Optimization of Airport Surface Planning and Scheduling Through Probabilistic Modeling and Analysis From Operational Data

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# Summary of project

The overall objective of the practicum is to demonstrate the use of probabilistic modeling and analysis tools to develop and implement scalable control and optimization algorithms to improve surface operations at large airports. This work builds upon and expands existing research being conducted at Ames Research Center in the following areas:

* The use of autonomous vehicles for taxiing aircraft and other logistics problems[15],[28];
* The use of probabilistic programming to model complex data[27];
* The application of planning and scheduling technologies to airport surface logistics[4]-[6],[12]; and
* The development of future architectures for ground traffic monitoring and control at NASA Ames Research Center[3],[14].

The research team will be deployed to work on three areas:

* Using probabilistic programming to develop realistic simulations of airport surface activity from operational data supplied by NASA;
* Applying the predictive capabilities of the probabilistic models to improve algorithms for surface movement planning and scheduling; and
* Conduct experiments in simulation using a system developed at NASA Ames to demonstrate the value of real-world operational data in the development of optimization algorithms to solve the surface logistics problem.

# Background and motivation

The world air transportation system operated nearly 85 million fights worldwide in 2014. The Asia Pacific region served more than a third of these flights, while Europe and North America served about a quarter each. Emerging markets in the Middle East are experiencing an annual growth in traffic of more than 10% annually.

Although there are nearly 42,000 airports worldwide, traffic demand tends to be concentrated at the top 30 airports that serve more than one-third of all passengers. The busiest airports in the United States (Chicago O'Hare, Atlanta and Los Angeles) each see more than 700,000 aircraft operations annually. The increasing demand for air traffic operations has strained this already capacity-limited system, leading to significant congestion, flight delays, as well as noise and air pollution [1].

Domestic flight delays in the US have been estimated to cost airlines over $19 billion and the national economy over $41 billion annually, waste 740 million gallons of jet fuel, and release an additional 7.1 billion kilograms of CO2 into the earth's atmosphere. The demand for airspace resources is expected to significantly in the upcoming decades. The networked nature of the air transportation system also leads to the propagation of delays from one part of the system to another. To prevent cascading delays and even congestive collapse, there is a need for new analysis techniques and operational strategies for air transportation systems[2].

# Technical challenges and relevant technologies

Airport surface operations present a difficult, large-scale logistics problem with a wide range of sub-problems requiring multi-criteria optimization, including: runway sequencing and scheduling; spot or gate release scheduling; gate allocation and taxi route planning and scheduling[16]-[19].

Airport surface movement optimization is NP-hard [18]. Several types of constraints are involved, including pushback times, taxiway layouts, and runway and taxiway separation. Surface movement planning and scheduling is dynamic, with aircraft continuously entering and leaving the operating space. Surface movement is unpredictable and prone to unexpected changes in operating conditions due to things like weather. In general, efficiency and safety are difficult objective to achieve in practice, due to the challenges posed by the presence of uncertainties, human factors, and competing stakeholder interests.

Current practice handles the dual problems of complexity and uncertainty in two ways: continuous planning and scheduling and sub-optimal heuristic scheduling[14]. Furthermore, virtually all planning and scheduling decisions are currently made by human operators. Typically, airport surveillance data and scheduling tasks (for departures and arrivals) provide inputs to planning and scheduling. To handle the dynamics of the operations, schedules are revised continuously (for example, every 15 minutes at busy airports). Second, the complexities of the planning and scheduling problem have until now forced the utilization of heuristic approaches to optimization that require reduced computational overhead while achieving useful results.

The impetus for the proposed research is the hypothesis that by leveraging the increasingly available operational data to build simple yet realistic models, and to use these models to develop and implement scalable control and optimization algorithms to improve system performance, it is possible to address the above-mentioned complexities and uncertainties. Better planning and scheduling through automated methods means more efficient operations while potentially reducing the workload of airport surface controllers.

