

Decentralization in Air Transportation

Udluft, Heiko

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DECENTRALIZATION IN AIR TRANSPORTATION

DECENTRALIZATION IN AIR TRANSPORTATION

Proefschrift

ter verkrijging van de graad van doctor
aan de Technische Universiteit Delft,
op gezag van de Rector Magnificus prof. ir. K.C.A.M. Luyben,
voorzitter van het College voor Promoties,
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door

Heiko UDLUFT

Master of Science in Mechanical and Process Engineering,
Technische Universität Darmstadt, Duitsland,
geboren te Frankfurt a. Main, Duitsland.

This dissertation has been approved by the

promotor: prof. dr. R. Curran

copromotor: dr. A. Sharpanskykh

Composition of the doctoral committee:

Rector Magnificus	chairman
Prof. dr. R. Curran	Technische Universiteit Delft
Dr. A. Sharpanskykh	Technische Universiteit Delft

Independent members:

Prof. dr. F Klügl	Örebro University, Sweden
Prof. dr. D. Delahaye	Ecole Nationale de l'Aviation Civile, France
Prof. dr. ir. B. van Arem	Technische Universiteit Delft
Dr. T. Bosse	Vrije Universiteit Amsterdam

Other members:

Prof. J.-P. Clarke	Georgia Institute of Technology, USA
--------------------	--------------------------------------

Prof. J.-P. Clarke of Georgia Institute of Technology has contributed greatly to the preparation of this dissertation.



Keywords: Air Transportation, Decentralized Control, Airport Surface Movement, Aircraft Taxiing, Airport Performance, Agent-Based Modeling and Simulation

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Front & Back: 2D histogram or aircraft positions around London Heathrow Airport

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To my parents

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SUMMARY

In this work, we demonstrate that decentralized control can result in stable, efficient, and robust operations in the Air Transportation System. We implement decentralized control for aircraft taxiing operations and use Agent-Based Modeling and Simulation to analyze the resulting system behavior. Decentralized controllers at each intersection of the airport taxiway system autonomously guide aircraft through the system. They achieve conflict-free operations with a minimum amount of information, coordinate their actions to improve system performance, and can dynamically accommodate disruptions such as runway configuration changes.

The demand for the Air Transportation System continues to grow, and in parts already exceeds the available capacity. Specifically, the lack of capacity at major hub airports and in busy sectors of the airspace affects the overall growth of the system. The international initiatives SESAR and NextGen are developing methods and tools to improve the performance, capacity, and environmental impact of Air Transportation System without affecting safety.

Aircraft taxiing contributes to the overall flight and airport performance and is an active area of research and development. More efficient use of the taxiway system at airports can improve the performance of arriving and departing flights and can increase the utilization of available runway capacity. Previous work, for example, focused on the development of methods for optimal aircraft routing with respect to cost and environmental impact, and means to reduce congestion of the taxiway system. Also, decentralized control has been previously researched for taxiing operations, where aircraft autonomously decided their route through the taxiway system.

The analytical solution to schedule aircraft push-back under uncertainty that is developed in Chapter 4 solves part of the optimization of aircraft taxiing and highlights the trade-off between aircraft delay and runway utilization. The results also show that the amount of uncertainty in taxi times constrains the achievable system performance. The uncertainty that we observe on a global, system-wide level results from various local effects that impact the taxi time. The uncertainty on a local level is much lower compared to the system-wide uncertainty. This observation motivates the idea to split up the taxiing problem into smaller parts, solve these partial problems locally, and put the system under decentralized control.

Decentralization of selected tasks and processes in the Air Transportation System can help to mitigate capacity constraints and allow to increase the fidelity of decision-making processes. The capacity of a control agent to make decisions is constrained by the rate at which it can collect, process and disseminate information. The vast amount of relevant information that is available about the Air Transportation System exceeds the capacity of the current centralized infrastructure, and increasing this capacity is difficult and expensive. Implementing decentralization in the system can reduce the workload of

the centralized controllers, and allow decentralized controllers to take local information into account when making decisions.

In order to demonstrate that decentralized control can lead to stable aircraft taxiing operations at an airport and to better understand the parameters that influence decentralized control, we conduct experiments using an agent-based simulator. In Chapter 5 we vary the scope of information to constrain the knowledge of each decentralized controller about the state of the system. The results show that a minimum amount of information is required to ensure conflict-free operations and that more information does not necessarily increase system performance. In Chapter 6 we compare different coordination strategies between agents. The results show that coordination improves system performance and that our auction-based coordination strategy can perform better than a static procedure that was designed for the specific traffic situation.

Decentralized systems can autonomously adapt to changing conditions, and the system level behavior of decentralized systems is not predefined, but instead, emerges from local interactions. Therefore, these systems can achieve good robustness and resilience. In Chapter 7 we analyze the emergent properties of the decentralized control for aircraft taxiing using entropy metrics and test how the decentralized control handles runway configuration changes, which are system-level disruptions for aircraft taxiing operations. The results do not show emerging traffic patterns during one simulation run but show a visible global traffic structure when looking at the average taxiway usage of all simulation runs. Furthermore, the results demonstrate that decentralized control for aircraft taxiing can accommodate runway configuration changes, and after a disruption return to performance levels that are similar to before the disruption.

1

INTRODUCTION

The air transportation system is a large, complex, interdependent, and highly dynamic infrastructure system. At a time where higher capacity and efficiency are needed to nourish a growing demand, these system properties are challenging the current centralized paradigm to model and control the system. The aim of this chapter is to motivate a decentralized approach to structure and manage the air transportation system. In this chapter, we position this work in the context of the current state of the air transportation system and provide an overview of the structure of this thesis.

AIR transportation is an enabling technology for the modern, globalized world and society. Being able to travel within hours between continents reduces the barriers to meet and trade with people in other countries and cultures. This exchange makes local goods and knowledge accessible globally and creates opportunities to advance well-being, wealth, and technology. Enabling people to easily travel between countries increases the understanding of each other's needs and motivation, which can ultimately reduce conflict.

The already high demand for air transportation is expected to continue to grow over the next decades. Decreasing prices for air travel and increasing wealth in new markets makes air transportation accessible to more people. It is understood that income is a "fundamental driver of the demand for air travel" [1]. According to market research done by the International Civil Aviation Authority, the demand for air transportation is expected to continue to grow by 5% annually over the next two decades. Albeit fluctuating with the global economy, the amount of both business and leisure air travel has been growing continuously. In busy areas and at major hub airports, demand for the air transportation system is reaching its capacity limits. When demand exceeds the available capacity, the flow of aircraft through the system is disturbed, and flight delays occur. In Europe in 2016, 15% of delays were accounted to Air Traffic Flow Management (ATFM) issues, counting 'ATFM En-Route', 'ATFM Airport' and 'Other Airport' categories [2]. The slot concept allows regulating the traffic flow into busy air traffic infrastructures such as London Heathrow Airport to ensure manageable and safe operations. Flights can only be scheduled if they have been assigned a slot. During peak time periods, slot demand exceeds the available capacity, which constrains the number of flights that airlines can operate, and thus the number of passengers transported.

Future demand cannot be accommodated by the current system and infrastructure. The current air transportation infrastructure has grown primarily based on traffic from Europe and North America, and can hardly accommodate the existing demand from those regions. If the general demand for air transportation increases, the capacity bottleneck that already exists will grow even further. As new international markets develop, different traffic patterns and routes are emerging, requiring changes to the airspace structure and physical infrastructure.

The ability to increase the capacity of the physical infrastructure is limited. Construction of new terminals, runways and supporting traffic infrastructure is costly and time-consuming. Furthermore public interest, regulation, and available space limit the realization of large-scale infrastructure projects, especially in metropolitan areas. Development projects are successfully increasing the physical capacity of airports in rural areas but are not being utilized due to a lack of traffic demand for those regions.

Multi-national research initiatives are seeking to improve operations to better utilize the available infrastructure. Most notably, the Single European Sky ATM Research (SEASAR) in Europe and Next Generation Air Transportation System (NextGen) in the United States are developing future air transportation systems. Their goals are to increase the system capacity, reduce cost and environmental impact, and improve performance while maintaining the current level of safety. A primary factor that is known to limit system capacity is the coordination resource of the system, such as the Air Traffic Controller. Air Traffic Controllers are human operators that are responsible for manag-

ing the traffic in a dedicated part of the airspace or airport. The amount of traffic is the major factor that causes workload to the air traffic controller, among other factors such as the traffic complexity. The acceptable workload is limited by the mental capacity of the air traffic controller to process information, interact with aircraft and make decisions. To ensure safe and stable operations in the current Air Transportation System, the amount and complexity of traffic in a sector must be constrained, and must not exceed the mental capacity of the air traffic controller.

Air traffic controllers constantly make decisions for various coordination tasks. They plan the operations of aircraft under their control and give instructions to guide aircraft to their intended destination. They are responsible for ensuring safe separation distances between aircraft. If they detect conflicting trajectories between aircraft, they have to take action to de-conflict. They also control the flow of aircraft from their part of the system into adjacent parts to ensure not to exceed the available capacity.

The decision-making processes, responsibilities, and control in the current air transportation system are set up following a centralized paradigm. In Europe, the Central Flow Management Unit (CFMU) assigns slots to aircraft to manage the available capacity of the system, and it de-conflicts high-level request for flights. Airlines schedule their flight and then manage their flight operations from a central unit, where the available flight information is managed and processed to ensure efficient operations, and respond to disruptions. Air traffic controllers are responsible for the operations of several aircraft at a time in a large area, and pilots must adhere to their commands.

To improve the performance of the centralized control, research activities within the SESAR and NextGen initiatives aim to introduce automated and decision support systems. These systems either take over or support the control task of the human operator to increase the efficiency and decrease the workload. They can handle higher demand, more complex traffic, and lower margins. As the system state constantly changes automation requires the development of efficient algorithms and provision of sufficient computational resources to compute solutions in real-time. The problem size and computational demand grow with the number of system parameters taken into account. The human operator is expected to serve as a backup for the automated system, which constrains the allowed complexity of the solutions.

Other research within these initiatives is focused on the restructuring of airspace. Airspace is divided into sectors that are usually each controlled by one air traffic controller. Changing the current airspace layout to increase the number of sectors also increases the number of controllers and the airspace capacity. Currently, the demand varies between sectors, leaving control capacity unused. Dynamically changing the airspace structure would allow making better use of the existing air traffic control capacity. However, the number of sectors is constrained, since aircraft must be handed off between sectors, which causes workload as well.

Another approach to increasing the available capacity of the central resources in the Air Transportation System is to reduce the number of tasks that they are performing, by decentralization of decision-making processes. In this specific context, decentralization is the process of moving decision authority, responsibility, and control away from centralized resources to distributed entities in the System. Example projects that embrace the benefits of decentralization are 'Free Flight', where aircraft determine their

flight trajectory themselves, and ‘Self Separation’, where aircraft ensure safe separations with other aircraft themselves. Decentralization of some of the tasks that are performed at the coordination resource would free up capacity to perform other tasks that can only be performed centrally.

While the air transportation system is commonly modeled and addressed as a centralized network, decentralized processes govern the actual performance and operations. Pilots are subject to their local conditions when deciding how to respond to a command given by air traffic control. The air traffic controller cannot directly influence the trajectory of an aircraft. As a flight is getting ready for take-off, several local processes, such as baggage and passenger loading, maintenance, and fueling have to be completed. Each of these processes can contribute to disruptions and delays. The progress of a flight is impacted by local conditions such as aircraft performance, weather, and other traffic. The large number of these local processes and their interactions leads to a very high system complexity, which can be difficult to capture and respond to by centralized coordination.

The motivation to move away from a strictly centralized paradigm and seek decentralized control in the air transportation system is twofold:

1. Implementing decentralized control reduces the number of tasks that are allocated to a centralized control unit. Decentralized controllers have access and capacity to take local information into account in their decisions. The capacity of a decentralized system increases as the system grows.
2. New distributed systems are being developed that challenge the centralized paradigm. ‘Free Flight’ and ‘Self Separation’ are proposed concepts for future operations. Drones that aim to become an integral part of the transportation infrastructure could be operated in a dedicated airspace outside the supervision and responsibility of Air Traffic Control.

In this work, the potential for decentralization applied to air transportation is investigated. While air transportation can benefit from implementing more decentralization, there are specific challenges of this paradigm that need to be addressed.

1.1. DECENTRALIZATION - BENEFITS AND CHALLENGES

Decentralization is the process of moving from a centralized network topology towards a distributed network topology. Figure 1.1 shows three network topologies that are commonly studied in network theory.

In general, networks are used to represent “a group or system of interconnected people or things” [4]. They are modeled as nodes, and edges that connect the nodes. With this simple representation concept, the behavior, exchange, and interaction of very complex processes and organizations can be modeled and studied. In a telecommunication network nodes can represent individual devices and links can represent the means to exchange signals between devices. In information networks, nodes can represent agents that store and process information and links represent information exchange between nodes. In infrastructure networks, such as energy or transportation, nodes can represent infrastructure hubs, and links can represent connections between those hubs.

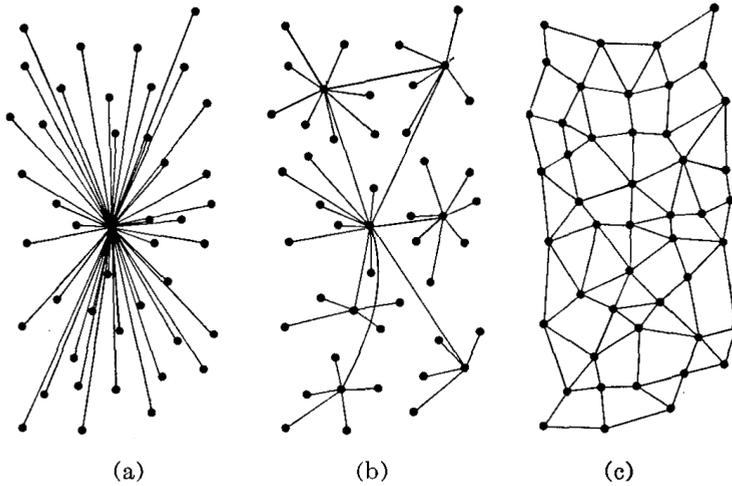


Figure 1.1: (a) Centralized, (b) Decentralized, (c), Distributed Network Topology [3]

Decentralized networks have demonstrated to be more robust, agile and resilient compared to centralized networks [5, 6]. Individual nodes can fail without major effects on the overall network. Such networks can adapt their structure to respond to changes in the environment. After a disruption, they can reconfigure to still perform their intended task.

Decentralization has been studied and successfully implemented in various domains. In biology the behavior of social insects [7] and colonies of fish [8] that collaboratively complete tasks without central coordination are examples of successful decentralization. Ant colonies, for example, forage and build their nest without a hierarchical organization. Robotics and control theory mimic the behavior of colonial insects in the field of swarm robotics. Ant Colony Optimization has been successfully applied in several optimization tasks. In computer sciences, clients in peer-to-peer networks share and access information. As information is redundantly distributed through the network, individual nodes can drop out without compromising the integrity of the information stored in the network. An example of a decentralized task in air transportation is the Traffic Alert and Collision Avoidance System (TCAS), which identifies and resolves conflicts between aircraft based on local information and coordination.

The globally observed behavior of a decentralized network emerges from the local behavior of nodes and cannot be precisely predicted. Nodes in decentralized networks act based on local knowledge, decision-making processes and interaction with other nodes. The local nodes can observe and predict the changes in their local environment. The global state of the network is observable, but not predictable, since the exact actions taken by local controllers are unknown. The properties of decentralized processes can prove to be beneficial for the Air Transportation. Shifting decision authority to decentralized agents in the system allows taking local effects into account in the decision process, and responding to local conditions without the need for central coordination.

This would allow improving the performance of local processes and free up capacity at the centralized coordination resource. Decentralization may contribute to solving the capacity bottleneck of the air transport infrastructure, increase system robustness, and get the air transportation system ready for the future.

However promising, there are system properties that need to be better understood to increase decentralization in the air transportation system. Specifically, there are three properties that need to be demonstrated before further processes can be decentralized:

- To be a viable paradigm for control and responsibility in the air transportation system, the envelope of operations must be predictable. The emergent behavior and properties of the decentralized network must be understood.
- The impact of decentralization on system performance must be clear. Since the available resources are constrained, only limited loss of performance is acceptable when introducing a decentralized solution.
- It needs to be proven that the emerging behavior leads to stable operations that do not violate global system constraints. Especially it must be demonstrated that no unsolvable conflicts occur during the operation.

There is a very high risk awareness in the aviation industry, which means that new technologies undergo thorough testing and skepticism in the community. For a decentralized system to be implemented in an aviation context, the issues mentioned above must be addressed.

1.2. AIM OF THE THESIS

The goal of this thesis is to evaluate the applicability of decentralized control in the air transportation context. As the current system is built following a centralized paradigm, decentralization should be demonstrated for a specific and relevant sub-area of the Air Transportation System to prove the viability of the approach.

There are several areas within the Air Transportation System where a decentralized approach could resolve some of the challenges with regards to capacity, efficiency, and safety. This thesis addresses the area of air traffic control, to test the applicability of decentralization in a realistic and relevant scenario. Within this area, the work focusses on aircraft taxing operations at airports as an example use case. This work has to achieve the following objectives to meet the aim of the thesis:

- Highlight the challenges and limitations of current centralized approaches for planning and control of air traffic control
- Specify and discuss relevant system performance indicators
- Implement, analyze, and evaluate a decentralized control approach in the context of air traffic control
- Identify critical parameters of the decentralized control and explore their impact on stability and performance of operations

1.3. OUTLINE

This dissertation is organized as follows:

Chapter 2 discusses the current literature in the fields of air traffic control ground operations and decentralization in infrastructure systems. This Section highlights the relevance of decentralization for Air Transportation and typical properties of decentralized systems.

Chapter 3 introduces metrics to quantify the performance of Air Transportation System using aircraft position data. The metrics introduced in this Chapter can be used to evaluate the operational impact of decentralization on a system-level.

Chapter 4 introduces an analytical solution for aircraft push-back scheduling at an airport. This Chapter shows the limitations of a centralized solution and highlights the trade-off between the two performance metrics throughput and delay.

In Chapter 5 it is tested how varying scope of information impacts global system performance. This section demonstrates that a limited scope of information is sufficient to perform Air Traffic Control ground operations.

In Chapter 6 different coordination mechanisms are implemented and compared with respect to the emerging system performance. It is shown that coordination can improve system performance.

In Chapter 7 the complexity and emerging traffic patterns of the operations under decentralized control is measured. Furthermore, the performance of the system in response to a disruptions is tested.

Chapter 8 discusses the impact of the work and highlights benefits and limitations to Air Traffic Control ground operations. Furthermore, the impact on other domains is discussed. This work is a first step towards a methodology to assess the viability of decentralization, and Chapter 8 provides an outlook how this methodology can be substantiated.

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2

RESEARCH MOTIVATION AND APPROACH

In the previous chapter, we motivated decentralization as a design paradigm to address current challenges of the air transportation system. To implement a change to the air transportation system, certain properties such as safety and capacity must be ensured. There is a strong interdependence between components in the system. Every component must stay within acceptable operational bounds to ensure desired global system behavior. Decentralized systems are difficult to predict since their behavior emerges from local interactions of the decentralized controllers, which raises the question of how to ensure global system properties. This chapter presents decentralization in the context of air transportation and presents the research approach for this work.

2.1. INTRODUCTION

IN THIS Chapter we present an initial problem statement for decentralization in air traffic management, and present examples of decentralized and centralized processes that are currently implemented.

2.1.1. BACKGROUND

The current Air Traffic Management (ATM) system's coordination tasks such as traffic flow management and air traffic control are performed by centralized authorities [2]. Centralized network optimization can find globally optimal solutions for given objectives such as: Use of resources, delay or capacity. A centralized coordination authority will monitor the global state of a network, and take decisions that ensure safety, capacity and efficiency.

The capacity of centralized resources, such as air traffic controllers, is limited. In some cases the demand meets or already exceeds current capacity, and is expected to grow further. There is a "pressing need to increase capacity" [3]. SESAR and NextGen initiatives are developing future ATM systems to solve the capacity bottleneck. Current developments are suggesting solutions which either add more resources to expand capacity, or make more efficient use of existing resources, i.e. through automation.

Operations of distributed systems, such as UAVs, are being implemented on an experimental scale. Companies and other stakeholders strive to introduce them on a large commercial scale. These systems share the airspace with current operations, which poses new challenges to the Air Transportation System. Such systems collect and process information, make decisions and take actions decentrally.

2.1.2. MOTIVATION

Decentralization can provide an alternative approach to current developments in dealing with the capacity bottleneck of coordination resources in the current Air Transport System. Decentralization strives to solve problems based on local coordination. Decentralized networks show a high level of resilience and robustness. Allocating tasks away from centralized resources is expected to have an effect on network stability and performance. These emerging effects are yet to be analyzed.

This Chapter compares centralized and decentralized systems. General examples for decentralized systems are highlighted, as well as examples for decentralized systems in aviation. It motivates further research in the area of decentralization in ATM.

2.2. NETWORK ORGANIZATION

In this Section we introduce different network structures and highlight the advantages and disadvantages of centralized and decentralized approaches in Network design.

2.2.1. DEFINITION

According to the Oxford Dictionary a network is "a group or system of interconnected people or things" [4]. There are different types of networks, such as communication (transfer of information), transportation (transfer people or goods), social (representing relationships), electrical and biological.

A network can be represented by the two main elements: nodes and links. Nodes are elements where information and goods are created, processed, or redirected. Links are elements that connect two nodes and represent the transfer of information or goods. The state of the information or goods can change as it travels through the network.

Depending on the type of network, various tasks are performed at network nodes, such as:

- Communication
- Decision making
- Transfer of goods / information
- Interpretation

Figure 2.1 shows three different types of networks, which are distinguished based on the interconnectedness of their nodes.

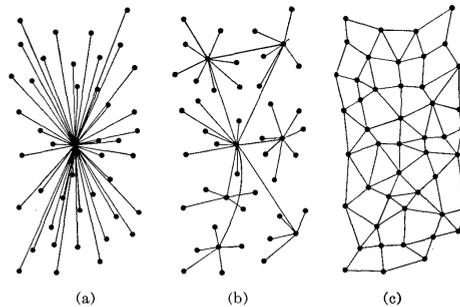


Figure 2.1: (a) Centralized. (b) Decentralized. (c) Distributed networks. [5]

In a centralized network (Figure 2.1(a)) one central node has links to all other nodes, and there are no other links. In a decentralized network (Figure 2.1(b)) there are clusters of nodes that are linked together. A distributed network (Figure 2.1(c)) has no hierarchical structure and nodes are equally connected to each other.

