13. Ravidas, A., S. Rathinam, and Z. Wood, *An optimal algorithm for a two runway scheduling problem.* Proc IMechE Part G: J Aerospace Engineering, 2012. **227**(7): p. 1122–1129.
14. Zeh, T., et al. *Zero Failure Management at Maximum Productivity in Safety Critical Control Room*. in *First SESAR Innovation Days* 2011. ENAC (Ecole Nationale de l'Aviation Civile), Toulouse, France: EUROCONTROL.
15. Langlo, J.A., et al. *Usefulness of FMECA for improvement of productivity of TWR process*. in *The Second SESAR Innovation Days 2012*. 2012. Braunschweig: EUROCONTROL.
16. Karahasanović, A., et al., *ZeFMaP: E.02.16-ZeFMaP-D1.2 - ZeFMaP Process Final*. 2013. http://dx.dio.org/10.13140/RG.2.2.34730.67529
17. Kjenstad, D., et al. *Integrated surface and departure management at airports by optimization*. in *Modeling, Simulation and Applied Optimization (ICMSAO), 2013 5th International Conference on*. 2013. Hammamet: IEEE Xplore Digital Library.
18. Eide, W.A., A. Karahasanović, and S. Kind, *ZeFMaP: E.02.16-ZeFMaP-D2.2-Evaluation plan and results (Phase 1)*. 2011. http://dx.dio.org/10.13140/RG.2.2.10823.14241
19. Gräupl, T., M. Mayr, and C.-H. Rokitansky, *A Method for SWIM-Compliant Human-in-the-Loop Simulation of Airport Air Traffic Management.* International Journal of Aerospace Engineering, 2016. **2016**.