The relevant software technologies that will be used in this project are:

* Operational architecture for a more automated airport surface management system
* Algorithms and probabilistic models
* Simulation and Visualization

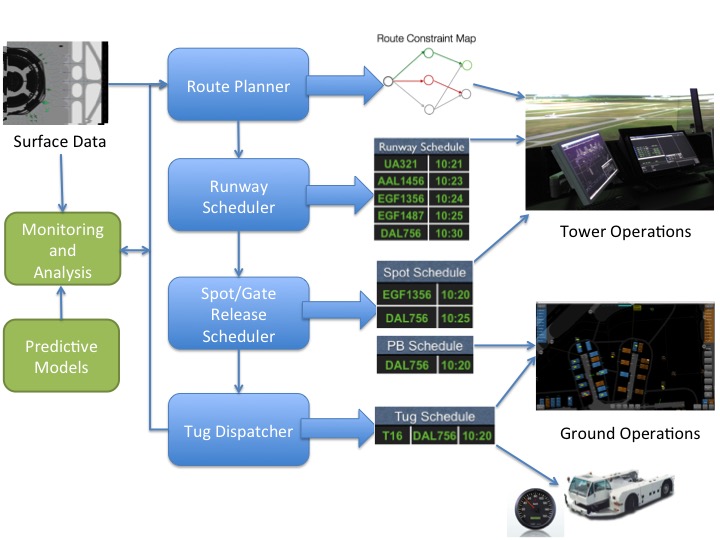


Figure 1. System Architecture for Airport Surface Management

## Operational Architecture

Figure 1 shows a nominal operational architecture for airport surface movement based on the combined use of automation and autonomy. This architecture arose from previous work conducted at NASA Ames through the NextGen project, as well as the SafeTug project for robotic towing[15]. There are four component capabilities: sensing for acquiring surface surveillance data, predictive models, monitoring and analysis tools, and human-machine systems for planning and scheduling. Data continuously provides input to both planning and monitoring systems. Predictive models, which are developed off-line and on-line through operational data, supply guidance to human and automated systems for planning and scheduling.

Planning and scheduling starts with route planning for aircraft (or as envisioned, a surface system for robotic towing an taxiing), and leads to scheduling gate pushback, spot (entrance to taxiway) release scheduling, and runway scheduling. The outputs of the system are routes and schedules (assignments of time to events for each arriving or departing aircraft), which are communicated by the tower to the aircraft. Parts of this architecture have been implemented in simulation, and will provide the basis for the work conducted here.



Figure 2. Predictive Model Generation Process

## Algorithms and Models

The practicum will utilize recent advances in probabilistic modeling, combined with advances in route planning and scheduling.

## Modeling and Analysis

Figure 2 provides an overview of the modeling and analysis tool to be used in this project. It is comprised of three main components: a log parser, an intermediate model generator, and a model generator. The log parser processes the input log, and uses definitions of a state and the transition function to generate the intermediate model. The intermediate model is defined as a generic automaton that allows for the generation of input models for different model checkers, e.g., reactive modules for the PRISM model checker[10]. The intermediate model consists of a state (an assignment of values to model variables) and transitions. Translating the intermediate model requires mapping states and transitions from the intermediate model to the target modeling formalism. The models can be analyzed automatically using a translation to the modeling formalisms of the PRISM and UPPAAL[11] model checkers. Finally, the models are analyzed based on queries written in temporal logics. Previous work[27] has demonstrated the feasibility of the overall approach.

For the proposed work of the practicum, we plan to refine our models in a number of ways, including the use of higher resolution grids that take into account more details about configuration of the airport. For example, a finer grid may take into account the gate area, taxiways, and runways and allow a decomposition of certain surface areas into polygons. To bootstrap the model-inference, we would also like to use random testing. We also plan to integrate the model in the dispatcher to minimize delays in taxiing, to avoid congestions, and to maximize throughput to increase capacity of the airport. Finally, we plan to investigate is the behavior of towing vehicles around intersections.