2.2.2. CENTRALIZED OPTIMIZATION / CENTRALIZATION

In a centralized network, information about the state of the entire network and about the consequences of actions is available at a central network node (authority). At the central node decisions are made, and information is collected, processed and distributed to all other nodes in the network. We understand centralization as the process of moving information availability and decision authority towards a central node in the network.

Centralization allows us to optimize the entire network. A global optimum can be found with respect to an objective function that is optimized by finding the optimal values of decision variables, subject to conditions. In a centralized approach, information about the state of the network nodes is available at a single point. The central node can directly communicate with all other nodes. These advantages allow for a direct coordination of the network.

For successful coordination in a centralized network, the central node must have sufficient capacity to process information and make decisions, and the network must provide sufficient bandwidth to distribute the information to and from the central node. These limitations can lead to constraints, not necessarily because of the network capacity, but because of the limited resources at the central coordination node. The lack of knowledge about local conditions can be another disadvantage of centralized coordination.

2.2.3. DECENTRALIZED OPTIMIZATION / DECENTRALIZATION

In a decentralized network the decision authority is distributed across several nodes. These nodes can have links within a local cluster, or act independently. They can also interact with each other. The decentralized nodes collect information and use knowledge about local conditions to make decisions. They have authority over their own behavior and over their local cluster. A network wide coordination emerges from the behavior of the decentralized nodes. We understand decentralization as the process of moving decision processes (and authority) away from central authorities to local entities. Thus in a decentralized network local entities collect information and make decisions based on their locally available knowledge. They can however follow globally defined procedures in the decision making process.

Decentralization can help freeing up capacity from central coordination resources. Decentralization can lead to networks with a higher robustness and resilience compared to centralized networks. Knowledge about local conditions and constraints can lead to more efficient solutions for local problems. Since the problem set is small, local resources can take into account local information and local mechanisms at a higher fidelity, which can result in more accurate predictions. Given the capacity to process information and make decisions is limited, decentralized coordination can respond faster to changes. Since information is primarily sent within a local cluster, less network bandwidth is used.

Local optimization may not result in a global optimum. Without a centralized coordination resource, the global network behavior emerges from local decision making and actions. The resulting emergent behavior of the entire network may be undesired. Local optimization may lead to inefficient use of global resources, and it can be challenging to prove overall network stability.

2.2.4. COMPARISON

In a centralized network all information is available at a single decision node, while in a decentralized network information is distributed across nodes. Centralization can ensure that constraints in the network are met. A decentralized solution can only ensure that local constraints are met, and protocols need to be introduced to ensure that the emerging network behavior meets global constraints. Centralized optimization is performed on the entire network, while decentralization performs a local optimization. In a decentralized system, the state of the system emerges from interactions between interdependent parts of the system. This emergent behavior can lead to unforeseen system states. In an ideal centralized system it is assumed that all system states are known and changes to the state of system are controlled by a centralized node. Thus, in an ideal

centralized system, there would be no unforeseen system states or no emergent behavior.

The capacity of nodes and links is limited. In centralized networks the demand by coordination tasks may exceed available resources. Links might not be able to provide the necessary transfer capacity. Decentralization provides a way to distribute demand across multiple nodes and avoid capacity bottlenecks. Timely available local knowledge may lead to more optimal solutions in a decentralized network. The benefits of centralization may well be outweighed cost for capacity and communication, which affects overall network performance.

2.3. EXAMPLES FOR DECENTRALIZATION

In this Section we highlight examples for successful decentralization from biology, technology and economics, and also present examples of decentralization in aviation.

2.3.1. BIOLOGY

Swarming behavior of social insect colonies are popular examples for successful decentralization in biology. These swarms of animals complete complex tasks such as routing, nest building and foraging without central coordination. Ant colonies are being studied extensively. These colonies complete complex tasks, where the "coordinated behavior of colonies arises from the ways that workers use local information"[6]. Depending on their type, ants allocate the tasks that they perform individually [7]. There is not a hierarchical organization of the colony and no ant coordinates the tasks of other ants. Instead of centralized control, there are different mechanisms at work, that are still subject to investigation. Ants use trail pheromones while foraging to explore territories and communicate efficient paths [8, 9]. Differences in hydrocarbon profiles of ants are used for task allocation [10]. Ants respond to their environment, and react on the behavior of neighboring colonies and the availability of food [7].

2.3.2. ROBOTICS AND CONTROL THEORY

The underlying principles that are studied in biology, have spawned the research field of swarm intelligence in computer science and controls. Algorithms mimic the swarm's behavior to solve optimization tasks. According to Dorigo et al. [11] Ant Colony Optimization (ACO) has been applied to routing, assignment, scheduling and other optimization problems. They also found that ACO has also been adopted by multiple companies. Another example for a decentralized, bio-inspired optimization algorithm is based on the single cell organism *Physarum polycephalum*. Tero et al. [12] developed this algorithm and applied it to solve shortest route problems in the US interstate highway network.

2.3.3. TECHNOLOGY

In computer networks, data typically is available at a single location, from where it is distributed across the network. One example for decentralization in technology are peer-to-peer networks, which are used for file-sharing. Instead of having a central node, every node in these networks can access the data, and make it available to other nodes. Thus the same data is available on several nodes. The resulting network is robust to various

disturbances. Nodes can enter and exit the network, and part of the network can be shut down, but the data remains available [13]. Similar approaches are being implemented in communication networks.

2

2.3.4. BUSINESS

In business and economics decentralization shifts responsibility and decision authority to local management units and away from central headquarters. Alonso et al. [14] compare the performance of a centralized structure, with vertical communication between division managers and the headquarters, to a decentralized structure, with horizontal communication between division managers. Through modeling a multidivisional organization they find that “decentralization can dominate centralization even when coordination is extremely important” and that in symmetric organizations “decentralization always outperforms centralization” [14].

Alonso et al. [14] also give examples of successful firms that implement decentralization: General Motors (GM) is a “multidivisional firm” with “vast authority to the division managers”. GM introduced committees that coordinate the divisions to meet the interests of the entire organization. British Petroleum (BP) split up BPX into “almost 50 semi-autonomous business units” [14] that coordinate within peer group, and incentives to ensure that managers are “contributing to the successes of other business units”. Also PepsiCo has “largely autonomous divisions” [14].

2.3.5. AVIATION

The air transport network is a complex socio-technical system where humans and technology interact with each other, following set international rules and procedures. Main coordination nodes in this network are Air Traffic Control (ATC), Traffic Flow Management (TFM) and the Airline Operation Control Center (AOCC), which act as “centralized authority” [2]. Among other tasks these nodes make decisions regarding flow control and aircraft routing.

One example for decentralization is the Traffic Alert and Collision Avoidance System (TCAS). “TCAS is a family of airborne systems that function independently of ground-based air traffic control (ATC)”. The TCAS system identifies conflicts between aircraft and follows a collision avoidance logic to solve conflicts. If both conflicting aircraft are equipped with TCAS, they exchange information to “ensure the selection of complementary resolution advisories” [15]. The TCAS system explicitly exploits the advantages of decentralization, uses local knowledge, acts independent of external systems and responds quickly in highly-dynamic situations. It “has prevented several catastrophic accidents” [16].

2.4. DISCUSSION

The examples in the Section 2.3 demonstrate that decentralization already is an established concept which is studied and applied in different domains. Several examples are described in biology that show decentralization resulting in robust, resilient and flexible organisms, colonies and swarms. In Business decentralization is studied and implemented to create organizational structures, where responsibilities are delegated, and independent business units collectively work for the success of the company. Decen-

tralization is already being implemented in technology with applications in computer networks and telecommunication that demonstrate the applicability especially in areas where stability and reliability are key. Decentralization also exists in Aviation; TCAS is an explicitly decentralized system that is implemented in commercial aircraft.

Albeit designed as a centralized system, several nodes in the air transportation network evaluate information and make decisions. The coordination authorities in the network plan and manage aircraft operations. They make decisions and command aircraft to take actions accordingly. Ultimately it is the pilot's responsibility to follow these commands and take action. Naturally they are subject to their local environment, evaluate the available information, and use local knowledge in the decision making process. The way they take actions can be affected by factors such as local conditions, workload, conflicting or incomplete information, performance limitations, and many more. Aircraft might deviate from, or delay the commanded actions and show behavior that is not intended by the coordination authority. Such decentralized effects and conditions lead to a high complexity of the air transportation network. They can be modeled as uncertainty in centralized optimization, and make it necessary to increase margins in schedules and routes.

As mentioned in Section 2.1.1, decentralization will increase in ATM with the introduction of future procedures and distributed systems. It is necessary to understand the effect of such systems on the overall network. Specifically this means understanding the emergence of system wide effects that results from local behavior. Methods need to be developed to estimate these effects for the ATM domain. Decentralization can be successful if it is possible to prove that the network is efficient and stable under decentralized conditions. A process and methodology to integrate these systems and procedures needs to be developed. Presumably not all tasks in ATM can be decentralized successfully and with reasonable effort. A set of criteria for decentralized tasks need to be developed.

As shown in Section 2.3, the success and benefits of decentralization has been demonstrated in other domains. Knowledge about the structure, logic and methods of successful decentralized systems is available to certain level of understanding, which potentially can be transferred to the ATM domain. Routing problems and resource allocation are successfully solved by social insect colonies and other swarming animals. Tasks and responsibilities are assigned in accordance with a common, overall goal by decentralized business units. Information are relayed and distributed by decentralized communication networks. Decentralization does not mean that every entity in a network acts according to their own preference, but rather entails a common set of rules, conditions and procedures, from which a desired network behavior emerges.

2.5. RESEARCH APPROACH

In this work, we explore implementing decentralization in the ATM domain. We chose aircraft taxiing at airports as its scope. As summarized by Atkin et al. (2010) taxiing is an area of past and ongoing research. It is of great relevance for the air transportation system, since airport capacity relates to a potential bottleneck in the system and improved taxiing operations can help increase airport capacity and efficiency [17, 18].

First, we need to understand system level constraints and performance requirements.

The constraints of the system define valid system states. Just like a centralized control, a decentralized control may not lead to violations of system level constraints. The performance requirements of the system describe the desired state of the system. We can evaluate the quality of the decentralized control based on system level performance measures.

The system level constraints and performance is affected by interdependencies between actors in the system. In a centralized system where one controller can affect the state of several actors in the system, these interdependencies can be addressed by the centralized controller. For decentralized control, where each controller can only affect his own state, interdependencies can lead to undesired system states.

If interdependencies exist, the decentralized controllers must utilize mechanisms to address these interdependencies. Communication can make information about other parts of the system available to local controllers. Implementing communication ensures that tasks which require such information can be performed by decentralized controllers. Controllers can coordinate actions with other controllers in the system. Coordination mechanisms can enable controllers to act jointly to ensure desired system-level properties.

It is a challenge to establish relations between local interactions and the global system properties and performance that emerges from these interactions. Because of the size and complexity of the ATS, it is difficult to approach modeling the system mathematically. We model and simulate the system as a Multiagent System (MAS). Multiagent systems are distributed control systems. Each component of the system can be modeled as an individual decision unit or agent. To study decentralization, we develop an agent-based model that represents the ATS. We model each agent and its behavior in the system and define the interactions between agents as well as the environment. Using agent-based modeling and analysis by simulation, we can implement and validate decentralized control. This agent-based model is implemented in an agent-based simulation environment to be able to run experiments. In this simulation environment, we run Monte-Carlo simulations, where we randomly perturb system states until we achieve a sufficient level of confidence in the behavior of the decentralized control.

We evaluate the performance and emerging behavior of the decentralized control. In order to judge if decentralized control is valid, we check if the system under decentralized control performed within its constraints. We use system-level performance metrics to assess the quality of the decentralized control. To check if the system behavior is regular and predictable, we analyze behavior and emergence of patterns in the decentralized control.

2.6. CONTRIBUTION TO THE STATE OF THE ART

This work aims to make novel contributions in four primary areas: airport performance, autonomous systems in air transportation, automated taxiing at airports, and intelligent transportation systems.

As we discussed in Chapters 1 and 2, airport performance has been a very active field of research, because of its impact on society, potential economic and environmental benefits. Furthermore, it poses interesting technical and scientific challenges in the area of system optimization. To better predict the performance of airport departures,

Simaiakis and Balakrishnan developed a queueing model which, as they showed, can accurately predict runway throughput and taxi-out time [19]. Roling and Visser developed a support tool that used Mixed Integer Linear Programming to optimize the planning of airport taxiing operations, which is designed to produce plans that are robust to uncertainty and "optimally solve taxi planning scenarios" [20]. This work provides a solution to improve airport performance that is robust with respect to uncertainty of traffic and demand structure in the system. Furthermore, this work aims to provide a solution that can benefit operations during the tactical phase, and not just the planning phase.

Ongoing research and development programs are striving to implement autonomous systems in the Air Transportation System. These systems embrace the paradigm of decentralization, as they shift decision authority away from centralized resources. Operational concepts such as free flight and self-separation break with traditional air traffic control practices and give autonomy to the aircraft. Various concepts for drones all incorporate the idea that some tasks during flight are autonomously handled by the aircraft. The role of the human operator in these concepts ranges from remotely piloting the aircraft system, or just requesting the aircraft to perform a mission autonomously. This work implements an autonomous and decentralized system in the airport infrastructure and highlights issues that can emerge in this systems and how to overcome them. Furthermore, this work suggests a way to demonstrate system viability through Agent-Based Modeling.

To improve aircraft taxiing operations, different concepts to automate control of aircraft taxiing have been researched. Cheng, Sharma, and Foyle analyzed taxi performance and evaluated potential benefits of automating part of airport surface traffic control [21]. Their findings motivated the development of the GO-SAFE automation tool for airport surface traffic, which was prototyped for Dallas Fort-Worth airport [22]. As part of project Modern Taxiing (MoTa), Chua, et al. developed an environment to simulate the interactions between autonomous taxi systems that could be built around technologies like TaxiBot, eTaxi with human air traffic controllers [23]. Within project MoTa Lancelot et al. developed a Multi-Agent System to dynamically optimize routing and scheduling for aircraft taxiing, with the aim to reduce fuel-burn and congestion at airports[24]. Sirigu et al. developed an algorithm to optimize the management of a fleet of autonomous taxi robots, that minimizes the cost and ensures conflict free ground operations [25]. This work contributes to this area and introduces an approach to automate aircraft taxiing. As opposed to other automation approaches, the control of the taxiing operations is decentralized; similarly to the MoTa project. While MoTa implemented the decentralized control with the aircraft, this work will implement decentralized controllers at the infrastructure. This approach avoids having to retrofit a large portion of the aircraft fleet at an airport and instead requires changes only to the local infrastructure.

In the area of Intelligent Transportation Systems, many methods to control and simulate traffic are developed. Bazzan and Klügl provide an overview of Agent-Based methods in traffic and transportation. Relevant to this work, they highlight various work in the area of "Agent-based traffic simulation" and work that used coordination to control and manage traffic [26]. This work applies methods from Intelligent Transportation Systems that have been used for research in road traffic to a different domain, specifically Agent-Based Simulation and traffic control. Furthermore, this work describes and takes

into account domain-specific constraints and requirements for handling and optimizing traffic, such as restricting taxiway use to one-way traffic.

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3

DEVELOPMENT OF ATM PERFORMANCE METRICS FROM AIRCRAFT POSITION DATA

In the previous Chapter, we discussed the motivation to implement decentralization in the Air Transportation System. It is a paradigm of optimization that a solution based on global knowledge will achieve higher performance compared to a solution based on local knowledge. To measure the impact of decentralization on the performance of the air transportation system we define a set of performance metrics for air traffic control, which are based on aircraft position data. In this chapter, we motivate the need to measure airspace performance and introduce our approach to develop such metrics. We present six metrics to measure airspace performance, apply them to example data, and discuss their relevance in the context of different stakeholder interests.

3.1. INTRODUCTION

3.1.1. BACKGROUND

THE airline industry is growing approximately 5% per year globally and the current air traffic infrastructure is unable to accommodate the growing demand [2]. The two bottlenecks for growth are airspace capacity and runway capacity at airports, which are constrained by safety requirements, increased costs to operators, and environmental regulations. To cope with the increasing number of traffic, the Next Generation Air Transportation System (NextGen) in the United States, and Single European Sky ATM Research (SESAR) in Europe were established. Both programs are intended to develop and modernize the current air traffic control system with the goal to increase capacity and reduce the environmental impact of aviation without compromising safety.

Since the construction of new runways and airports is challenging and limited, new air traffic infrastructure and new operational concepts are developed to achieve higher airspace and runway capacity. These new concepts allow aircraft to fly closer to each other both en route and in the terminal area, in order to enhance the performance of the airspace system. This study discusses how aircraft position data can contribute to various ATM performance measurements.

The result of this research can be of interest for air transport carriers, airport operators, government authorities, and air traffic and air navigation service providers (ANSPs). The goals and objectives vary between these stakeholders. Airlines may be interested in evaluating distances and flight times in sectors, as their primary concern is to fly shorter flights to reduce fuel burn. Air carriers are also interested in safety factors, such as adequate separations between aircraft both en-route and on approach. Airport operators have other goals, such as to generate higher revenues by increasing throughput, and by reducing delays. Flight tracks also need to be considered for environmental regulations, such as noise emissions and pollution. Government authorities desire safe and efficient operations with reduced delays and minimum environmental impact. ANSPs are interested in preventing delays and congestion in the airspace, but their primary objective is to meet safety requirements at all times as efficiently as plausible.

Analyzing aircraft position data can provide a detailed overview of current ATM operations, as it contains time based and distance based variables, as well as simple capacity indicators. Aircraft position data can be used to measure time based and distance based separations, as well as average buffer on approach and en-route. All of these measures are important safety factors for airlines, ANSPs, and authorities. Flight track data can also be used for basic capacity measures, such as number of landings or traffic count in a sector under a specified time period, which can benefit airports. Aircraft position data can capture a range of stakeholder goals and interest, and hence it was chosen as the primary data source for this study [3].

3.1.2. MOTIVATION

The goal of this study is to identify the attributes of aircraft positional data that can be related to ATM performance and to define associated metrics that can help assess that performance. Monitoring radar tracks of arriving and departing aircraft in the terminal area can provide insight into key performance areas of safety, environment, capacity, and

cost-efficiency [4]. According to Graham and Young, these key performance indicators are increasingly recognized as a standard way of expressing ATM system performance, and they are aligned with ICAO's eleven top-level key performance areas [5].

Earlier ATM studies considered runway throughput and delays as primary indicators airport performance [6]. These indicators alone, however, are not user oriented performance measures, as parameters such as user service requirements and levels of service are not included. According to Bolczak et al. runway capacity is not an adequate indicator of performance on its own, maximizing efficiency also needs to be considered for performance studies [7].

Current U.S. ATM operations use the Monitor Alert Parameter (MAP) as an indicator or maximum capacity for each airspace sector [8]. The MAP establishes a numerical trigger value, based on the average time an aircraft spends in a sector, to provide notification to controllers that sector/airport efficiency may be degraded during specific time periods. The MAP value of a sector indicates the maximum number of aircraft that can be safely handled by a controller at a given time [9]. This study proposes several performance metrics by taking advantage of modern radar surveillance, aircraft transmitter, and ADS-B radar track data. Aircraft position data can serve as a performance indicator; for instance, it can be used to measure average time spent in a sector, similarly to the MAP explained above. The results of this paper indicate that airspace performance metrics such as aircraft pair based minimum separation, minimum separation in final approach, average buffer over minimum separation standards, landing time interval, average time in sector and average distance in sector, all account for different metric attributes. The impacts of these metrics differ for various stakeholders.

The results of this study illustrate the implications, strengths and weaknesses of the introduced performance metrics, which can benefit decision makers in future ATM system developments.

3.2. METHOD

Modern aircraft surveillance technologies have opened up new opportunities to collect, analyze, and report ATM data with high accuracy. With the growth of these technologies, aircraft position data has also become more accessible.

Nowadays, ground based secondary radars carry out the vast majority of aircraft surveillance. For approach control, short-range radars, such as Airport Surveillance Radars (ASR), can track aircraft. The ASR system has a range of 40 to 60 NM with a 4.8 second update rate (ASR-9) [10]. When the aircraft begins its final approach, a Precision Approach Radar (PAR) can provide aircraft position information with a quicker update rate of one second [11]. Some airports with close parallel runways also use a high update rate Precision Runway Monitor (PRM) radar system that also scans at a rate of once per second to allow a more accurate monitoring of approach corridors [12]. Air Route Surveillance Radar (ARSR) usually monitors en-route traffic, which is a long-range radar with a slower update rate [13]. Multilateration is another technique to accurately locate aircraft by employing a number of ground stations and by using a time difference of arrival method. Ground stations receive replies from transponder-equipped aircraft, including radar and Automatic Dependent Surveillance-Broadcast (ADS-B) avionics, and determine aircraft position based on the time difference of arrival of the replies [14]. ADS-B enables the

transition from ground-based surveillance to satellite-based air traffic control by broadcasting aircraft position, heading, and speed to ground stations, which transmit the information to controllers [15]. The above-mentioned surveillance techniques are summarized in Table 3.1 along with their application areas.

Table 3.1: Aircraft surveillance techniques and their application

	ASR	PAR/PRM	ARSR	Multilateration	ADS-B
Approach	x	x			x
En-route			x	x	x

It is also possible to combine surveillance reports from multiple sensors, including traditional ground based radars, ADS-B and multilateration ground stations into single flight tracks. Fused flight tracks provide improved aircraft position data for controllers. One such joined system is the Airport Surface Detection Equipment, Model-X (ASDE-X) that can be used for tracking arriving or departing flights. ASDE-X is an automated, high-resolution surveillance radar system that provides aircraft position data and aircraft identification in the terminal area with a one second update rate [16]. The position information is a combination of surface radar, aircraft transponder, and ADS-B information. The collected fields include flight track numbers, aircraft types, callsigns, altitude, latitude, and longitude. An example of ASDE-X recorded flight tracks is shown in Figure 3.1 for Newark Liberty International Airport (EWR).

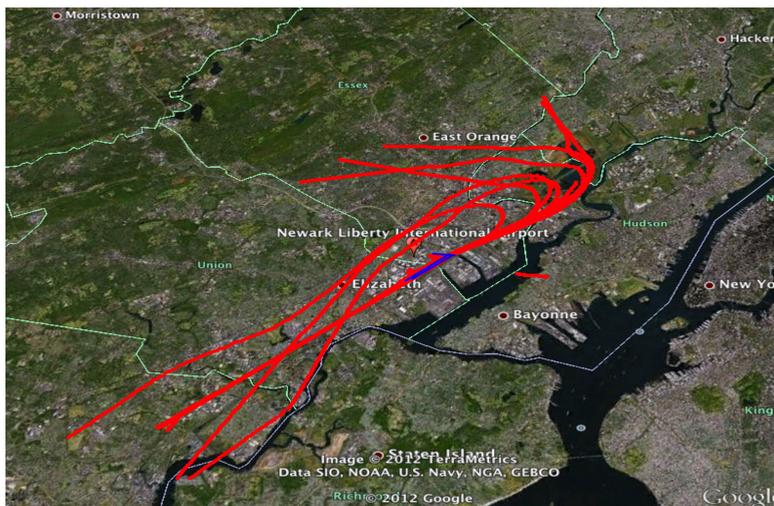


Figure 3.1: ASDE-X flight tracks of arriving aircraft to EWR

Similarly, the Performance Data Analysis and Reporting System (PDARS) calculates a range of measures, including traffic counts, travel times in sector, travel distances, and in-trail separations based on data collected from the Automatic Radar Terminal System

(ARTS) [17]. PDARS collects data for en-route traffic, whereas ASDE-X collects information in the terminal area. These fused data sources provide previously unavailable comprehensive tools and methods for the detailed monitoring of the ATM system.

Since these new data sources are available, is it possible to identify the attributes of aircraft positional data that are related to ATM performance? Many of ICAO's top 11 key performance areas correspond to current day system performance indicators. Aircraft position data provides very little insight into Access and Equity evaluation, but it is strongly related to Capacity for example. Runway throughput can be measured by creating an algorithm that counts the number of landings based on position data in a given time period, for example in 15 minutes, or in an hour. Average separations and minimum separations are also captured in ASDE-X data, which are not only capacity indicators, but also Safety measures. The minimum observed final approach separation can be compared to the minimum allowable separation to look at safety margins in the system. Go-arounds, missed approaches, and holding patterns in the terminal area are also closely related to efficiency, which can be measured for en-route flights as well. Aircraft position data contains information on the time flown in a sector, as well as information on the distance flown in a sector.

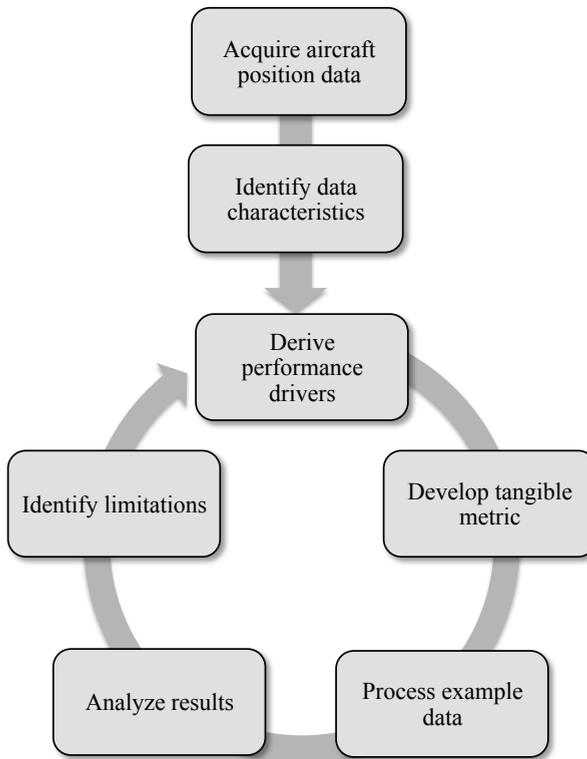


Figure 3.2: Metric development cycle

Figure 3.2 shows the development cycle that was used to generate metrics. After aircraft position data is acquired, the key characteristics of the data are identified. These show what information is captured by the data and can be analyzed further. The characteristics are formulated into performance drivers, and a tangible metric that measures the performance drivers is developed. A sample dataset is processed based on the defined metric. The results are analyzed to verify that the performance drivers are captured as expected and helped to identify limitations of the metric. Taking into account the limitations, new metrics were generated to better capture other characteristics of the data. This iterative process was used to generate six metrics that are introduced in section 3.3.

Although previous studies do mention some of these performance indicators, there is very limited information on how to form a system performance metric based on aircraft position data that is able to capture all, or most key performance areas. These metrics do not address all performance areas, but they do focus on efficiency, safety, and capacity of the system based on aircraft position data characteristics. The advantages and shortcomings of these metrics are also identified that are explained in section 3.3.

3.3. PERFORMANCE METRICS

Aircraft position data permits both time-based and distance-based measurements. In this section six time-based and distance-based performance metrics are introduced, which are summarized in Figure 3.3. As previously mentioned, aircraft position data cannot identify all key performance areas and these six metrics were selected based on how well the data set describes a subset of performance areas. This subset or performance areas focuses primarily on efficiency and safety. The metrics were selected such that they include both terminal area and en-route traffic to account for ATM operational performance. Figure 3.3 shows an overview of the performance metrics and distinguishes metrics in Time Based Metrics and Distance Based Metrics.

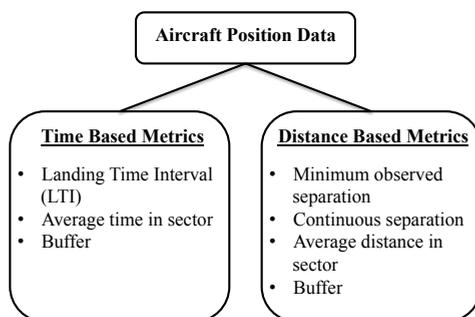


Figure 3.3: Performance metrics based on aircraft position data

Section 3.3.1 through 3.3.4 describes performance metrics on final approach, and sections 3.3.5 and 3.3.6 describe metrics for en-route traffic.

3.3.1. MINIMUM OBSERVED SEPARATION

The minimum observed separation is defined as the minimum distance between two consecutive arriving aircraft on a common final approach path. Although minimum observed separations in this study are distance based, other time-based separation concepts have also been established [18].

At least two aircraft need to be on final approach to measure the minimum observed separation between them. Surveillance equipment records a set position data during final approach. For every aircraft pair the position data from each aircraft is used to compute a set of distances between the aircraft pair during final approach. The minimum observed separation is the smallest value from the set of distances between two aircraft during final approach. Aircraft position data can be recorded by various sources, but a source with higher update rate is preferred for more accurate results. One ideal data source for position data can be ASDE-X (Airport Surface Detection Equipment, Model X) for instance, which is available at a one second update rate.

Minimum observed separation often exceeds the minimum allowable separation due to low arrival demand, mixed departure and arrival sequencing on the same runway, or an additional safety buffer. Although this buffer increases safety, it also increases inter-arrival separation, and leads to reduced runway throughput. The additional safety margin may be in interest of controllers and authorities, but it reduces operational performance for airports.

Figure 3.4 shows an example output for minimum observed separation of Large-Large aircraft pairs on final approach to runway 27 at Boston (BOS). The data was recorded on a bad weather day when the airport was operating under instrument meteorological conditions (IMC). The runway was used only for arrival movements. The metric is plotted in relation to time of day.

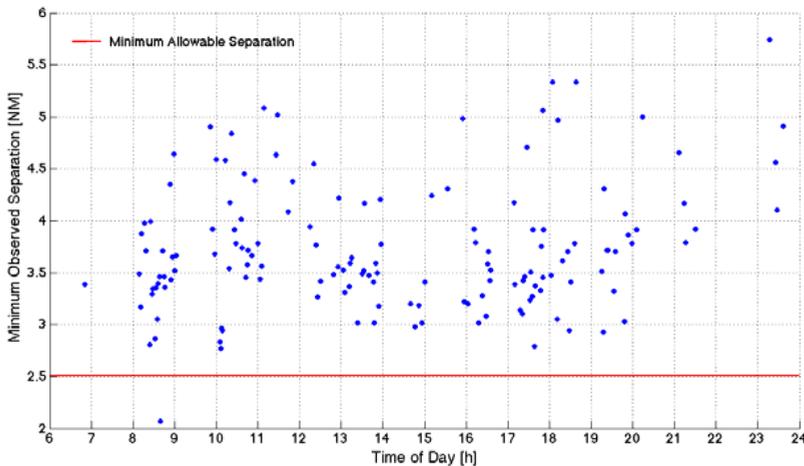


Figure 3.4: Example minimum observed separation

In Figure 3.4 it can be observed that high arrival demand occurs in the morning hours between 08:00 and 09:00, between 10:00 and 11:00, and in the afternoon shortly after noon, as well as from 16:00 to 20:00. Longer separations can be observed during low arrival demand periods. In some cases, as large as 6 NM separations can also be observed, but the cause of this cannot be determined based solely on minimum observed separation data. The 2.5 NM line is the minimum radar separation (MRS), which represents the minimum allowable separation between Large-Large aircraft. The minimum observed separation never exceeds 2.5 NM except for one aircraft pair, which might have been due to a visual landing clearance. There is no indication from the data whether the aircraft was cleared for a visual approach or not.

Changing runway configurations and shared used runways (used for both arrivals and departures) increase the complexity of evaluating minimum separations. Runway configurations can change frequently throughout the day, which may result in longer than normal separations and abnormal measurements for some aircraft pairs. Additionally, when a runway is used for both arrivals and departures, inter-arrival separations are usually longer to allow departures between arrival movements, which is not accounted for in this metric.

Minimum observed separations is a spatial metric, which measures safety. Comparing minimum observed separations to minimum allowable separations can determine the magnitude of additional safety buffer in the system which is explained in section 3.3.3.

3.3.2. CONTINUOUS SEPARATION MEASUREMENT

As opposed to measuring the minimum separation for every aircraft pair (as discussed in 3.3.1) on final approach, the continuous separation metric only captures those aircraft pairs where the minimum separation occurs at a given time. The minimum observed separation between aircraft pairs, as defined in section 3.3.1, results in a discrete output. It provides an indication of safety and efficiency performance, but in some cases it can be more useful to measure continuous separation between aircraft.

This metric can be applied for aircraft on approach, as well as for aircraft en-route. This study, however, focuses on the final approach stage for an initial performance metric development. The metric is calculated based on aircraft position data and the geographical location of the final approach fix for a runway. For the most accurate results, a data source with a high update rate is necessary. A lower update rate can increase uncertainty of aircraft position measurements. An example output of this metric is illustrated in Figure 3.5.

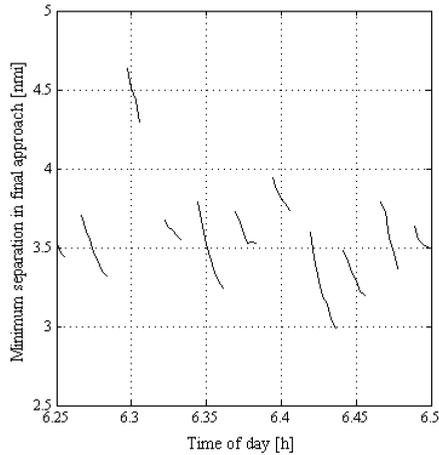


Figure 3.5: Example continuous separation measurement

As arrival demand fluctuates throughout the day, and the calculation of the metric requires at least two aircraft on final approach simultaneously. The metric can only be calculated when there is a continuous arrival demand. Compression effects can also be observed from Figure 3.5, as aircraft get closer to the runway threshold, separation between two successive flights decreases. This is due to the leading aircraft slowing down to its landing speed ahead of the trailing aircraft.

The metric measures separation between aircraft and therefore assesses safety performance. It is relevant for stakeholders who are responsible for ensuring safe operations in the terminal area, as well as in the airspace, such as for ANSPs and for aviation authorities.

3.3.3. AVERAGE BUFFER OVER MINIMUM SEPARATION STANDARDS

Average buffer is the additional spacing added to the minimum allowable separation to increase safety. It is the difference between the minimum observed separation and the minimum allowable separation averaged over the number of aircraft pairs.

Aircraft position data, information about the sector layout, and separation standards in the sector are needed to calculate the metric. Figure 3.6 below shows an example buffer for runway 27 arrivals to BOS from the same data as in Figure 3.4. The buffer is calculated by subtracting the minimum allowable separation from the minimum observed separation. Since this data sample captures Large-Large aircraft pairs, the minimum allowable separation between them on final approach is the MRS, which is 2.5 NM in this case. The average final approach buffer is 1.3 NM, which is the sum of the buffers for each pair divided by the number of aircraft pairs, indicated by the black line.

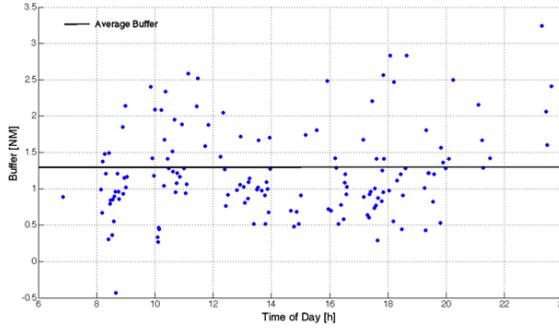


Figure 3.6: Average final approach buffer for Large-Large pairs on runway 27 at BOS

During time periods with low demand the buffer is expected to be large due to the small density of aircraft. With increasing demand the buffer is expected to decrease. In high demand situations air traffic controllers might intentionally give additional buffers to account for unforeseen events.

A small and constant separation allows for a high runway throughput. The metric directly shows margins over minimum separation, and their changes over time. Therefore it is relevant for ANSPs and airports, as it shows safety margins and indicates potential capacity increases.

3.3.4. LANDING TIME INTERVAL (LTI)

As defined by Andrews the Landing Time Interval (LTI) “is the time separation between two successive landings.” “It is the difference between the time one aircraft crosses the runway threshold and the time the previous landing aircraft crossed the same threshold.” [19] In some cases, separation can also be measured at the outer marker (OM).

$$avgLTI(t) = \frac{\sum_{n=1}^{numAC(t)} LTI_n}{numAC(t)} \quad (3.1)$$

Runway capacity is often lost in strong headwind conditions when distance based separation rules are applied. Implementing time based separation rules can recover that lost capacity, and hence, measuring landing time intervals can provide performance measures.

For the calculation of this performance metric, aircraft position data and the location of the runway threshold is necessary. Following the definition of LTI, the metric can be calculated directly from aircraft position information. To detect any changes throughout the day, the average LTI at a time period t can be calculated using equation 3.1, where $numAC(t)$ is the number of aircraft at time t . Figure 3.7 illustrates an example output of the LTI metric of a dataset used by Andrews for Dallas/Ft.Worth International Airport (DFW) over 10 hours on February 10th 2000 [19].

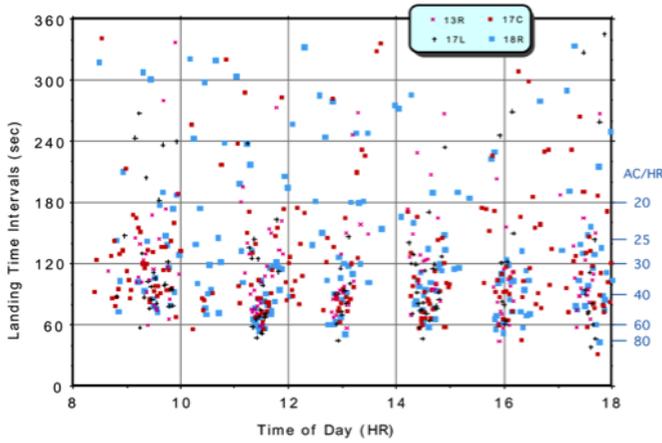


Figure 3.7: Example landing time interval (LTI) by Andrews [19]

The figure shows the LTI for 4 runways throughout the day. Andrews identifies six arrival rushes, during which the LTI reaches a minimum value. This minimum is related to separation standards for aircraft on final approach.

The ANSP's and airport's goal is to increase airport capacity, and to maximize runway and airport utilization. The LTI metric provides an accurate assessment of the performance on the runway. A small and steady LTI is an indicator of high utilization of the runway, which may signal the need for higher capacity.

3.3.5. AVERAGE TIME IN SECTOR

The average time in sector is defined as the time interval an aircraft spends in a sector from entering a sector by crossing the sector boundary to leaving a sector by crossing another sector boundary.

The previously mentioned performance metrics can be used for aircraft on final approach, but radar data provides information about en-route traffic as well. This data can be used to evaluate how much time an aircraft spends in a sector, similarly to the MAP, which is a previously proven performance indicator.

In close proximity of airports, the runway threshold can also be used as a sector boundary for departing or arriving aircraft. To calculate the average time spent in a sector, accurate aircraft position data and the location of the sector boundaries are required. Equation 3.2 introduces the formula to calculate the average time spent in a sector, T_{sector} , in a given time period t . $numAC(t)$ is the number of aircraft inside the sector boundary during the time period t . $t_{n,in}$ and $t_{n,out}$ are the points in time when aircraft n enters and exits the sector.

$$avg T_{sector}(t) = \frac{\sum_{n=1}^{numAC(t)} t_{n,out} - t_{n,in}}{numAC(t)} \quad (3.2)$$

Figure 3.8 gives an example of the output of the metric over a 3-hour period at Ams-

terdam Schiphol Airport (AMS).

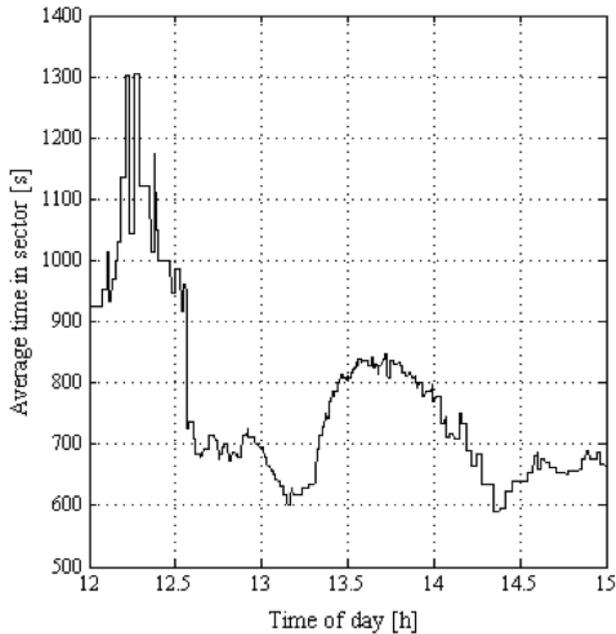


Figure 3.8: Example for average time in sector

The figure shows that the average time in sector varies from about 1300 seconds to about 600 seconds. The value depends on various aspects of the current state of a sector, such as weather, demand, traffic patterns, etc. The high values at 12:15 in Figure 3.8 could be the result of an aircraft flying two patterns on runway 22, but it could also be due to a slow flying aircraft. High values can indicate holding patterns, arrival queues due to high demand, or disturbances in traffic, such as runway changes or weather impacts. The low values of the average time in a sector can be seen as reference to how fast traffic can travel through the sector.

The minimum values indicate the maximum achievable performance of a sector. The average time in sector is a fair efficiency performance indicator, but it is limited by airspeed. As aircraft fly at different speeds, very little can be concluded from average time in sector alone.

3.3.6. AVERAGE DISTANCE FLOWN IN SECTOR

Similarly to time spent in a sector, the distance of a flight within a sector can also be calculated as an efficiency performance metric.

The average distance traveled in a sector is defined as the distance the aircraft travels from entering the sector by crossing a sector boundary to leaving the sector via another

sector boundary. In close proximity to airports, the runway threshold can be used as sector boundary. Position data and data about the sector boundaries is necessary for the calculation. Equation 3.3 describes how the average distance travelled in sector $D_{sector}(t)$ is calculated. $p(s)$ is the position in x and y direction as a function of the running variable s along the flight path. $numAC(t)$ is the number of aircraft in the sector during a time period t .

$$D_{sector}(t) = \frac{\sum_{n=1}^{numAC(t)} \int_s p_n(s) ds}{numAC(t)} \quad (3.3)$$

Figure 3.9 gives an example of the output of the metric over a 3-hour period at Amsterdam Schiphol Airport (AMS).

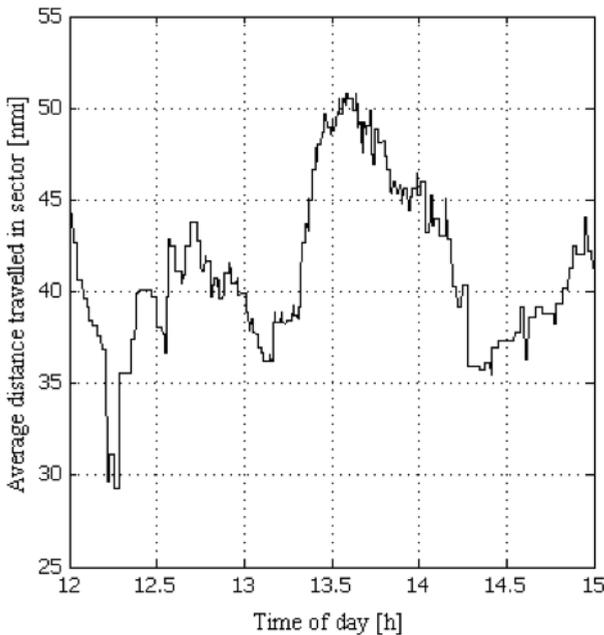


Figure 3.9: Example for average distance flown in sector

The figure shows that the average distance travelled in sector varies from about 50 *nmi* (nautical miles) to about 30 *nmi*. The low values at 12:15 could indicate that an aircraft exited the sector very close to where it entered the sector, as opposed to the long distances flown at 13:30.

The distance travelled cannot go to zero as this value depends on sector inbound and outbound fixes. The minimum values for the various fixes, however, can be used as reference for the shortest achievable flight paths. Flight paths are influenced by external constraints such as weather impact or noise regulations. Therefore the minimum values

measured by this metric are not always achievable. Since operational constraints can also apply to flight paths, the minimum values are not necessarily equal to the great circle distance between sector fixes or waypoints.

Although this metric is also a fair efficiency performance indicator, very little can be concluded from average distances in sector alone. However, if average time in sector and average distance in sector were analyzed together, it would provide a much more informative overview of the sector performance. For instance, at 12:15, the average sector time was very high, but the average sector distance was very low. The combination of the two metrics clearly indicates that this was due to a slow flying aircraft (probably general aviation) that was determined to be flying a pattern around the airport. An even more desirable metric would be to analyze average distances in sector for aircraft traveling between common sector entry and exit points.