## Planning and Scheduling

NASA Ames Research Center is a leader in developing planning and scheduling algorithms and systems for a wide range of problems in aeronautics and space exploration. For this proposed practicum the focus will be on two areas:

* Applying recent advances in Multi-agent Path Finding (MAPF) algorithms[4],[5],[13],[20]-[26] to generate optimal routes for autonomous towing vehicles; and
* Enhancing predictive surface planning models by integrating the probabilistic models described above.

Both of these areas (MAPF and more expressive planning models) are currently active areas in the Artificial Intelligence planning community.

As indicated in Figure 1, Surface movement planning starts by generating routes for arriving and departing aircraft over a certain planning horizon. Here MAPF algorithms will be applied with guidance provided by surveillance data and predictive models. Routes are then refined through a process of assigning times for pushbacks, spot release, and runway queue management, as well as tug assignment [9],[15],[28]. Again, we will investigate different ways in which decisions made by these modules will benefit by querying the analysis tool to make decisions. For example, queries such as “Given the current schedule of gate pushbacks for the next 15 minutes, what is the likelihood that there will eventually be congestion at the runway queue?” will assist scheduling gate release activities.

To collect statistics related to these metrics, we will utilize a fast time Python-based simulator called ASSET (Airport Surface Simulator and Evaluation Tool) developed at NASA Ames. ASSET is based on the SARDA framework for scheduling, but with reduced capabilities that allows for rapid prototyping of route planning and scheduling algorithms.



Figure 3. ASSET Visualization of DFW airport terminal 3

## Simulation and Visualization

To collect statistics related to these metrics, we utilize the ASSET tool mentioned above. ASSET contains three components: a scheduler, a simulator, and visualizer and analysis tools. The inputs to the simulator include a graphical model of an airport; a model of aircraft (including wing span, length and average taxi speed); and a scenario, a list of departure and arrivals for different aircraft, and the times at which they enter the surface system. The simulator, in conjunction with the scheduler, outputs the surface track information (i.e. the flow of traffic) over time. The simulator also models the ‘intent’ of the towing vehicles by automatically enforcing the separation constraints and other rules governing safe surface traverse.

The ASSET visualizer reads simulator output and displays the progress of the scenario on the airport surface (Figure 3 is a screen shot of the visualizer tool). The evaluation tool reads the simulator output into an SQL database, from which statistical inferences can be made and plotted, relevant to the four metrics listed above.

# Project goals, outcomes and deliverables

Dr. Morris will lead the overall effort, and focus on the planning and scheduling development. Dr. Pasearanu will lead the development effort for the probabilistic analysis tool.

The goal of the proposed practicum is to demonstrate the use of probabilistic modeling and analysis tools to develop and implement scalable control and optimization algorithms to improve surface operations at large airports. The practicum team will use NASA operational data for Dallas Fort Worth and Charlotte airports to build predictive models that will form the basis of a predictive analysis tool. In parallel, the team will expand the planning capabilities of the ASSET scheduler by implementing the MAPF algorithm in Python for use in route planning. Strategies for integrating the predictive models into different phases of the surface movement planning and scheduling process with autonomous towing vehicles will be devised and implemented.

In evaluating the overall system, four performance metrics will be used:

1. Efficiency, in the form of maximizing throughput;
2. Reducing complexity of operations, primarily in the form of workload for flight crew, tower personnel or ground crew;
3. Safety, specifically the ability to maintain separation constraints and avoiding potentially dangerous events such as runway incursions; and
4. Environmental and economic benefits through reduced fuel emissions and reduced maintenance costs through less wear on airplane engines.

Using the ASSET simulator, the overall outcome of the project is the ability to measure the improvement in system performance with and without the use of probabilistic analysis. The deliverables for this project will be the enhanced ASSET system and a detailed NASA technical report summarizing the overall effort.

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