As direct routes are preferable for fuel burn and flight time, this metric is relevant primarily for airlines and ANSPs, both of whom wish to optimize flight paths to reduce fuel burn and optimize airspace efficiency.

3.4. APPRAISAL OF POSITIONAL-BASED PERFORMANCE METRICS

The goal of this study was to identify and develop airspace performance metrics based on position data. The motivation was to develop metrics that would allow investigating the impact of the state of a sector and disturbances in a sector on sector performance. Metrics, which are related to key performance areas, have been introduced and discussed in section 3.3, and their short summary is shown in Table 3.2.

Table 3.2: Summary of ATM performance measures

	Minimum observed separation (3.3.1)	Continuous separation measurement (3.3.2)	Average buffer over minimum separation standards (3.3.3)	Landing Time Interval (3.3.4)	Avg. time in sector (3.3.5)	Avg. distance flown in sector (3.3.6)
Safety performance	x	x	x			
Efficiency performance				x	x	x
Capacity performance			x	x		

Minimum observed separation, continuous separation measurement and average buffer over minimum separation standards can be used to measure safety performance. Landing time interval, average time in sector and average distance flown in sector can be indicators of efficiency performance. Average buffer over minimum separation standards and landing time interval can be measures of capacity performance.

3.5. CONCLUSIONS AND FUTURE WORK

In this study aircraft position data was used to develop ATM performance metrics. It was found that developing metrics that contribute to the measurement of different aspects of ATC performance is plausible based on aircraft position data. As an initial step in this study, six metrics were established. Some of the metrics (minimum separations, average buffer time) are only applicable on final approach, whereas sector times and distances can be applied for en-route traffic as well. The metrics cannot be compared directly to each other, as they measure capacity, efficiency, or safety performance. None of the metrics are able to assess all key performance areas individually, which means that a combination of these metrics may be the most informational metric for ATM performance measures.

As the next step of this project, further research will be needed to validate these six proposed performance metrics and to form new ones. Field experts or literature reference could evaluate the results. Alternatively, the results could be tested across multiple data sets or could be compared to results of existing performance studies.

The current performance metrics focus on efficiency and safety indicators, but they existing can also be extended to capacity measures. Aircraft position data can be used to for new metrics, such as traffic flow rate, traffic count in sector, and landings per minute, which are all basic throughput measures.

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4

AN ANALYTICAL SOLUTION FOR AIRCRAFT PUSH-BACK SCHEDULING UNDER TAXI-TIME UNCERTAINTY

Previously we motivated that airport capacity is a bottleneck in the air transportation system, and established metrics to measure system performance. One challenge of centralized optimization methods for aircraft taxiing is dealing with uncertainty during operations. In this chapter, we present an analytical approach using cumulative density functions to solve part of the scheduling problem for taxiing operations. We highlight the trade-off between aircraft delay and runway utilization and show the impact of uncertainty on system performance. First, we introduce the problem of scheduling aircraft taxiing operations, then develop our analytical model, present and discuss example results using our model, and close with concluding remarks and ideas for future work.

4.1. INTRODUCTION

THE congestion that occurs at airport runways is caused by a capacity gap, i.e. when the available capacity does not meet arrival and departure demand. This capacity gap will continue to occur if planned infrastructure improvements are not implemented, and the traffic at core airports grows as forecast between 2015 and 2035 [1–3].

Flight delays typically occur during peak hours, when demand exceeds capacity and aircraft are waiting [4, 5]. It has been shown that 37% of flights in 2014 were delayed on departure [6]. These departure delays result in increased costs to airlines, inconvenience to passengers, higher fuel burn and environmental impact, and can disrupt Air Traffic Management (ATM) operations [7, 8].

Global initiatives such as Single European Sky ATM Research (SESAR) and the Next Generation Air Transportation System (NextGen) are therefore working on measures to increase capacity and reduce delays in the Air Transportation System (ATS) [9, 10]. In this context, previous work has focused on two primary areas of research: a) Methods and algorithms to sequence aircraft and thereby better utilize the available runway resources, and b) optimizing the push-back schedule to reduce departure delays and taxiway congestion.

With regard to runway sequencing and scheduling, Sölveling and Clarke implemented a stochastic branch and bound algorithm and were able to reduce the time to process a sequence of aircraft by 5-7% compared to a deterministic model [11]. Sölveling et al. also optimized the runway-scheduling problem for reduced environmental cost at 30 major US airports and achieved environmental cost savings in the range of \$9.4 to \$19.1 million compared to first-come, first-served policies [12]. Atkin et al. demonstrated a tool that optimized take-off and push-back schedules at London Heathrow Airport, and were able to reduce the waiting time of aircraft between 27% and 50% [13]. Jung et al. developed a tool for Dallas/Fort Worth International Airport that provided sequence and timing decision support, which helps reduce departure delay and the number of aircraft stops [14]. Simaiakis et al. demonstrated a method that metered aircraft push-backs to avoid congestion, which showed a significant reduction in fuel burn during field tests at Boston Logan Airport [15].

The work presented here is focused on push-back time scheduling, given a desired take-off schedule. Specifically, an analytic approach to achieving a desired runway utilization under uncertainty is presented, and the trade-off between utilization and delay via scenarios with varying levels of uncertainty and desired utilization is highlighted.

4.2. MODELING

4.2.1. PROBLEM STATEMENT

In this work an analytic solution for the push-back scheduling problem is developed.

It is assumed that the desired take-off sequence is known, there are n consecutive departures scheduled for a single runway, there is a minimum separation between consecutive departures, aircraft must taxi from their gates to the runway, and taxi times are not constant but depend on factors such as weather, traffic density, aircraft type and airline.

Further it is assumed that the associated uncertainty in the taxi times can be repre-

sented by a Probability Density Function (PDF), and that push-backs are scheduled to meet the desired take-off schedule while achieving a desired runway utilization. Obviously, because of the uncertainty in taxi times, 100% runway utilization cannot be achieved, and some aircraft will arrive at the runway before it is available for the next departure. The aircraft will therefore experience a delay. This trade-off between runway utilization and departure delay cannot be avoided.

The presented analytic approach to achieving a desired runway utilization while minimizing departure delays can be applied to different scenarios.

The specific scenario considered in this work is a sequence of n consecutive departures scheduled from a single runway. This can occur at an airport that has a night curfew after which a number of aircraft have to depart in the morning in quick succession, or at an airport with a designated departure runway.

An actual example for this situation is John Wayne Airport (SNA), where between 22:00 and 07:00 a curfew prohibits commercial departures [16]. Figure 4.1 shows that 11 aircraft departed in a 15-minute window when the curfew was lifted at 07:00 .

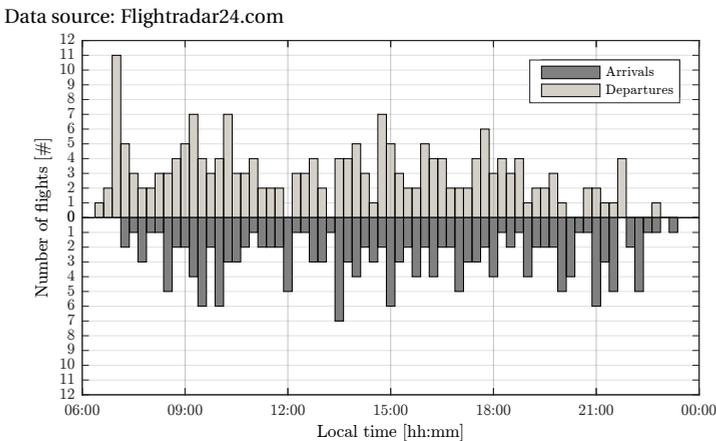


Figure 4.1: Number of arrivals and departures at SNA on July 17, 2015

Another application would be in 2-stage approaches for departure scheduling as presented by Atkin et al. [13]. The method presented in this paper can be used to create the push-back schedule using an analytic solution instead of a computational optimization used in other work [17, 18].

The analytic approach presented in this work can also complement methods that require a suggested push-back rate [15, 19]. Typically, historical data is used to suggest the number of aircraft that should be released from the gate to achieve a desired take-off rate. By using Probability Density Functions the method presented here can take the factors known to influence taxi times into account to improve the prediction of the desired push-back rate.

4.2.2. DESCRIPTION OF RESOURCES

In this work two main resources are modeled: the aircraft, and the runway.

The probability that each resource is ready or available for a take-off can be expressed by a Probability Density Function (PDF). Generally, a $PDF(x)$ describes the likelihood of a random variable or the likelihood of an event occurrence. For the runway the PDF gives the likelihood that the runway is available for take-off. Similarly for the aircraft the PDF describes the likelihood of the aircraft arriving at the runway for take-off.

The integral of the PDF is the Cumulative Distribution Function (CDF). Using equation 4.1 the CDF gives the probability that an event occurs by a given time t .

$$CDF(t) = \int_0^t PDF(x) dx \tag{4.1}$$

In this work the CDF of the aircraft (CDF_{AC}) is defined as the probability that an aircraft is ready for departure at the runway, at time t . Similarly the CDF of the runway (CDF_{RWY}) is defined as the probability that the runway is available for departure at time t .

Various factors like traffic and weather have an impact on the time it takes an aircraft to taxi from the gate to the runway. Taxi-time is considered as the time from the end of push-back until the time the aircraft both arrives at the runway and is ready for departure. The taxi-time is modeled as the aircraft PDF (PDF_{AC}), and it is assumed that the PDF_{AC} covers all uncertainty that occurs during taxiing.

To simplify the model a uniform distribution for all aircraft is assumed. For a more realistic model a lognormal or log-logistic distribution specific to the gate, runway, aircraft type and airline can be implemented.

The PDF_{AC} and the CDF_{AC} can be determined using aircraft position data. Figure 4.2 shows the PDF_{AC} and CDF_{AC} of taxi times based on data for London Heathrow Airport (LHR), as well as Lognormal and Uniform fits of the data, to highlight how accurately the fits can represent the uncertainty in the data.

Data source: Flightradar24.com

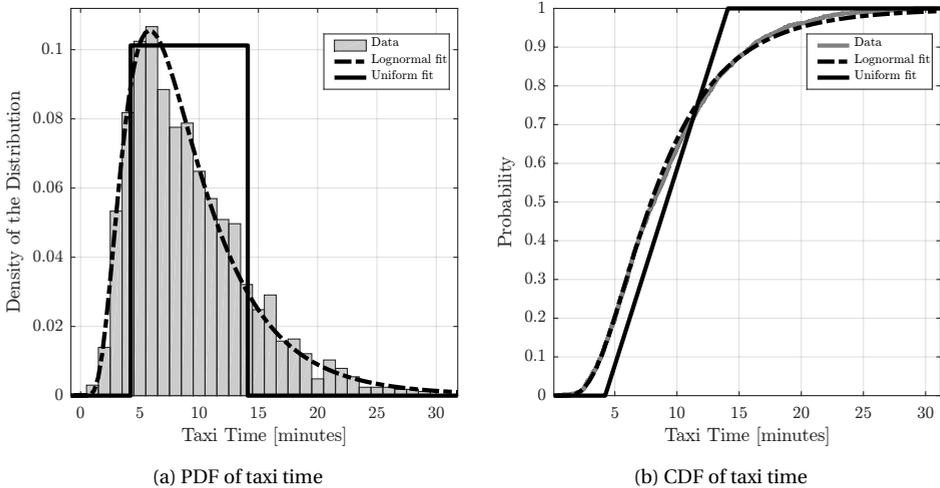


Figure 4.2: Distribution of taxi times from terminal 5 to runway 27R at LHR

In this work it is assumed that the runway availability is constrained by a curfew that is lifted at time t_0 , after which the runway is immediately available for departures.

Hence, CDF_{RWY} is modeled as a step function at time t_0 , where the value changes from zero (runway inactive) to one (runway active). The corresponding PDF_{RWY} is an infinitely short Dirac delta function.

The runway availability for departures is also constrained by the minimum separation between consecutive departures. In Section 4.2.3 the interdependency of runway and aircraft resources is modeled.

4.2.3. MODELING INTERDEPENDENCY OF A RUNWAY AND AIRCRAFT

In this Section the modeling of the interdependency of the aircraft and runway is described. It is assumed that an aircraft takes-off immediately when the runway is available and the aircraft is ready for departure. Equation 4.2 defines the probability of take-off of aircraft number i in a sequence at time t ($CDF_{TO,i}$) as a combination of the $CDF_{AC,i}$ and $CDF_{RWY,i}$. The timeshift τ is introduced as a means to shift the aircraft availability relative to the runway availability, where larger τ corresponds to an earlier push-back time.

$$CDF_{TO,i}(t) = CDF_{AC,i}(t + \tau) \cdot CDF_{RWY,i}(t) \quad (4.2)$$

After the minimum separation time (t_{sep}) between consecutive departures, the runway is available for the next departure. Equation 4.3 defines the probability that the runway is available for a departure of aircraft number $i + 1$ in a sequence.

$$CDF_{runway,i+1}(t) = CDF_{TO,i}(t - t_{sep}) \quad (4.3)$$

Figure 4.3 visualizes the modeling of the interdependency between runway and aircraft, with a step function for $CDF_{RWY,i}$ at time t_0 , and a uniform PDF_{AC} .

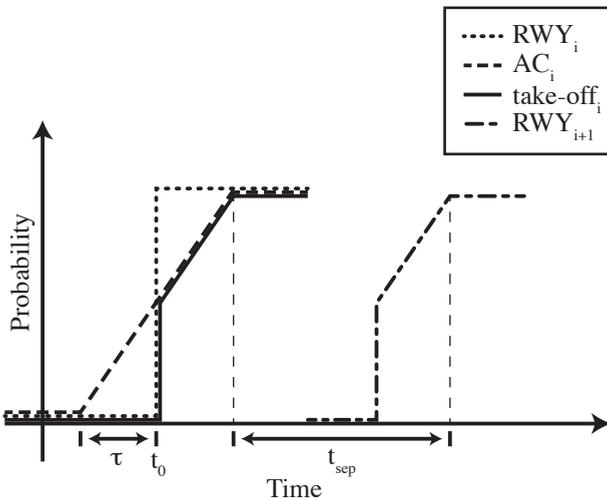


Figure 4.3: Interdependency of runway and aircraft resource

Figure 4.3 shows that aircraft i (AC_i) is shifted by τ with respect to the time that runway i (RWY_i) becomes available. Aircraft i takes off (take-off $_i$), and after the minimum separation time t_{sep} the runway is available for departure of aircraft $i + 1$ (RWY_{i+1}).

4.2.4. DEFINITION OF DEPARTURE DELAY AND RUNWAY UTILIZATION

The runway capacity is a bottleneck for the throughput of the airport system. The runway utilization should be high to maximize the use of this constrained resources.

In Section 4.2.3, τ was introduced as the time that the CDF of the aircraft is shifted by relative to the CDF of the runway.

Depending on τ , either the aircraft or the runway becomes available first.

In this work a 95% runway utilization is defined as a 95% probability that an event of ‘aircraft ready for take-off’ occurs prior to an event ‘runway becomes available’.

In the following section this definition is described mathematically.

4

MATHEMATICAL DESCRIPTION OF RUNWAY UTILIZATION

Equation 4.4 defines the probability of event A happening before event B, where $PDF(t)_B$ is the likelihood of event B happening at time t and $CDF(t)_A$ is the probability that event A occurs by a given time t [20].

$$P(A < B) = \int_0^{\infty} PDF(t)_B \cdot CDF(t)_A dt = 1 - P(B < A) \quad (4.4)$$

In the case of ‘aircraft ready for take-off’ (AC) and ‘runway becomes available’ (RWY), the utilization U is defined as:

$$U = p(AC < RWY) = \int_0^{\infty} PDF(t)_{RWY} \cdot CDF(t + \tau)_{AC} dt \quad (4.5)$$

Since the first runway availability is a discrete event (opening of the runway at a specific time), the runway PDF contains a Dirac delta function. Using the Dirac delta function can be avoided with the alternative formulation:

$$U = 1 - p(RWY < AC) = 1 - \int_0^{\infty} PDF(t + \tau)_{AC} \cdot CDF(t)_{RWY} dt \quad (4.6)$$

Consequently, equation 4.6 can be solved for τ with a desired utilization $U = U_d$.

MATHEMATICAL DESCRIPTION OF TAKE-OFF DELAY

In this paper delay is considered to be a loss of the available aircraft resource, while a low runway utilization (introduced in Section 4.2.4) is a loss of available runway resource.

The focus of this work is on the effect that runway utilization has on delay, and take-off delay is defined as the time that the aircraft is waiting at the runway, from when the aircraft arrives at the runway until the departure.

The expected delay is calculated using the expected take-off time and expected aircraft availability, with the general equation for the expected value:

$$E[f(X)] = \int_{-\infty}^{\infty} x \cdot f(x) dx \quad (4.7)$$

The expected delay of aircraft number i in a sequence is defined as:

$$E_{delay,i} = \int_{-\infty}^{\infty} t \cdot PDF_{take-off,i}(t) dt - \int_{-\infty}^{\infty} t \cdot PDF_{AC,i}(t) dt \quad (4.8)$$

4.3. EXPERIMENT SETUP

In this work the aircraft availability is assumed to be a uniform distribution, with $a - b = \Delta$, to simplify the mathematical representation. The departure sequence is predefined with a given sequence of aircraft, where all aircraft in the sequence are represented by the same PDF_{AC} . No interactions with other traffic flows that could impact taxi times are explicitly modeled. Instead these are assumed to be incorporated already by the PDF_{AC} . The runway availability for the first aircraft is assumed to be a discrete event, hence the CDF_{RWY} becomes a step function. The uncertainty in runway availability for any subsequent aircraft i in a sequence results solely from the uncertainty in the departure times of the preceding aircraft. It is also assumed that the runway is only used for departures.

Two variables are changed in the experiments. The desired runway utilization U_d is varied in the range from 90% to 98% in order to highlight the impact of runway utilization on expected aircraft delay. This range is assumed to represent congested airports with a high desired runway utilization. The difference Δ between the parameters of the uniform PDF_{AC} is varied in the range from 0 to 1 to show the effect of different levels of uncertainty.

4.4. RESULTS

In this section the equations from section 4.2.4 are used to generate example results for different desired runway utilizations and varying levels of uncertainty. To calculate the timeshift τ_i for a desired utilization, Equation 4.6 must be solved. MATLAB was used to calculate τ_i values for a sequence of up to 100 aircraft, with varying desired runway utilization levels (U_d) and differing levels of uncertainty Δ .

Figure 4.4 shows the timeshift τ_i for each aircraft i in a sequence of 100 aircraft for varying levels of U_d . A general trend can be observed from Figure 4.4 in that higher val-

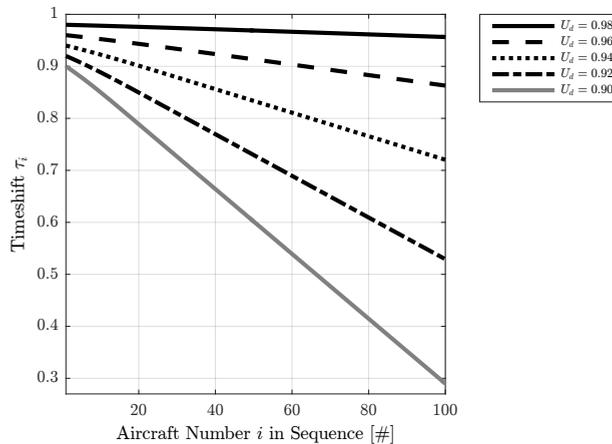


Figure 4.4: Timeshift τ_i between consecutive departures

ues of τ are necessary to achieve higher desired utilizations U_d . This result is expected, since high values of τ result in an early push-back and arrival time at the runway, which leads to a high probability that and aircraft are available before the runway is available, corresponding to a high utilization, as defined in Equation 4.6.

The values for τ in Figure 4.4 show a highly linear relationship, after an initial number of aircraft in the sequence have been accommodated. Consequently it is interesting to examine the difference in τ between consecutive departures, which is shown in Figure 4.5. It can be seen from Figure 4.5, that the difference in τ_i between consecu-

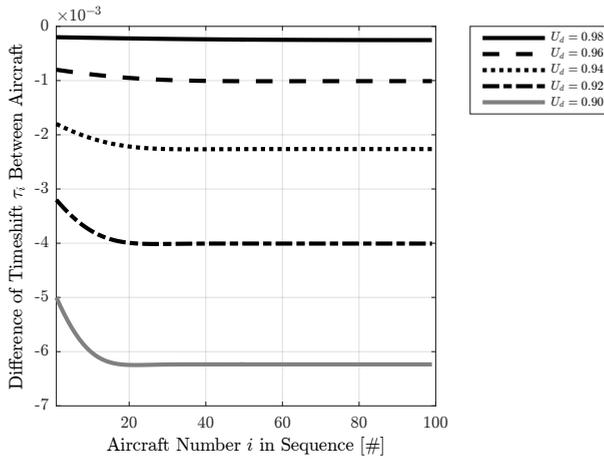


Figure 4.5: Difference of timeshift τ_i between consecutive departures

tive departures quickly assumes a constant value. Furthermore, it can be observed that this value is higher for higher values of U_d . Figure 4.5 also shows that for higher U_d , a constant difference between τ_i occurs ‘later’ in the sequence.

In Figure 4.6 the difference of difference in τ_i (second derivative of τ_i with respect to t), between consecutive departures is plotted, in order to check convergence for the difference in τ . Figure 4.6 shows that the difference of difference of τ_i converges to zero for all U_d values considered. Based on this result it can be confirmed that the difference in τ_i for consecutive departures converges to a constant value. Again it can be noticed that the values converge ‘later’ in the sequence for higher U_d values, although to a minor degree and most pronounced between AC number 20 and 40.

One of the main observations from the result is the trade-off between delay and utilization. Figure 4.7 shows the accumulated expected delay of a sequence of 40 aircraft over the desired utilization, for varying levels of Δ .

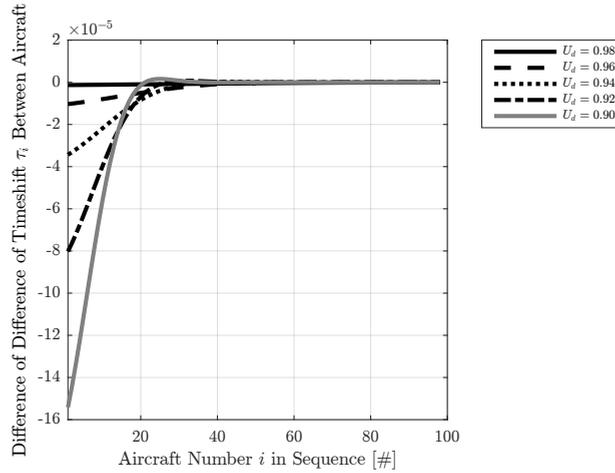


Figure 4.6: Second derivative of timeshift τ_i between consecutive departures

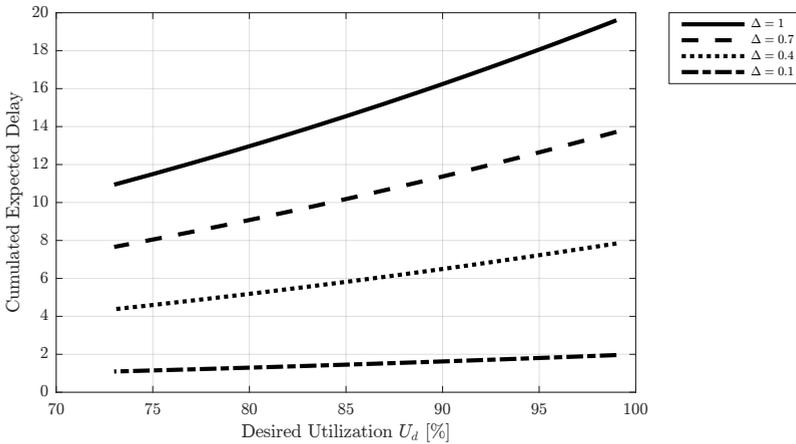


Figure 4.7: Accumulated expected delay of a sequence of 40 aircraft

It can be seen from Figure 4.7 that higher runway utilization results in higher expected delay. This result corresponds to the observations noted from Figure 4.4, that higher desired utilizations require high τ values, and that the aircraft arrives early at the runway. Furthermore, it can be observed that high levels of Δ lead to higher expected delays. The level of uncertainty corresponds to Δ . Under high uncertainty, some aircraft will arrive earlier at the runway in order to ensure a desired level of utilization, leading to longer delays. It should be highlighted that while a solution for $U_d = 100$ could be found for the uniform distribution, it is not plotted here since for a realistic PDF_{AC} the resulting expected delay would approach infinity.

4.5. DISCUSSION

In other work [11, 12], numerical optimization methods were used to create push-back schedules. The presented work demonstrated that an analytical solution for this problem is feasible. For a given departure schedule the method presented in this paper can be implemented to generate an optimal push-back schedule to achieve a desired runway utilization.

This method could be used to complement the push-back metering method that was introduced by Simaiakis et al. [15], which used historical data for congested conditions to determine a maximum number of taxiing aircraft to avoid congestion. This requires definition and identification of congested conditions at an airport. The method presented here could be used to suggest an ideal push-back rate that puts constant pressure on the departure runway for a desired runway utilization. Factors that are known to impact aircraft taxiing times, such as weather and runway configuration, could be taken into account in the PDF_{AC} by measuring taxi times under varying conditions using position data from aircraft taxiing.

The results in section 4.4 demonstrate the viability of the analytical solution. The applicability of the values that are presented is somewhat limited, by the assumption of a uniform PDF for aircraft taxiing times, that would allow planning for a 100% runway utilization, which in reality is not possible.

As shown in Figure 4.2b a log-normal distribution would be more representative to also capture the occurrence of very large aircraft taxi times.

4.6. CONCLUSION

4.6.1. CONCLUSIONS

This work introduces an analytical solution to the generation of a push-back schedule for a known sequence of aircraft departures, that takes into account representative uncertainty in aircraft taxiing times.

The method presented in this work could also be used to suggest a push-back rate for specific airports that results in a constant pressure on the runway.

Instead of using fixed departure slots and expected values to optimize the push-back schedule, the method presented uses Cumulative Distribution Functions (CDFs) to model the interaction between aircraft and runway availability. The CDFs of consecutive departures in a sequence are simply multiplied to model conditional probabilities between aircraft. Using this method, one can take into account the effects of uncertainty in taxiing times that propagate through the departure sequence.

Based on the results one can distil four general principles.

- There is a trade-off between runway utilization and expected delays. Since aircraft taxiing times are uncertain, a desired runway utilization can only be achieved if the aircraft is scheduled to arrive early at the runway. Hence, a higher desired utilization results in larger expected delays.
- With lower uncertainty in aircraft taxiing times a desired runway utilization can be achieved with lower expected delays.

- For realistic PDFs where aircraft taxiing times can be infinite, a 100% runway utilization cannot be achieved.
- For a desired runway utilization the difference in aircraft push-back times between consecutive departures with identical uncertainty converge to a constant value.

4.6.2. FUTURE WORK

In future work a more realistic probability density function for the aircraft taxiing times (PDF_{AC}) should be implemented. As discussed in section 4.5 the PDF_{AC} can be derived from aircraft positional data, in order to represent varying conditions such as weather, runway configurations, traffic count, etc. Using PDF_{AC} that are representative for different traffic scenarios and conditions would allow definition of actual push-back schedules for a given airport.

To further strengthen this methodology, an analytical convergence proof would allow the direct calculation of the ideal difference in push-back times for consecutive departures, while also exploring the limits of the applicability of the method.

This work could also be tested with an airport case study. Airports have a need to utilize their available resources as efficiently as possible and this work can help achieve a high runway utilization with limited aircraft delays. This need has also been identified as a major challenge by SESAR and NextGen.

The method presented could also be applied in other domains e.g. manufacturing process optimization, where resources such as machine tools in a manufacturing plant are strongly interdependent, and high utilization is essential to maximize production rates.

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5

DECENTRALIZED CONTROL FOR AIRCRAFT TAXIING: THE IMPACT OF SCOPE OF INFORMATION

In previous chapters, we demonstrated that uncertainty during aircraft taxiing operations limits the achievable system performance of centralized optimization approaches. In other domains, decentralized approaches have shown to be adaptive, resilient and perform well under uncertainty. While these are desirable properties for air traffic control systems, it is unclear if the emergent behavior of decentralized control will result in safe and efficient operations, and how much information about the state of the system must be available to the decentralized controller. In this chapter, we demonstrate a decentralized control for aircraft taxiing operation that results in stable operations. The results show that local information is sufficient to avoid conflicts between traffic and that global knowledge is not necessary to achieve good system performance. We first motivate decentralized control for aircraft taxiing, then describe the experiment setup, present the results of the experiments, and close the chapter with conclusions and suggestions for future work.

5.1. INTRODUCTION

AIR Transportation System (ATS) demand is expected to continue to grow over the coming decades. Thus, a system that is already experiencing capacity bottlenecks will see greater numbers and severity of bottlenecks if nothing is done to mitigate their root cause, particularly at airports [1, 2]. These bottlenecks not only limit the demand that can be accommodated but also result in delays and inefficient operations that cause added cost to airlines, negative impact on the environment and inconvenience to passengers [3, 4]. Global initiatives such as the Single European Sky ATM Research (SESAR) and the Next Generation Air Transportation System (NextGen) strive to ready the ATS for current and future challenges. Their primary goals are to reduce the environmental impact of aviation, increase the capacity of the system, and reduce operating cost, without compromising safety, by embracing new technologies and operations for the ATS [5, 6].

While en-route infrastructure can be changed and updated to accommodate higher demand, changes to the physical infrastructure at airports to increase capacity are costly, time-consuming and constrained by public interests [7]. Thus, prior work to improve airport operations has focused on changing the operational procedures at airports, specifically, optimizing taxiing for fewer delays, shorter routes, and overall higher efficiency to avoid unnecessary fuel burn, delays, cost, and time-on-ground, which is summarized in [8]. Once a flight is airborne, recovering delays that occurred on the ground require flying at higher and less fuel-optimal airspeeds. Furthermore, the amount of delay that can be recovered during flight is limited. Improvements in ground operations can reduce both delays and fuel burn. Various external and internal local factors, such as conflicting traffic and runway configuration changes, disturb the taxiing process. On a system-wide level, these local disturbances are observed as uncertainty in total taxiing times. Margins are introduced during planning to account for this uncertainty, which leads to underutilization of critical resources, for instance: runways and aircraft. In the presented work we focus on improving the performance of aircraft taxiing operations at an airport, specifically addressing Air Traffic Control challenges of aircraft routing and traffic de-conflicting during the tactical phase of taxiing operations.

Air Traffic Control (ATC) is a centralized coordination resource responsible for guiding flights safely and efficiently in the ATS. Airspace capacity is constrained by the workload of the human air traffic controller [9]. Decision-making processes of air traffic controllers have been studied, and methods are being developed and deployed to reduce the mental workload of air traffic controllers [10–14]. The two main paradigms that these methods follow are automation and re-distribution of the decision-making tasks to mitigate the controller workload.

A limitation of these paradigms is that they rely on a centralized coordination resource which has a finite capacity to receive, process and disseminate information. Centralized automated systems have a maximum bandwidth to receive and send information, and limited computational resources to perform calculations in order to provide decision support. This limits the fidelity of solutions for real-time applications and thus, the possible performance gains.

In this work, we explore decentralized control as an alternative approach to handling aircraft taxiing at an airport. In a decentralized system, the overall system behavior emerges from local conditions and interactions. We test if the decentralized control can

handle traffic without conflicts. Compared to local optimization, a centralized solution can find a global optimum and might achieve higher performance. Therefore, we investigate the performance penalty due to the decentralized decision making. With respect to overall airport taxiing operations, we expect that:

1. System performance depends on the amount of information available to the controller about the state of the system.
2. Global information achieves the highest system performance.

To validate these two aforementioned relationships we vary the distance at which the decentralized controller can observe traffic, which we introduce as the scope of information.

We introduce autonomous local controllers at each intersection that command the traffic approaching the intersection to implement a decentralized control. These controllers base their decisions and planning on local knowledge. For larger and more complex taxiway systems that comprise more intersections, the number of decentralized controllers increases which gives the overall system a higher capacity for the decision-making process. Compared to implementing decentralized control at each aircraft, this approach only requires a change of equipment at the airport, and not throughout an entire fleet of aircraft. Previous work by Lämmer and Helbing has shown the viability of decentralized control for infrastructure systems and also demonstrated that decentralized systems are beneficial regarding robustness and resilience [15]. These benefits further motivate the application of decentralization for aircraft taxiing operations.

In [16] a decentralized approach for ground handling fleet management at airports is introduced. From a methodological point of view this approach is based on mathematical programming techniques and is closely related to the area of distributed constraint satisfaction. The authors propose a normative model of operations for which optimal solutions are identified. In contrast to this work, our approach is methodologically closer to Complexity Science paradigm, which is more explorative, aiming at understanding how variations at the level of local system components and interaction between them cause emergence of global systemic phenomena – in our case - measures of runway and taxiway system performance.

In [17] a decentralized multiagent approach to air traffic control is described, in which individual agent aircraft are responsible for conflict resolution with other agents by negotiation. The main difference with our approach is that beside aircraft agent, we introduce an intermediate level of intersection agents, which are able to observe a larger part of the system than individual aircraft agents, and, thus, potentially are able to make more informed decisions. Understanding the effects of the scope of information available to these agents on the global runway and taxiway system performance is the main research focus of this paper.

In [18] a decentralized algorithm for self-merging and self-spacing in ATC is proposed. This approach focuses largely on efficient and safe merging of aircraft on a line during the approach flight phase. This process is quite different from aircraft surface movement considered in this paper, and thus, a different type of distributed control mechanisms needs to be employed.

A related research on distributed aircraft taxiing route planning is presented in [19]. Similarly to intersection agents in our approach, a set of resource node agents and the routing management agent are introduced in [19]. However, the latter agent, responsible for planning of aircraft routes, is endowed with abilities of obtaining global information about the system, whereas this paper explores the effects of a varying scope of information on the system performance. Furthermore, in [19] a list of priorities of aircraft used in planning is assumed. It is not evident whether and how these priorities could be updated dynamically when the traffic situation changes or when previously defined plans are violated.

The aim of this work is to test if decentralized control can handle aircraft taxiing control at an airport. Furthermore, we aim to evaluate if local knowledge is sufficient to achieve comparable performance to global knowledge about the system. In section 5.2 we introduce the scenario, simulator, and agent definition that is used in the experiments. The results of the experiments are presented and discussed in section 5.3. Concluding remarks and suggested future work are stated in section 5.4.

5

5.2. METHODOLOGY

5.2.1. AGENT-BASED MODELING

Agent-Based Modeling (ABM) provides a suitable methodology to simulate the interactions between aircraft and control agents within the taxiway infrastructure, and to investigate the emerging behavior and performance of the system.

It allows observation of how interactions between agents lead to emerging structures and system-wide effects, specifically in highly decentralized networks and changing environment. An agent in ABM is an active unit in a system that monitors its environment, makes decisions based on its knowledge, and interacts with other agents. ABM enables modeling of complex decision-making processes in large structures and organizations. Varying levels of information and different characteristics of the agent can be taken into account [20].

Agent-based modeling and simulation process is performed along general methodological steps as described in [21], including such phases as problem definition, conceptual and formal model development, model implementation and simulation, analysis and interpretation of simulation results. A specification of a multiagent system usually comprises the following types of dynamic temporal properties: local behavioral and cognitive (or internal) properties of individual agents, interaction properties between agents describing communication and coordination among agents, environmental properties, and properties describing interaction between agents and the environment. To specify agent-based models formally often rule-based or hybrid logic-based languages are used, such as Temporal Trace Language [22].

The processes in comparable complex infrastructure systems such as roads, trains, and power networks have successfully been modeled using Agent-Based Modeling [20, 23–26]. Agent-based models have also previously been used for analysing and improving airport surface movement operations [19, 27].

For this work, an Agent-Based model and simulator are developed. Agents at the intersections of the taxiway system observe the traffic situation and send heading com-

mands and routes to taxiing aircraft.

5.2.2. SCENARIO

A generic taxiway structure is used for the simulation. The layout of the taxiway system is shown in Figure 5.1.

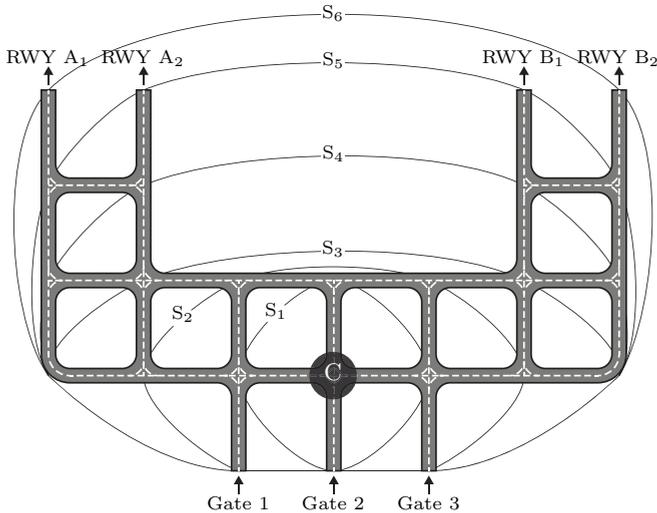


Figure 5.1: Layout of the taxiway system for the simulation and scope of information for one example controller "C"

As Figure 5.1 shows, aircraft are added to the taxiway system at one of three gates. The taxiway system leads to two runways that each have two runway entry points where aircraft leave the taxiway system. The distance between intersections is 600 meters.

There are several unsafe or forbidden system states that may not occur during the simulated taxiing operations:

- Aircraft cannot perform 180° turns on the taxiways.
- Aircraft cannot pass each other on a taxiway.
- An intersection cannot process a situation where traffic is incoming from all connected taxiways.

Path-planning, de-conflicting, and separation-assurance tasks must be performed during the simulation to avoid and reduce the occurrence of these unsafe states. These tasks are performed by agents in the simulation, which are introduced in section 5.2.4.

5.2.3. INDEPENDENT VARIABLES

In the experiments we test the performance of the decentralized control under varying conditions. Specifically, we vary the demand on the system by changing the aircraft

spawn rate, and the knowledge available to the decentralized control by changing the scope of information. We define these two variables as follows:

- The scope of information S_i is the maximum geodesic distance i of links at which a controller can observe the traffic situation, specifically, the flow rate and direction of traffic on a link. It constrains the information available to a controller in the decision making.
- The aircraft spawn rate is the number of aircraft added to the simulation per hour. As congestion at the gates can prevent that aircraft are added to the simulation, we differentiate between the desired spawn rate which is the number of aircraft that were intended to be added to the simulation and the actual spawn rate which is measured as the number of aircraft that were actually added to the simulation.

5.2.4. AGENT DEFINITION

To model the decision making for the simulation, we define three elements: The intersection agent, the aircraft agent, and the environment. The environment is a directed graph representation of the taxiway structure that was introduced in Figure 5.1. The intersections, gates, runway entry points and turns in the taxiway system are represented as nodes in the graph. Taxiway segments are represented by edges. The graph representation of the taxiway system is used to compute the route from origin to destination, using the Dijkstra algorithm for shortest paths. We use the estimated taxi time $t_{taxi,est}$ time for each taxiway segment as edge values for the Dijkstra algorithm, assuming a speed based on Greenshield's model [28]:

$$t_{taxi,est} = \frac{L_t}{v_{max} * (1 - \frac{d}{d_{max}})} \quad (5.1)$$

with the length of the taxiway segment L_t , the current density of aircraft on the taxiway segment d , the maximum taxi speed v_{max} and the maximum density of the taxiway segment d_{max} .

There are two types of agents implemented in the simulation: the aircraft agent and the intersection agent. These agents observe the environment, make decisions and interact with other agents. For each agent, there are inputs, outputs and decision processes described below. The aircraft agent observes the position of other aircraft agents, as well as heading and stop commands.

The two main tasks of aircraft agents are to keep separation from other aircraft and react to the commands that it receives. The aircraft agent is modeled as point mass that is moving in a 2-D environment. The movement of each aircraft is characterized by a x - and y -position in Cartesian coordinates, a heading h , a speed v , and an acceleration a or deceleration d . The aircraft agent updates its state and makes decisions based on the following rules:

1. An aircraft agent updates its speed v based on its acceleration a . A positive acceleration increases the speed and a negative acceleration decreases the speed.
2. An aircraft agent updates its position in x - and y -coordinates based on its speed v and its heading h .

3. If possible, an aircraft agent will always accelerate to taxi at the maximum taxi speed $v_{max,taxi}$.
4. If an aircraft has to stop it decelerates immediately until its speed is $v = 0$. No aircraft can pass an aircraft that is stopped on a taxiway.
5. An aircraft agent follows turn and stop commands as they are received from an intersection agent.
6. An aircraft agent detects conflicts with aircraft taxiing on the same taxiway as itself, on the next taxiway that it will enter, and aircraft that are heading to the same taxiway to keep separation and come to a stop if necessary.
7. If it approaches a turn the aircraft agent decelerates to the turn speed $v_{max,turn}$.

The aircraft agent broadcasts its position, destination and route to other agents. Figure 5.2 shows a flowchart of the decision making process of the aircraft agent. Each aircraft agent is performing the decision logic from Figure 5.2 at every simulation time step.

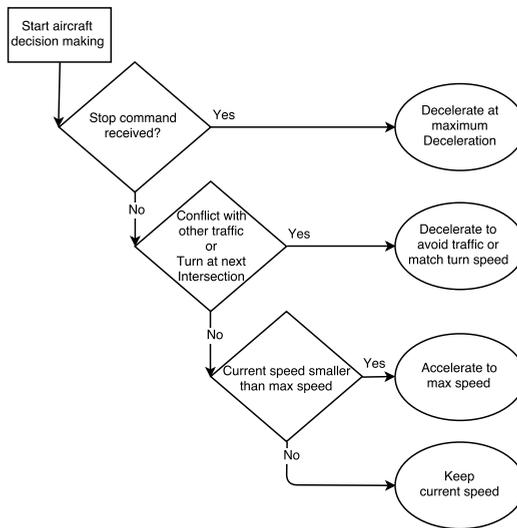


Figure 5.2: Decision making process of the aircraft agent

The intersection agent controls the traffic. It commands all incoming aircraft taxiing on adjacent taxiway segments. It knows the position, destination, and route of aircraft that are under its control, as well as the structure and traffic density of the environment. The knowledge about the traffic density in the environment is limited depending on the scope of information S_i , as introduced in section 5.2.3. The intersection agent assumes no traffic for taxiways outside the scope of information.

The intersection agent continuously computes the shortest path to the destination of each aircraft under its control using the Dijkstra algorithm. Thus it dynamically responds to changes in the traffic situation. If the destination of the aircraft cannot be reached, it

tries to compute the shortest path to one of the waypoints from the current route of the aircraft. It commands the aircraft to stop immediately if it cannot find a path to the waypoint at a distance 2.

To ensure that the intersection agent can accommodate all traffic that it is handling it can reserve its adjacent taxiway segments. As an aircraft is approaching an intersection and is not able to come to a stop on the current taxiway segment, the intersection agent reserves the next taxiway segment for the aircraft. If there is traffic incoming from all adjacent taxiway segments except one, the intersection agent reserves this one taxiway segment for outgoing traffic to ensure that all incoming traffic can be accommodated.

The intersection agent sends the aircraft agent heading commands, as well as the route to the destination of the aircraft agent. Figure 5.3 shows a flowchart of the decision making process of the intersection agent.

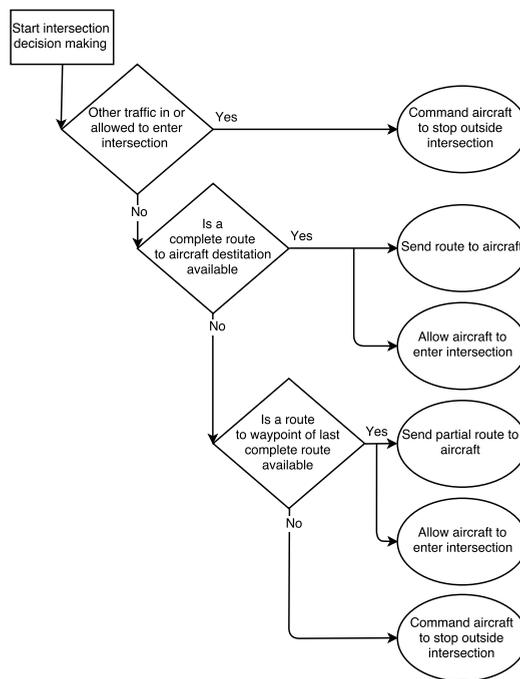


Figure 5.3: Decision making process of the intersection agent

For each aircraft under its control each intersection agent is performing the decision logic from Figure 5.3 at every simulation time step.

5.2.5. DEPENDENT VARIABLES

Three metrics are recorded during the simulations to measure the performance of the aircraft taxiing operations:

1. Average taxi speed is the average speed of an aircraft during taxi as measured from

gate departure until take-off. Higher average taxi speeds are an indication of good system performance.

2. Throughput is the number of aircraft that are processed through the system per hour. A higher system throughput indicates better system performance.
3. The number of unsolvable conflicts is the total count of forbidden or unsafe system states during a simulation. Any number > 0 indicates an undesired system behavior.

Average taxi speed and throughput are measures for system efficiency. The number of unsolvable conflicts tests if the control system is viable and safe.

5.2.6. SIMULATOR SETUP

In this work we modified and extended the Open Source Simulator for ATM Research (OSSAR) to enable an agent-based simulation of taxiing aircraft. OSSAR is a fast-time simulation targeted at the ATM community that is implemented in Python. It is an open source simulation that can be extended and modified based on user needs. The modified OSSAR version we used in this work supports decision-making at simulation runtime and outputs the relevant metrics for our experiments. We implemented a simple aircraft taxiing model that describes aircraft position, speed, and acceleration. The parameters used for the aircraft model are listed in Table 5.1.

Table 5.1: Parameters of the aircraft model

Description	Symbol	Value
Maximum taxi speed	$v_{max,taxi}$	30 <i>kts</i>
Maximum turn speed	$v_{max,turn}$	10 <i>kts</i>
Acceleration	a	0.26 m/s^2
Maximum deceleration	d_{max}	5.14 m/s^2
Comfort deceleration	$d_{comfort}$	0.80 m/s^2

The values for the speed, comfort acceleration, and comfort deceleration are average values based on observations from one week of aircraft position data for Amsterdam Schiphol Airport. The value for maximum deceleration is based on the maximum pedal braking published in [29].

Using the simulator described above, we run simulation experiments with a standard variant of the Monte Carlo simulation method. The simulation time for each run is 60 minutes, which is sufficiently long time to observe multiple aircraft pass through the system and to observe if traffic density builds up at bottlenecks, while keeping short computation times. For each run, random traffic is generated: Departure gate and runway entry point are selected based on a uniform distribution. Aircraft are spawned at a constant time interval determined by the spawn rate, with uncertainty from a normal distribution. The code sequence for the execution of one run of simulation is described in Algorithm 1.

Algorithm 1 Code sequence for one simulation run**Require:** Spawn-rate, scope of information (S_i)

- 1: Generate random taxiing schedule based on spawn-rate
- 2: **for** each timestep in simulation time **do**
- 3: All aircraft agents update their positions.
- 4: All intersection agents make traffic routing decisions and send decision to aircraft agents.
- 5: All aircraft agents decide acceleration and heading for next time step.
- 6: Spawn new aircraft agents from taxiing schedule.
- 7: **end for**

The sample size for each simulation experiment is set to a minimum of 500 simulation runs. The simulation is stopped if the 95% confidence interval is smaller than 10% of the sample mean, or if the sample size is 2000. The 95% confidence interval is also used to determine if differences between the results of each dependent variable are significant or not.

5

5.3. RESULTS AND DISCUSSION

In this section, selected results of the aircraft taxiing simulation are presented. The purpose of the simulations is to test the performance and applicability of the distributed control. As presented in the previous section, simulation experiments were conducted for different scenarios from a range of aircraft spawn rates and varying scopes of information. The three performance metrics throughput, average taxi speed, and occurrence of conflicts are measured, which were introduced in section 5.2.5.

5.3.1. NUMBER OF CONFLICTS

To test the applicability of the distributed control approach, Figure 5.4 shows the number of unsolvable conflicts, as introduced in section 5.2.2, which occurred in the experiments. The results in Figure 5.4 show that for a global scope of information no conflicts occur in the simulated spawn rate range. Similarly, no conflicts occur for a scope of information of at least S_2 .

For scope of information S_1 , where only local information about the traffic situation is available, no conflicts occur for spawn rates less than 60 aircraft per hour. If the spawn rate is increased further a maximum number of 0.5 conflicts per hour occur on average during each simulation run. The local information is not sufficient to avoid unsolvable conflicts. Not knowing the traffic situation on the next two links, a controller may send aircraft on a link that the adjacent intersection must use to accommodate outgoing traffic, resulting in an unsolvable conflict. Since no conflicts occur for scope of information S_2 or higher, these results indicate that decentralized decision making can be applied to control aircraft taxiing, given knowledge about a sufficient number of nodes is available. The minimum required S_i may be different for other taxiway layouts.

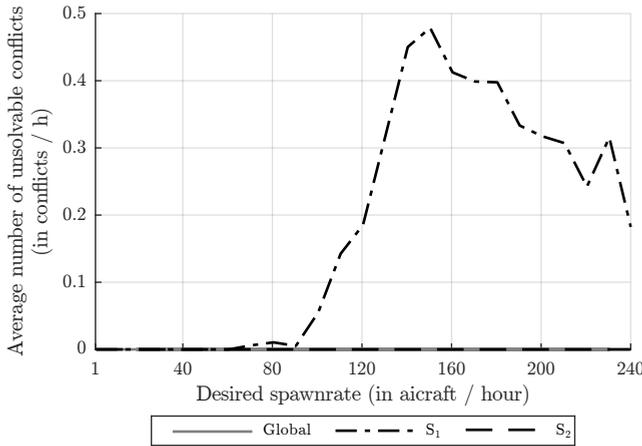


Figure 5.4: Average number of conflicts vs. aircraft spawn rate for varying information scope S_i

5.3.2. SYSTEM THROUGHPUT

Figure 5.5 shows the throughput of the taxiway system for a range of spawn rates and three scopes of information.

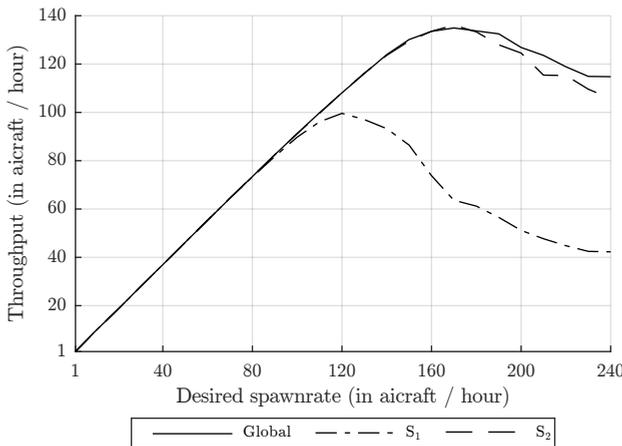


Figure 5.5: Average throughput vs. aircraft spawn rate for varying information scope S_i

In Figure 5.5 three spawn rate ranges can be distinguished for each information scope. For low spawn rates up to about 90 aircraft per hour throughput increases linearly. This indicates that aircraft that are added to the taxiway system reach the runway without being impeded by other traffic. One would expect that in the unimpeded case desired spawn-rate and throughput are equal. Due to the limited simulation time not all aircraft

that are spawned reach the runway during the simulation time.

Throughput reaches a maximum if the spawn rate is increased beyond the linear range. The throughput of the taxiway system is limited by congestion at the gates, which limits the effective spawn rate into the system, and congestion on the taxiway system. For the global scope of information, the average throughput reaches a maximum of 137 aircraft per hour at a spawn rate of 169 aircraft per hour. For scope of information S_1 , the average maximum throughput is 101 aircraft per hour, at a spawn rate of 125 aircraft per hour. If the spawn rate is increased further, the average throughput decreases and the standard deviation increases. Since the maximum system throughput is limited, congestion under high spawn-rates is increasing in the system which affects system performance. The results show that for high spawn rates scope of information has an impact on system throughput, and that S_2 achieves similar performance to the global scope of information.

5.3.3. TAXI SPEED

Figure 5.6 shows average taxi speed plotted against spawn rate for three different scopes of information. The results in Figure 5.6 show that average taxi speed decreases with

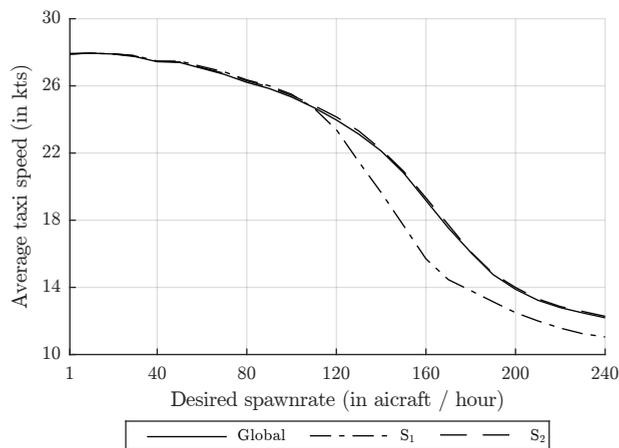


Figure 5.6: Average taxi speed vs. desired spawn rate for varying information scopes S_i

higher spawn rates for all scopes of information. With higher spawn rates the traffic density increases and taxiing operations are impeded by other traffic resulting in lower taxi speed. For very high spawn rates the average taxi speeds seem to start to stabilize. This behavior is due to the effect discussed in section 5.3.2, that the effective spawn-rate of aircraft is limited due to congestion at the gates, thus resulting in similar average taxi speeds for higher spawn rates.

Three main spawn rate ranges can be distinguished; comparing the average taxi speed for the controller with global scope of information to the controllers with local scopes of information. For spawn rates up to about 35 aircraft per hour, the scope of information has no impact on the average taxi speeds. In the spawn rate range between

41 and 105 aircraft per hour the scope of information S_1 results in about 0.6% higher taxi speeds compared to the global scope of information. Similarly, the scope of information S_2 results in about 0.4% higher taxi speeds compared to the global scope of information in the spawn rate range between 41 and 140 aircraft per hour. This could indicate that controllers with local scope of information direct traffic on shorter paths even if these paths are occupied with other traffic, as they are not aware of the global traffic situation. For spawn rates greater than 105 aircraft per hour scope of information S_1 results in taxi speeds that on average are 10.4% lower than the results for the global scope of information. For spawn rates greater than 140 aircraft per hour, the average taxi speed for scope of information S_2 is not significantly different from the global scope of information. The results show a significant impact of scope of information on average taxi speed and most notably, that for spawn-rates between 41 and 105 aircraft per hour S_1 and S_2 achieve higher performance than the global scope of information.

5.3.4. INFLUENCE OF SCOPE OF INFORMATION

To emphasize the impact of the scope of information on taxiing performance, in Figure 5.7 the average taxi speed is plotted against the scope of information, with 95% confidence bounds. The plotted aircraft spawn rates are selected to highlight the trends that were observed in Figure 5.6. The results in Figure 5.7 show that for higher spawn rates,

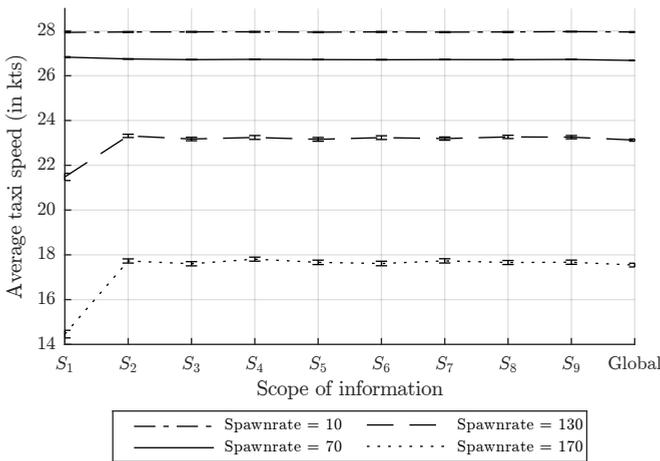


Figure 5.7: Average taxi speed vs. scope of information for varying aircraft spawn rates. Errorbars represent 95% confidence interval

the average taxi speed decreases. At a spawn rate of 10 aircraft per hour, the scope of information does not influence the average taxi speed. For a spawn rate of 70 aircraft per hour scope of information, S_1 shows 0.6% higher average taxi speed compared to the global scope of information. For spawn rates of 130 and 170 aircraft per hour, scope of information S_1 shows 7.1% and 17.6% lower performance than the global scope of information. Scope of information S_2 shows a 0.8% higher average taxi speed than the global scope of information at a spawn rate of 130 aircraft per hour. The average taxi speed for

any scope of information greater than S_1 is not significantly different compared to the global scope of information at a spawn rate of 170 aircraft per hour.

Since the results for the other performance metrics show similar trends to the average taxi speed, we omit presenting them here.

The primary observation from Figure 5.7 is that higher scope of information does not necessarily improve performance. In the specific scenario that was simulated S_2 achieved similar performance to a global scope of information. Thus, local knowledge about the state of the system is sufficient to achieve high global performance.

5.3.5. DISCUSSION

Decentralized control can successfully be applied to taxiing operations at an airport, provided that a minimum amount of information about the state of the system is available. This was substantiated by the results in section 5.3.1, where no conflicts occurred for scope of information of at least S_2 .

The results highlight the impact of the scope of information on global system performance. For any scope of information greater than S_2 the measured performance metrics are similar to the global information scope. This result highlights that in the simulated scenario there is no performance gained from using global information, compared to sufficient local information.

Furthermore, the results in Section 5.3.2 motivate that spawn rates should be limited to the value of the maximum throughput since throughput decreases for higher spawn rates. This indicates a saturation effect of the system.

Taking into account the greater resilience and robustness of decentralized systems compared to centralized systems, the decentralized control approach implemented in this work could provide significant benefits to aircraft taxiing operations at airports.

5.4. CONCLUSIONS AND RECOMMENDATIONS

5.4.1. CONCLUSIONS

In this work, we demonstrated a decentralized control approach for airport taxiing operations. We implemented autonomous controllers at each intersection that gave routing commands to aircraft. The hypothesis tested was that the scope of information S_i of the decentralized controllers, as defined and proposed in this paper, has a direct causal impact on global system performance, and that higher S_i has a benefit on performance.

We recorded the number of unsolvable conflicts that occur to test system stability, and throughput and average taxi speed to evaluate system performance. The results show that distributed control can be successfully implemented in this application if information about a finite number links is available to the controller. No unsafe states (conflicts) occur if a minimum level of knowledge is available. It was also observed that there is a threshold number of links, after which the performance of taxiing operations does not increase. For the specific infrastructure, control task and simulation parameters that were simulated, providing information of more than two links to the controller showed no significant performance gain compared to providing global information.

Overall the trend was observed that increasing aircraft spawn rates had a negative impact on the average taxi speed. There is a distinct maximum throughput of the taxi-

way system corresponding to a set aircraft spawn rate, for each scope of information. Increasing the spawn rate beyond the maximum throughput reduces the performance of taxiing operations. For low spawn rates, the scope of information has no impact on taxiing performance.

Therefore, it has been shown that there is strong evidence through the current modest application case study that there is a significant impact of scope of information on global system performance, and local knowledge is sufficient for successful decentralized control.

5.4.2. FUTURE WORK

In our simulation, controllers at the intersection observe the current traffic situation and command aircraft actions based on the aircraft intention. The controllers coordinate their actions with other controllers implicitly by observing the actions of other controllers within the same environment.

Implementing explicit coordination between controllers could improve the system performance, because controllers could collaboratively prioritize individual flights and major traffic streams. This coordination could lead to a more continuous traffic flow in the system and fewer delays for individual flights. Planning of taxi operations with future states would allow to predict and avoid congested areas which could lead to a higher system performance. Anticipatory routing is one example method for planning for future states that was applied to vehicle routing in [30].

The results should be validated and compared to an actual airport layout and a realistic traffic mix with varying aircraft types, taxi speeds, accelerations, and decelerations.

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6

THE IMPACT OF COORDINATION SCOPE ON GLOBAL SYSTEM PERFORMANCE IN DECENTRALIZED CONTROL OF AIRPORT TAXIING OPERATIONS

We demonstrated in the previous chapter that our concept for decentralized control results in stable aircraft taxiing operations. We did observe situations where the lack of coordination between the controllers in the system leads to low performance. In this chapter, we implement explicit coordination between control agents based on an auction mechanism and compare different coordination strategies. We first introduce the problem that we are addressing, then define the Multi-Agent system, describe the experiment set up, present and discuss results, and conclude with a summary and suggestions for future work.

6.1. INTRODUCTION

DEMAND for air transportation is growing continuously [1]. As a fundamental of the air transportation system, airports have to be able to accommodate growing demand. Today at major hub airports the traffic demand exceeds the available capacity [2, 3]. As part of global initiatives such as SESAR and NextGen, research is focused on developing new airport processes and technologies to improve airport operations. Specifically, their goals are to increase airport capacity, reduce the taxi time of aircraft, and lower the environmental impact of airport operations safely.

The processes related to aircraft taxiing operations can be divided into phases. Operations are planned during the pre-tactical phase and executed during the tactical phase. A number of disruptions that affect aircraft taxiing, such as delays of aircraft and runway configuration changes due to environmental constraints, add uncertainty to the execution of aircraft taxiing operations. Currently, taxiing operations are monitored and controlled by human air traffic controllers. The complexity of taxiing operations is limited by the mental capacity of the air traffic controller. Commonly controllers handle operations according to best-practice procedures that define how to use the taxiway system, are for a specific runway configuration and traffic situation. Such procedures limit the ability to respond to unforeseen or uncommon traffic situations. Switching between procedures can lead to conflicting traffic flows, which increases the complexity of the traffic situation.

A large body of work has introduced automated tools to support or replace tasks of the human controller to improve the performance of airport taxiing operations. Various research applied optimization methods in the pre-tactical phase in order to improve the planning of taxiing operations. Clare and Richards [4] applied mixed integer linear programming to the improve the taxiway routing and runway scheduling and demonstrated that one could significantly reduce taxiing time over a first come first serve approach. Roling and Visser [5] developed a taxi planning support tool based on mixed-integer linear programming that deconflicts taxi routes and optimizes for low delays and short taxi-times. Marín [6] used Branch-and-Bound, and Fix-and-Relax approaches in a taxi planning model applied to a network representation of Madrid-Barajas airport. Rathinam, Montoya, and Jung [7] presented a mixed integer linear programming optimization to optimize taxiing operations at Dallas/Fort Worth International airport, that takes into account safety constraints in the optimization. Balakrishnan and Jung [8] developed an optimization and compared controlled pushback and taxi rerouting approaches to improve the performance of operations at Dallas/Fort Worth International Airport. While these methods provided viable plans for taxiing operations, the execution of those plans was prone to uncertainty. In their review paper of research in the airport ground movement problem Atkin, Burke, and Ravizza concluded that future research should develop methods “which are more robust against such uncertainty” [9].

Other work developed tools to support the human air traffic controller during the tactical phase of taxiing operations. Simaiakis, et al. [10] implemented a push-back rate control to reduce congestion and fuel-burn. Depending on the current traffic density they would recommend the rate to release aircraft from the gate to the air traffic controller. They validated their approach in field tests at Boston Logan airport.

To automate the guidance of aircraft surface movements, Chua [11] developed con-

flict resolution strategies for autonomous taxiing as part of the MOTA project. Within the MOTA project Chua, et al. [12] furthermore evaluated the viability of a Multi Agent System that autonomously controls trajectories during aircraft taxiing, and also tested human machine interfaces that allow air traffic controllers to manage and observe the traffic situation. Such automated systems need to be robust and resilient to be able to respond to deviations from the intended schedule that occur during taxiing operations.

Multi Agent Systems that are based on decentralized control have demonstrated robust and resilient behavior in different infrastructure and traffic applications. Bazzan implemented a decentralized approach for traffic signal coordination [13] and found that agents develop coordination strategies to achieve higher performance. Chen and Cheng provided an overview of the application of Multi Agent Systems (MAS) in traffic and transportation. They suggest that MAS provide better ability to deal with uncertainty in traffic systems, and should be tested in real world applications [14]. Claes, Holvoet, and Weyns implemented an agent coordination mechanism to implement anticipatory vehicle routing in a road-traffic environment and demonstrated that their approach could reduce the travel time [15]. Agent based approaches are also being developed for applications in smart electrical grids, where uncertainty needs to be managed both on the supply and demand side [16, 17].

In the work presented herein, we investigate a decentralized control for airport taxiing. For an arbitrary airport layout we demonstrate the viability of decentralized control and test the resulting system performance. Furthermore, we investigate the impact of coordination on system performance. We vary the scope of coordination, which is the maximum geodesic distance between agents that can coordinate with each other, in order to compare the performance of local coordination and higher scopes of coordination.

The approach taken implements a controller at each intersection that plans and controls routing of incoming aircraft. These decentralized controllers coordinate with each other to improve the system performance in an auction mechanism. There is no pre-tactical planning implemented in the system and the decentralized controllers base their decisions on the current traffic situation. Other research in the area of airport taxiing implemented a decentralized controller for each aircraft, which would require a fleet-wide retrofitting of equipment [12]. In comparison, our approach requires a limited number of changes to the system and can be implemented locally at an individual airport.

In this work, we demonstrate that coordination improves the performance of decentralized control for aircraft taxiing. Furthermore, our results show that higher scopes of coordination can achieve better performance than a procedure that is designed for a specific airport-layout and traffic-situation. The performance of the airport taxiing operations emerges from local decisions of decentralized controllers. We use system-wide performance metrics to evaluate the performance of the decentralized control algorithm.

In Section 6.2 we introduce the set-up of the multi agent system model and define behavior of the aircraft agent, the intersection agent, and the coordination mechanism. The description of the experiment set-up in Section 6.3 describes the airport layout, performance metrics, independent variable, and simulator that is used in the experiments. We present and discuss the results of the experiments in Section 6.4. We end the paper

with concluding remarks and suggestions for future work in Section 6.5.

6.2. THE MULTI AGENT SYSTEM MODEL

We set up a multi agent system (MAS) model to be able to define and simulate the decentralized control. There are two types of agents in the simulation. The aircraft agents move through the taxiway system and ensure safe separation with other aircraft. They follow routing commands that they receive from the intersection agent. At any given time each intersection agent controls the aircraft that are taxiing towards the intersection on adjacent taxiway segments.

For each of these agents, we define a set of individual behaviors. We also define mechanisms on how several instances of these agents interact and coordinate with each other.

6.2.1. AIRCRAFT AGENT BEHAVIOR

The aircraft agent is responsible for ensuring safe separation with other aircraft, follow routing and stop commands that they receive, and determining their taxi speed. The aircraft agent observes other aircraft that are taxiing on the same taxiway segment, the next taxiway segment, and the aircraft that will be on the same taxiway segment in the future.

We modeled aircraft as points moving in Cartesian coordinates, using the common equations of motion for acceleration (a), speed (v), and horizontal-position (x , y). To simplify the model we assumed that aircraft can change their heading instantaneously.

$$a = a_0 \quad (6.1)$$

$$v(t) = a_0 * t + v_0 \quad (6.2)$$

$$x(t) = \sin(\text{heading}) * v(t) + x_0 \quad (6.3)$$

$$y(t) = \cos(\text{heading}) * v(t) + y_0 \quad (6.4)$$

We measure common aircraft accelerations and decelerations during taxiing from ADS-B data, which we define as comfort acceleration and deceleration. To determine the maximum deceleration (d_{max}) we use a value published by the Flight Safety Foundation for the maximum pedal braking [18].

Table 6.1 summarizes the acceleration and deceleration values used for the aircraft model. All aircraft in our simulation experiments use these values. Every aircraft always

Table 6.1: Accelerations and decelerations for the aircraft model

Acceleration type	Value
Comfort acceleration	$0.26m/s^2$
Comfort deceleration	$0.80m/s^2$
Maximum deceleration	$5.14m/s^2$

tries to accelerate to the maximum taxi speed ($v_{max,taxi}$) of 30 knots. The maximum taxi

speed of the aircraft determines the rate at which aircraft travel through the system and limits the maximum throughput of a taxiway segment.

There are cases where an aircraft will decelerate or stop. It will decelerate to keep the minimum separation distance with other aircraft on the same taxiway segment, aircraft on the next taxiway segment, and aircraft taxiing to the same next taxiway segment. This behavior ensures safe separation between aircraft. An aircraft will stop and hold its position if required. If it has to turn at the next intersection, the aircraft will decelerate to the maximum taxi speed for a turn ($v_{max,turn}$) of 10 knots.

When the aircraft agent receives a stop command, it will decelerate and come to a stop at the commanded distance. The aircraft only decelerates if the deceleration that is required (d_{req}) to meet the speed or stop goal is greater or equal to the comfort deceleration (see Table 6.1). We derive the required deceleration to change the speed from the current speed ($v_{current}$) to the goal speed (v_{goal}) within a specific distance (d) from the equations of motion as:

$$d_{req}(d, v_{goal}, v_{current}) = -\frac{v_{goal}^2 - v_{current}^2}{2 * d} \quad (6.5)$$

The aircraft changes its heading for the next taxiway segment when it reaches the intersection. We assume that this heading change is instantaneous.

6.2.2. INTERSECTION AGENT BEHAVIOR

The agents at each intersection decide how to route aircraft through the taxiway system. They base their decisions on the current traffic situation. It is a system level constraint that the routing decision may not lead to deadlocks in the system and that aircraft can reach their destination. This means avoiding unsafe system states, specifically:

- Aircraft trying to taxi in opposite directions on the same taxiway segment.
- Aircraft approaching an intersection from all adjacent taxiway segments.

At each simulation time-step, all intersection agents go through three steps in their decision making. First, they update their current knowledge about the traffic situation of the taxiway system and available taxiway segments. Then they coordinate with other intersection agents to determine if any taxiway segments should be reserved to accommodate any specific traffic. Last, they plan the route for each aircraft under their command and send the updated route to the aircraft, using a Dijkstra shortest path algorithm. The Dijkstra algorithm requires a graph representation of the taxiway system. Intersections, gates, and runway entry points are represented by graph nodes. Taxiway segments are represented by graph edges. The weights of the graph edges are based on the taxi time for each taxiway segment. The taxi time is estimated using the length of the taxiway segment and the average taxi speed on that segment. Figure 6.1 shows an pseudo code representation for the decision making of the intersection agent.

```

1: loop All intersection agents
2:   graph ← getStateOfTaxiwaySystem()
3:   bidsWonLost ← auctionWithOtherAgents()
4:   loop All aircraft under control
5:     acCommand ← planAircraftOperation(graph, bidsWonLost)
6:     sendCommandToAircraft(acCommand)
7:   end loop
8: end loop

```

Figure 6.1: Decision loop of intersection agent

The intersection agent has to ensure that no aircraft blocks the intersection for other traffic. Therefore, the intersection agent commands aircraft to stop at a distance of one minimum separation from the intersection, and only allows an aircraft to enter the intersection if there is no other aircraft on the next commanded taxiway segment at a distance of at least two minimum separations.

There can be situations where multiple aircraft approach an intersection. In this case, the intersection allows the aircraft with the highest value, measured by the total taxi time of the aircraft, to proceed, and commands all other aircraft to hold.

6

6.2.3. INTERACTIONS BETWEEN INTERSECTION AGENTS

A focus of the contribution of this work is the implementation of coordination between the intersection agents. We investigate if coordination can improve the performance of the decentralized control with respect to the metrics introduced in section 6.3.4.

The agents coordinate with each other during the decision making process. We implement an auction between agents, where agents use a defined budget to bid against other agents. The outcome of this auction determines which taxiway segments they can use for the path planning, which effectively increases or decreases the agent's option space. Using the model from Wittenbaum, et al. this coordination mechanism can be classified as In-process planning as it is explicit and occurs during the interaction of agents [19].

BUDGET

In the auction, agents allocate a budget to bid on a taxiway segment. We implement a mechanism to specify the budget of each agent and allocate the budget to each adjacent taxiway segment.

We define that each agent has a total budget (B_t) proportional to the value (V_n) of the N aircraft (n) under its control :

$$B_t = \sum_{n=1}^N V_n \quad (6.6)$$

We used the total taxi time of each aircraft as a measure of its value. This ensures that the coordination gives priority to aircraft that have been taxiing for a longer duration. An alternative approach to the current implementation could be to use taxi delay.

The total budget that is available to the intersection agent changes if the value of the aircraft under its control changes.

BUDGET ALLOCATION

To place a bid on an adjacent taxiway segment the intersection agent has to allocate part of its total budget to the taxiway segment. The goal of introducing coordination between agents is to improve the system performance with respect to the metrics that are introduced in section 6.3.4. Therefore, we allocate the highest budget to the taxiway segment that allows aircraft to pass through the taxiway system on the shortest possible route.

The auction budget is allocated based on the unimpeded taxi times t_s from each intersection to the destination of the aircraft, when using a specific taxiway segment s . We allocate the budget of each aircraft n (B_n) individually for each possible taxiway segment s from the set of available taxiway segments S . We define the budget allocated to each taxiway segment s , for aircraft n :

$$B_{s,n} = \frac{B_n}{\sum_{i=0}^S \frac{t_s}{t_i}} \quad (6.7)$$

The total bid on each taxiway segment s is:

$$B_s = \sum_{n=1}^N B_{s,n} \quad (6.8)$$

Equation 6.8 ensures that the bids are distributed to each taxiway segment proportionally to the inverse the unimpeded taxi times to the destination of the aircraft using that taxiway segment. This means that a taxiway segment that takes twice the time as another to get to the same destination receives half the budget.

AUCTION

Intersection agents coordinate the use of taxiway segments with each other through an auction mechanism. They bid on behalf of the aircraft agents, meaning they distribute the budget associated with an aircraft to best meet the interests of the aircraft agents under their control. In this auction, they compare how much budget they allocate on a taxiway segment with adjacent intersection agents. The agent which allocates more budget wins the auction and is allowed to use the taxiway segment. If two agents bid the same amount, a winner is randomly chosen. To avoid deadlock situations in the system, each intersection agent must always have at least one taxiway segment available for outgoing traffic. Therefore, if an agent is bidding for the last available outgoing taxiway segment it automatically wins the auction. An auction is triggered once an aircraft crosses a set threshold. This reduces the amount of unnecessary communication between agents.

AUCTIONS WITH DIFFERENT SCOPE OF COORDINATION

Depending on the scope of coordination of the experiment, agents at different geodesic distances are included in the auction. To include another agent in the auction, the amount of the winning bid is transferred to the losing agent. The losing agent immediately starts an auction where he uses the transferred amount and its current budget in the bidding. The scope of coordination limits the number of times that a bid can be transferred, and we ensure that a bid does not travel back to agents that were previously involved in the auction.

6.3. EXPERIMENT SETUP

In this work, we investigate the impact of scope of coordination on the system performance of decentralized control of airport taxiing operations. We set up an environment to measure, model, and simulate aircraft surface movements. In this environment, we implement a decentralized control strategy and coordination mechanism between the agents.

6.3.1. AIRPORT LAYOUT

We set up a generic airport layout that has 3 gates, 2 runways, and 2 runway entry point for each runway. Figure 6.2 shows the layout of the airport taxiway system.

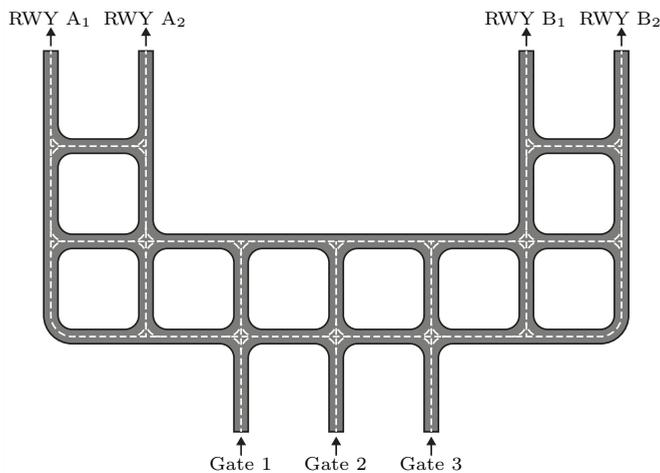


Figure 6.2: Taxiway layout for experiments

The system is set up with parallel taxiways to be able to accommodate traffic flows in different directions, and overpasses to allow more flexibility in traffic routing. The length of each taxiway segment is 600 meters. We put homogeneous demand of departing traffic on the taxiway system. Aircraft enter the system at one of the gates and have to reach one of the runway entry points.

6.3.2. INDEPENDENT VARIABLES

We investigate the behavior and performance of the system under different conditions. We vary the aircraft spawn-rate to test the impact of changing the demand on the performance of the taxiway system. The aircraft spawn rate determines the number of aircraft added to the simulation per unit time, or in turn the desired time between aircraft added at the gate. The spawn-rate is the number of aircraft that call ready for push-back at the gate. If the taxiway at the gate is not available due to other traffic, the aircraft will hold at the gate. We implement different coordination strategies that are introduced in

section 6.3.3. For each combination of spawn-rate and coordination strategy, we run Monte-Carlo simulations. We randomly perturb the time at which each aircraft is added to the simulation. We also randomly select the gate at which each aircraft is added to the simulation and the runway entry point.

6.3.3. DECENTRALIZED CONTROL STRATEGIES

We set up three different decentralized control strategies and compare their impact on system performance. Conflicts between traffic should be avoided or resolved quickly to achieve high performance..

The first strategy is a case without coordination. The intersection agents plan operations based on the currently available links. The option space for their decision-making is constrained by other traffic that is using the taxiway segments.

As a second strategy, we implement a procedure that is designed to decouple major traffic streams on our airport layout going from the gates west towards runway A and east towards runway B. Figure 6.3 shows the procedure.

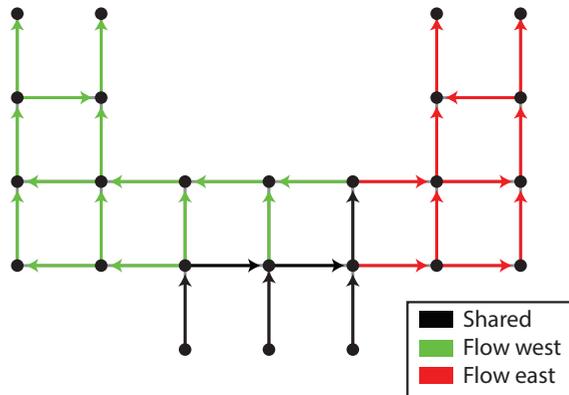


Figure 6.3: Taxiway graph representation with procedure to decouple traffic streams

The procedure constrains the option space in the decision making for the decentralized controller, as it only permits one traffic direction on each link. This type of strategy is currently employed by air traffic controllers for instance at Amsterdam Schiphol Airport (AMS).

The third strategy is the implementation of the coordination mechanism as described in section 6.2.3. For this case, we implement different scopes of coordination C_i . Higher scopes of coordination are achieved by propagating bids to neighboring intersection agents as described in section 6.2.3.

6.3.4. PERFORMANCE METRICS FOR AIRPORT TAXIING OPERATIONS

The results of the experiments need to capture the impact of different control strategies on the performance of the taxiway system. Specifically, we measure taxi time, system throughput, number of stops, and average taxi speed.

We measure taxi time (t_{taxi}) from the time an aircraft departs from the gate (t_{dep}) to the time when an aircraft arrives at the runway (t_{arr}).

$$t_{taxi} = t_{arr} - t_{dep} \quad (6.9)$$

A low taxi time indicates high system performance.

Based on Helbing's definition [20] for throughput of an individual point (Q_e), we measure the total system throughput (Q_s) as sum of the number of aircraft (N_{arr}) that pass through any of the four runway entry points (e) during the simulation time (t_{sim}):

$$Q_s = \sum_{e=1}^4 Q_e = \frac{\sum_{e=1}^4 \Delta N_{arr,e}}{t_{sim}} \quad (6.10)$$

A high system throughput indicates good performance. The system throughput is constrained by the throughput of runways, as well as the maximum taxi speed of the aircraft.

The average taxi speed ($\varnothing v_n$) of each aircraft n is measured at T discrete simulation timestamps τ at which the aircraft is taxiing with the speed $v_n(t)$:

$$\varnothing v_n = \sum_{\tau=0}^T \frac{v_n(\tau)}{T} \quad (6.11)$$

We measure the total number of stops S as the sum of the number of stops for each aircraft S_n during the simulation time, where N is the number of aircraft:

$$S = \sum_{n=1}^N S_n \quad (6.12)$$

6.3.5. AGENT-BASED SIMULATOR FOR AIRCRAFT GROUND MOVEMENTS

Using an Agent-Based simulator, we can define and study agent interactions and observe the resulting global system behavior. We use the Agent-Based simulator Open Source Simulator for ATM Research (OSSAR), which is an Agent-Based simulator specifically developed for simulating air traffic.

We expanded the taxiing version of OSSAR that we used in previous work. Specifically, we added support for coordination mechanisms between agents. The simulator allowed us to implement and test different coordination strategies.

For each configuration of demand and coordination strategy, we run 1000 simulation runs of one hour simulation time, with a simulation time step of 0.5 seconds.

6.4. RESULTS AND DISCUSSION

In this section we present the results of the simulation experiments. The metrics that we use for the analysis were introduced in section 6.3.4.

The experiments highlight the impact of different decentralized control strategies on the system performance. As a first metric for system performance figure 6.4 shows the average taxi time:

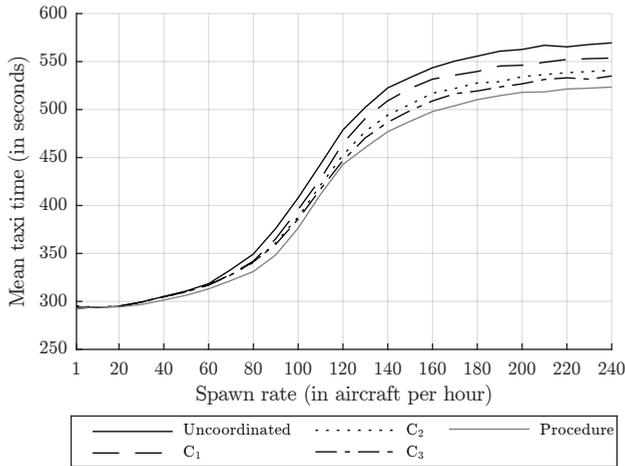


Figure 6.4: Average taxi time vs. aircraft spawn rate for varying coordination scope C_i

Figure 6.4 shows that for all simulated cases the lowest taxi time of about 300 seconds occurs for the lowest demand. The taxi time increases with higher spawn rates and for each case asymptotically approaches a maximum value. For spawn rates of up to 20 aircraft per hour, there is no significant difference in taxi time between the cases. For spawn rates that are greater than 20 aircraft per hour the procedure results in the lowest taxi time, and the uncoordinated case results in the highest taxi time. Coordination reduces the taxi time. Compared to the uncoordinated case, the cases C_1 , C_2 and C_3 result in lower taxi time for spawn rates greater than 80 aircraft per hour. The cases C_2 and C_3 result in lower taxi time compared to C_1 for spawn rates greater than 80 aircraft per hour. Higher scope of coordination reduces the taxi time. C_3 further reduces the taxi time compared to C_2 at about 120 aircraft per hour.

For very low spawn rates the aircraft density is so low that there are no conflicts between taxiing aircraft. For this spawn rate range, aircraft can taxi on the shortest route for all cases. This is why we cannot observe any significant difference between the cases, all resulting in the lowest taxi times. Conflicts between traffic slow aircraft down and result in higher taxi times. The significantly lower taxi time for spawn rates > 20 aircraft per hour of the procedure case indicates that the traffic flow is improved. The procedure successfully decouples the conflicting traffic streams. For spawn rates > 80 coordination improves the system performance significantly compared to the uncoordinated case. Higher scopes of coordination further improve the performance.

The taxi time is impacted by the number of times that an aircraft has to stop during the taxiing operation. Therefore figure 6.5 shows the number of stops during the taxiing operation:

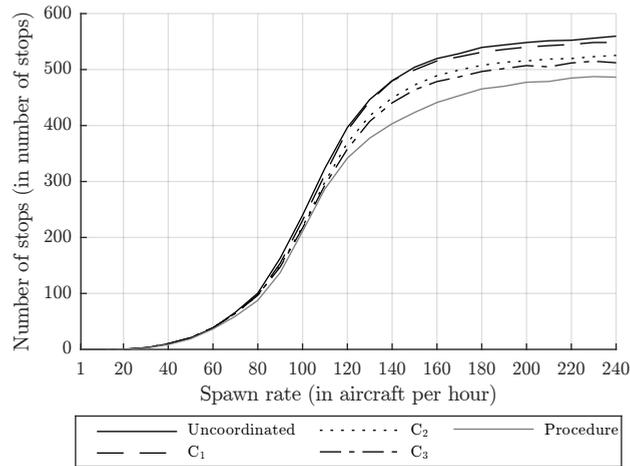


Figure 6.5: Average number of stops vs. aircraft spawn rate for varying coordination scope C_i

6

The results presented in figure 6.5 show that no stops occur for spawn rates less than 20 aircraft per hour. For all spawn rates greater than 20 aircraft per hour the procedure results in the lowest number of stops, and the uncoordinated case in the highest number of stops. The number of stops increases for higher spawn rates and reaches a different maximum for each control strategy. Coordination reduces the number of stops compared to the uncoordinated case. C_1 , C_2 , and C_3 reduce the number of stops for spawn rates greater than 80 aircraft per hour. Higher scopes of coordination further reduce the number of stops. C_2 and C_3 reduce the number of stops compared to C_1 for spawn rates > 90 aircraft per hour, and C_3 reduces the number of stops compared to C_2 for spawn rates > 110 aircraft per hour.

For spawn rates less than 20 aircraft do not need to stop as they taxi from the gate to the runway. This indicates that the aircraft do not encounter any conflicting traffic. For higher spawn rates aircraft have to stop during taxiing. For spawn rates greater than 80 aircraft per hour coordination gives a performance benefit. The best performance in terms of number of stops during taxiing results from the procedure. The procedure is set-up to decouple the traffic flowing east and west to reduce the number of intersections that are used by conflicting traffic stream.

Each aircraft stop represents a disruption of the traffic flow. Another metric that measures the traffic flow is the taxi speed, which is plotted in figure 6.6:

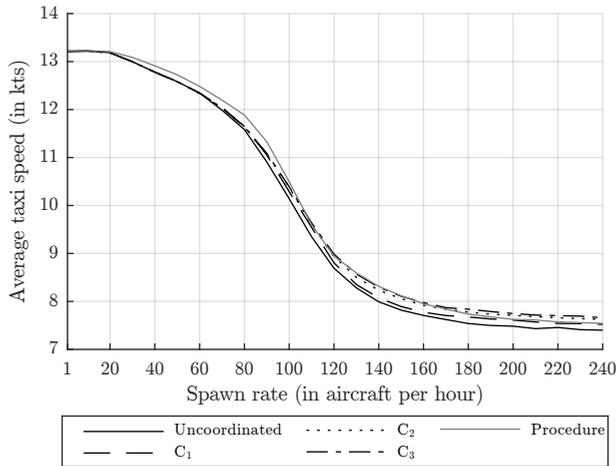


Figure 6.6: Average taxi speed vs. aircraft spawn rate for varying coordination scope C_i

Figure 6.6 shows that in general, the average taxi speed decreases for higher spawn rates. For all cases that were simulated, the average taxi speed does not change for spawn rates up to 20 aircraft per hour. For very high spawn rates the average taxi speed asymptotically approaches a distinct minimum, which is different for each case. For spawn rates between 20 and 110 aircraft per hour, the procedure results in the highest taxi speed. Coordination improves the performance compared to the uncoordinated case. C_1 , C_2 , and C_3 result in higher average taxi speeds for spawn-rates greater than 70 aircraft per hour. Higher scope of coordination results in higher average taxi speeds. C_2 and C_3 result in higher average taxi speeds compared to C_1 for spawn rates greater than 90 aircraft per hour, and C_3 results in higher average taxi speeds compared to C_2 for spawn rates greater than 130 aircraft per hour. For spawn rates greater than 180 aircraft per hour C_2 and C_3 results in higher average taxi speeds compared to the procedure

Similar to the taxi time and the number of stops, the performance with respect to taxi speed decreases for higher spawn rates. The results for taxi speed show that coordination improves the performance compared to the uncoordinated case, and higher scope of coordination further improves performance. While the procedure performs better for spawn rates between 20 and 110 aircraft per hour, it results in worse performance than scope of coordination C_2 and C_3 for very high spawn rates greater than 180 aircraft per hour. This finding indicates a disadvantage of the procedure constraining the option space of the controller. The unconstrained controller in cases C_2 and C_3 can accommodate more traffic. We now look at the system throughput, which similar to average taxi speed measures the flow rate through the system.

The throughput is plotted in figure 6.7

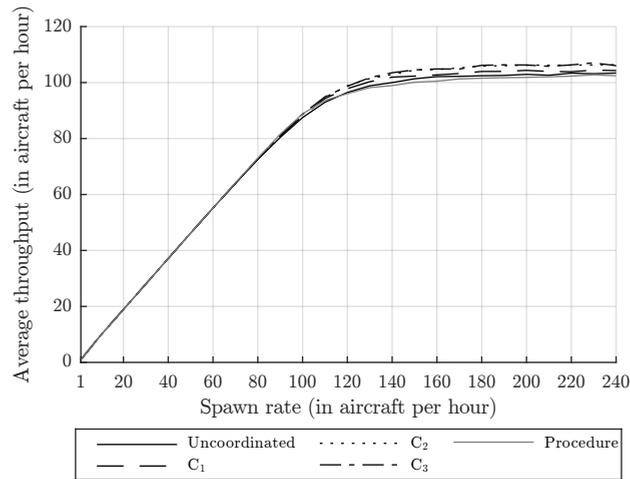


Figure 6.7: Average throughput vs. aircraft spawn rate for varying coordination scope C_i

6

In figure 6.7 it can be seen that in general throughput increases with spawn rate until it reaches a maximum throughput that is different for each case. This result is similar to findings of Pujet et al. [21] and Simaiakis et al. [22], that measured take-off rate as a function of taxiing aircraft. There is no significant difference between the cases for spawn rates that are less than 80 aircraft per hour. Coordination improves performance compared to the uncoordinated case. C_1 , C_2 , and C_3 result in higher throughput compared to the uncoordinated case for spawn rates greater than 90 aircraft per hour. Scope of coordination C_2 and C_3 result in higher throughput compared to C_1 for spawn rates greater than 120 aircraft per hour. For spawn rates greater than 130 aircraft per hour the procedure results in lower throughput compared to the uncoordinated and coordinated decentralized control.

Higher scopes of coordination improve the performance compared to the uncoordinated case. The results for the system throughput highlight the negative effect of the procedure. The procedure constrains the option space, which limits the number of taxiway segments that can be used. When the demand is high, this results in lower performance of the procedure compared to the other cases. The system throughput is limited by the throughput of each taxiway segment. It increases almost linearly with the spawn rate until the system is saturated and no more aircraft can be accommodated. This effect starts to affect the throughput at a spawn rate of about 90 aircraft per hour and results in no significant increase in throughput for spawn rates greater than 180 aircraft per hour. This saturation effect will show as an increase in gate delay, which is the time that aircraft are waiting at the gates before they can start moving.

The gate delay is plotted in figure 6.8

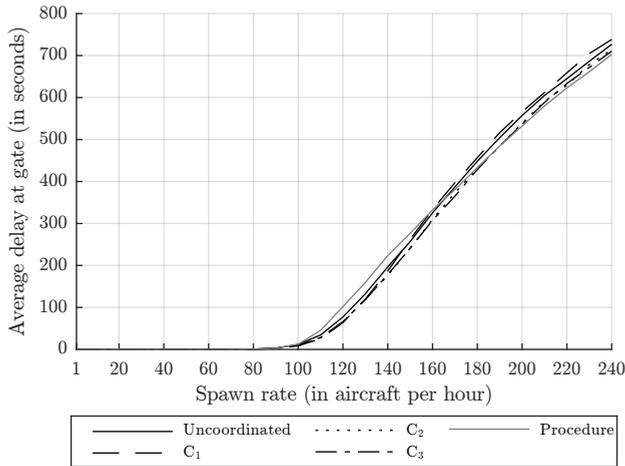


Figure 6.8: Average gate delay vs. aircraft spawn rate for varying coordination scope C_i

Figure 6.8 shows no gate delay for spawn rates less than 90 aircraft per hour. For higher spawn rates the gate delay increases. The procedure shows higher gate delay compared to the unconstrained cases for spawn rates between 100 and 160 aircraft per hour.

These results support that the taxiway system starts to become saturated for spawn rates greater than 90 aircraft per hour. For very high spawn rates the gate delay seems to decrease at a lower rate. Aircraft that have not left the gate within the simulation time of one hour are excluded from the measurement, which explains this observation. The noticeably higher gate delay for the procedure for spawn rates between 100 and 160 aircraft per hour indicates that the procedure cannot utilize as much capacity of the taxiway system as the unconstrained controllers in that specific spawn rate range.

6.5. CONCLUSION

6.5.1. CONCLUSIONS

In this Chapter, we demonstrated that coordination improves the performance of a decentralized control applied to taxiing aircraft. The goal of the decentralized control is to achieve high system performance. To measure the performance of aircraft taxiing operations, we used taxi time, average taxi speed, number of stops during taxiing and system throughput. We chose an agent-based modeling approach to implement the decentralized control. In our experiments, there are two types of agents that are interacting. Aircraft agents ensure safe separation to other aircraft and receive heading commands as they move through the taxiway system. Agents at each intersection control aircraft that are inbound to the intersection. They coordinate with other intersection agents to improve the traffic flow. As coordination mechanism, we implemented an auction between the intersection agents. We used an arbitrary taxiway layout for the experiments with a homogeneous traffic demand going from three gates to four runway entry points. To mimic the behavior of current taxiing operations we defined a procedure specific to the

given runway configuration. This procedure constrains the options of the decentralized controllers. It is designed to decouple the major traffic streams and serves as a reference for the performance of the unconstrained decentralized control. To test the effects of varying traffic demand we ran experiments with different aircraft spawn-rates at the gates. We also varied the scope of coordination, by changing the maximum distance at which other intersection agents were included in the auction. The simulations were run using a modified version of the Open-Source Simulator for ATM Research (OSSAR). To perform the experiments we added functionality to support our agent coordination mechanism.

Based on the experiments we can derive the following observations from our results:

- Coordination improves performance of the decentralized control for taxiing aircraft.
- Higher scope of coordination increases performance.
- The procedure achieves higher performance with respect to taxi-time and number of stops than any other simulated case for all simulated spawn-rates.
- For very high spawn-rates the procedure performs worse with respect to average taxi speed and system throughput than decentralized controllers with scope of coordination 2 and scope of coordination 3, since it limits the taxiway segments that can be used by the controller.

While the procedure results in good performance for static demand patterns, it cannot adapt to changes. If for example a taxiway is blocked or the runway configuration changes, the procedure would have to be changed as well. In current taxiing operations, this results in a set of procedures that take into account different scenarios. This is one major benefit of our decentralized control approach. Inherently it is adaptive and continuously responds to changing traffic situations. This property makes the decentralized control suitable to accommodate runway configuration changes and unforeseen disruptions of taxiing operations.

6.5.2. FUTURE WORK

There are several opportunities for future research based on the methods and experiment setup that we developed in this work. Using an auction between agents is just one of several coordination mechanisms that could be suitable for the intersection agents. Future work could explore how other coordination mechanisms impact the performance of the decentralized taxiing control. The route planning that we implemented is based on observation of the current traffic situation. The traffic in the system is continuously changing, and the changes are based on decisions of the intersection agents. Therefore, the future traffic situation can be anticipated by the intersection agents, and we expect that the system performance can be improved using anticipatory routing. We used an arbitrary airport layout for the experiments. The decentralized control should also be tested with real airport layouts and demand data to work towards a validation of the approach for real applications. One advantage of decentralized control is the ability to respond agile to changes in the system. A study on the response to configuration

changes and disruptions of the taxiway system, using example cases for the arbitrary airport layout and real airports, could evaluate the resilience of the decentralized control. The experiments with scope of coordination 2 and 3 showed similar performance to the procedure. This result could indicate the emergence of traffic patterns. Future work should investigate the emergent behavior of the decentralized control, and apply different complexity metrics to quantify the structure of traffic in the system.

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7

COMPLEXITY AND EMERGING BEHAVIOR OF DECENTRALIZED CONTROL FOR AIRCRAFT TAXIING

We implemented decentralized control for taxiing aircraft in previous chapters. Our results showed that the approach results in stable and efficient operations, even when the scope of information and coordination is limited. So far we focused on the system performance, but have not analyzed the traffic patterns that emerge from the decentralized control. In this chapter, we apply complexity metrics to measurements from previous experiments to understand the emerging behavior. We also test the response of the decentralized system to disturbances, which is one indicator for resilience. First, we introduce different complexity metrics. Then we apply these metrics to the experiment results. We set-up a runway configuration change as an example of a disruption to the taxiing system, and measure the response of the decentralized controller to this disruption. We close the chapter with a discussion of the performance of the decentralized controller in the context of traffic complexity and disturbance rejection.

7.1. INTRODUCTION

IN THIS chapter, we analyze the data that was gathered during the experiments in Chapter 6. Instead of analyzing the performance, the focus of this Chapter is on system complexity and emergent behavior traffic patterns. The aim of this chapter is to gain a better understanding of the mechanisms that result in the observed system performance.

In Chapter 6 we found that our implementation of decentralized control for taxiing aircraft results in different system performance depending on the coordination strategy. Most notably coordination strategies with higher scopes of coordination C_i resulted in a similar performance to a procedure that was designed for the taxiway layout and demand profile. Based on Monte-Carlo simulations we are confident that the differences in performance are significant. Thus far, we did not identify the cause of the differences in performance. The global system behavior of the decentralized control is not controlled explicitly. Instead, it emerges from local conditions and interactions of agents. Higher performance could be explained by the emergence of more optimal traffic patterns for the current traffic situation. Direct quantification of these traffic patterns is challenging. We can use traffic complexity as a measure of the existence of traffic patterns. For structured traffic that follows patterns, complexity is lower than for unstructured traffic. There are different ways to measure traffic complexity that we discuss in section 7.2. We expect a correlation between global system performance and traffic complexity. The procedure that we introduced in Chapter 6 forces all aircraft to follow a specific route. This behavior should result in the lowest traffic complexity.

7

As discussed in Chapters 2, 5, and 6, the resilience of Multi-Agent Systems is a desirable property for the Air Transportation System, which motivates implementation of decentralized control. So far we focused on the impact on performance and did not explicitly measure the resilience of our decentralized controllers. We designed our decentralized controller to respond continuously to changing conditions. The ability to adapt to changes is a requirement for a resilient system. Following the definition of Helbing [1], we understand resilience as the ability of a system to recover from disruptions. A system with higher resilience recovers faster from a disruption and loses less performance than a system with lower resilience. To compare the resilience of the different decentralized control concepts that we implemented, we measure the response of the system to disruptions. Runway configuration changes are common disruptions to airport taxiing operations. Accommodating these changes is challenging today's air traffic control concepts, which uses demand specific procedures. High resilience of the control system would improve utilization, by reducing the time until the performance of airport taxiing operations recovers from the runway configuration change. We, therefore, measure the system response to a runway configuration change to estimate the resilience of our implementation for decentralized control of taxiing aircraft.

In Section 7.2 of this chapter we introduce how we measure traffic complexity and define the experiment set-up and metrics for the disruption study. We present and discuss our results in Section 7.3. In Section 7.4 we present the conclusion of this chapter.

7.2. METHODOLOGY

In this Section, we introduce different metrics that are available to measure traffic complexity. We apply these metrics to measurements we recorded during experiments in Chapter 6, and analyze the impact of the different decentralized controllers on traffic complexity. We say that traffic is structured if it has low complexity, and unstructured if it has high complexity.

To identify traffic patterns we need to measure how aircraft travel through our taxiway system. Aircraft in our simulation travel through the system on specific taxiway segments. These segments connect taxiway intersections that we modeled as discrete points in cartesian coordinates. Instead of analyzing the movement of aircraft in Cartesian coordinates, we use the time series when aircraft are at the location of a specific intersection ID. This time-series represents the route that an aircraft takes through the system. Figure 7.1 shows a graph representation of the taxiway system.

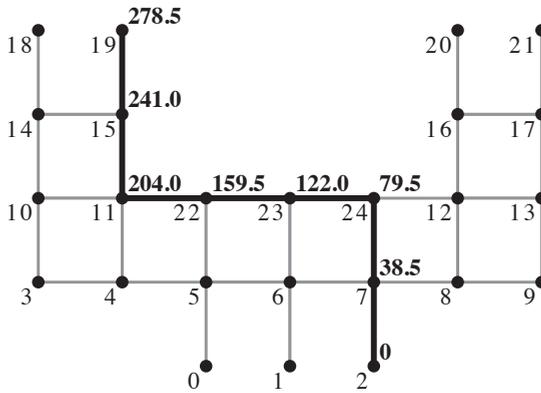


Figure 7.1: Graph representation of the taxiway system with waypoint IDs and example route with timestamps

In Figure 7.1 the intersection ID is written on the bottom left of each node. We highlighted an example route that an aircraft could take from Gate 2 to Runway Entry Point 19. The timestamps when it reaches each intersection is written in bold on the top right of each node. Table 7.1 shows the corresponding time series for this route.

Table 7.1: Time series of example route from Gate 2 to Runway Entry Point 19

Timestamp	0.0	38.5	79.5	122.0	159.5	204.0	241.0	278.5
Waypoint Id	2	7	24	23	22	11	15	19

Note that the timestamps of this time series are not equally spaced and discretized to the timestep of 0.5 seconds that was used in the simulation. These properties of the time series must be supported by the complexity metrics that are used.

A crude metric for complexity is the Standard Deviation of route length for a set of aircraft. If traffic is structured, aircraft follow similar routes through the taxiway system.

The length of the route, which is the number of waypoints that aircraft travel through, is similar for all aircraft and the Standard Deviation of route length is low. A higher Standard Deviation of route length indicates less structured traffic and higher traffic complexity. We measure the average standard deviation of route length for the entire simulation time to characterize the traffic complexity of a whole simulation run. To see if traffic patterns emerge during the simulation, we calculate a rolling average of the standard deviation throughout the simulation run. Periods of time with similar values for the standard deviation of route length, that are distinctly different from values during other time periods, would indicate the emergence of traffic patterns.

Another group of metrics for complexity are entropy measures. Entropy is a measure of disorder in the system and was first applied to information theory by Shannon [2]. In this context, time series data of a system with low disorder will have regular patterns, while a system with high disorder will have an irregular pattern. Applied to traffic complexity, low entropy in the time series of routes indicates low complexity and structured traffic. To analyze the time series data we use two different entropy measures from literature. Approximate entropy as defined by Pincus is "a measure for system complexity" [3]. Sample entropy is related to Approximate Entropy and was introduced by Richman and Moorman [4]. We used the existing MATLAB implementations of Approximate Entropy ApEn¹ and Sample Entropy SampEn² that are available in the MATLAB file exchange to analyze the time series data. Entropy metrics are used to identify traffic patterns in network traffic. An example application was demonstrated to monitor internet traffic, where unexpected changes in traffic complexity could indicate a cyber attack on the network [5].

To visualize and observe the emergence of traffic patterns, we plot usage of the taxiway system. We calculate the average number of aircraft that passed through each taxiway segment during a run. We plot the intersections of the taxiway layout in Cartesian coordinates. The thickness of the lines between the intersections represents the traffic density. Straight lines indicate one-way traffic. Curved lines show that the taxiway segments were used by aircraft taxiing in both directions. We evaluate the plots to see if there is a clear structure visible in the usage of the taxiway system.

We need to be able to quantify the response of our decentralized controllers to a disruption. After a disruption occurs, the system performance will be reduced. A system with high resilience will be able to:

- eventually achieve performance similar to before the disruption
- take less time to recover from a disruption.

We define both of these properties specific to the disruption that we introduce. As we motivated in Section 7.1 of this Chapter, we will introduce a runway configuration change. Specifically, we switch between Runway Configuration 1 and Runway Configuration 2 for departures, as defined in Table 7.2.

¹<https://www.mathworks.com/matlabcentral/fileexchange/32427-fast-approximate-entropy>

²<https://www.mathworks.com/matlabcentral/fileexchange/35784-sample-entropy>

Table 7.2: Active gates and runway entry points for Runway Configuration 1 and Runway Configuration 2

	Active gates	Active runway entry points
Configuration 1	[1, 2, 3, 4]	[18, 19]
Configuration 2	[1, 2, 3, 4]	[20, 21]

Aircraft leave the gates and taxi to the active runway, while any aircraft that are added to the simulation after the time of the configuration change (t_{change}) are sent to the new active runway. We assume that the two runways can operate independently.

We measure the rolling average of the throughput of both runway entry points to characterize the runway use over time. The ideal system behavior in response to the runway configuration change would be:

- No more aircraft take off from the previously active runway after t_{change} .
- Aircraft immediately take off from the new active runway after t_{change} .
- After the switch, the throughput of the new active runway is equal to the throughput of the previously active runway, within a short period of time.

We measure time delays between the disruption and the system response to evaluate the resilience of the system. Smaller time delays are preferable, and essentially:

- We define bleed-time (t_{bleed}) as the time from the runway configuration change to the last aircraft reaching one of the entry points of the previously active runway.
- We define lead-time (t_{lead}) as the time from the runway configuration change until the first of at least five consecutive throughput observations of the new active runway, which are greater than 95% of the average throughput of the previous runway configuration.

Figure 7.2 shows an example how the lead- and bleed-time are measured.

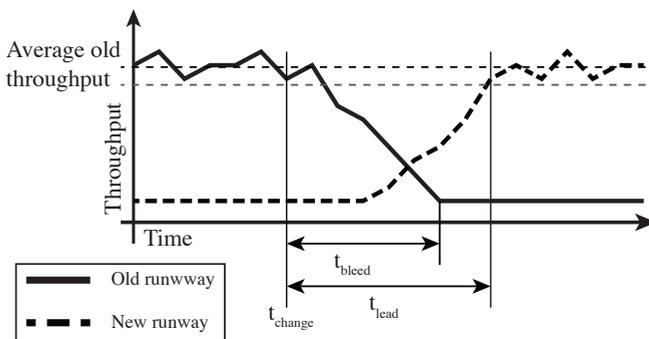


Figure 7.2: Lead-time and bleed-time after a runway configuration change

We run 100 simulations for each decentralized control strategy and simulate 6 hours of traffic in each run. We simulate a homogeneous traffic demand with different demand

levels, which we implement by a set aircraft spawn-rate at the gates. The runway configuration changes every 30 minutes between Configuration 1 and Configuration 2. We measure and compare the bleed- and lead-times for each decentralized control strategy.

7.3. RESULTS AND DISCUSSION

In this Section, we present the results for the metrics that we introduced in Section 7.2. We first relate the traffic complexity that occurred during the simulations to the system performance and then discuss the disruption response of our decentralized controllers. The experiment setup is the same as in Chapter 6, which was introduced in Section 6.3.1. We test and compare the same coordination strategies that we used in Chapter 6:

Table 7.3: Coordination Strategies

Case	Description
Uncoordinated	No coordination between control agents
C_i	Coordination between the control agents using scope of coordination i
Procedure	The control agents are constrained by a procedure to decouple traffic streams; No coordination

7.3.1. TRAFFIC COMPLEXITY

STANDARD DEVIATION OF ROUTE LENGTH

As it is the most basic complexity metric that we defined in Section 7.3, we first plot the Standard Deviation of route length averaged over 500 simulation runs.

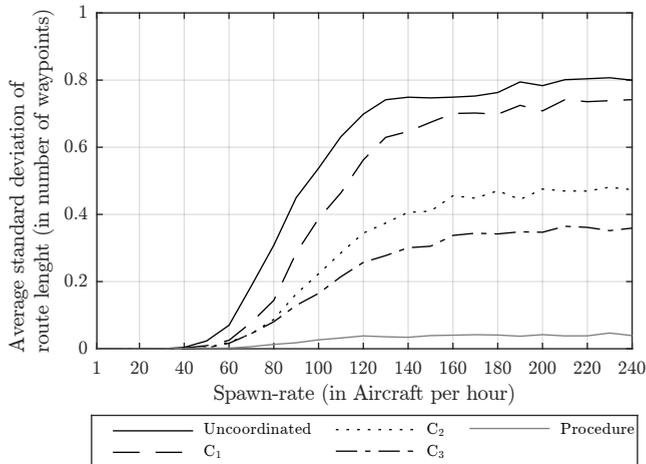


Figure 7.3: Average standard deviation of route length for different coordination strategies

In figure 7.3 all cases show that there is no significant Standard Deviation of path length for spawn rates of up to 40 aircraft per hour. All aircraft take routes of the same

length from their gates to the runway entry points. Due to the low traffic density, there are no conflicts between traffic streams and aircraft do not have to deviate from the shortest route.

For spawn-rates between 40 and 160 aircraft per hour the standard deviation of route lengths increases for all cases. Controllers reroute aircraft away from the shortest route to resolve conflicts with other traffic.

Starting with the spawn-rate range between 130 and 170 aircraft per hour, all cases asymptotically approach a maximum standard deviation of route lengths. Two different effects contribute to this behavior: Naturally, there is a maximum number of possible paths to get from the gate to the runway entry point, so the path length must be bounded. Also, as we discussed in Section 6.4, the effective spawn-rate is limited due to throughput constraints of the taxiway system.

The highest complexity is recorded for the uncoordinated case. Without coordination, there are no constraints in place which route aircraft take through the system.

The lowest complexity occurs for the procedure. In the procedure case, the possible paths between gate and runway entry point are constrained. The procedure is set up to decouple traffic streams. This behavior results in fewer conflicts, which reduces the need to reroute traffic in order to resolve conflicts.

Coordination results in lower complexity compared to the uncoordinated case, and higher scopes of coordination further reduce complexity. Our coordination mechanism is set-up to avoid unnecessary detours and have aircraft wait until a taxiway segment becomes available. As a result, the coordination mechanism simplifies the traffic structure.

It is interesting to note that the spawn rates at which significant differences between the cases occur correspond to the spawn rates at which significant differences in performance occur in chapter 6.4. For up to 40 aircraft per hour, there is no difference between the cases. At 60 aircraft per hour C_1 is significantly different from C_2 and C_3 , and at 90 aircraft per hour C_2 shows significantly lower Standard Deviation of route length than C_1 .

APPROXIMATE ENTROPY

Figure 7.4 shows approximate entropy for the different cases as a function of spawn rate. The results are presented as averages of 500 simulation runs. The results in Figure 7.4 show that the lowest values for approximate entropy occur for low spawn rates. Since traffic density is low for these spawn rates, there is no need to reroute aircraft and aircraft follow the same route from their origin to their destination. For spawn-rates up to 130 aircraft per hour the approximate entropy for all cases increases. This increase again indicates that the traffic complexity is increasing with higher spawn-rates. For all cases, the approximate entropy asymptotically reaches a maximum at spawn-rates in the range between 140 and 180 aircraft per hour. The uncoordinated case results in the highest approximate entropy, where there is no structure imposed, and the traffic complexity is high. Similar to the other complexity metrics, the Procedure results in the lowest approximate entropy. Coordination reduces complexity as measured by approximate entropy, and a higher scope of coordination further reduces complexity. For spawn-rates greater than 90 aircraft per hour, cases C_2 and C_3 result in markedly lower complexity than the uncoordinated case and C_1 . This result again corresponds to the spawn-rate where the performance was significantly different in Section 6.4.

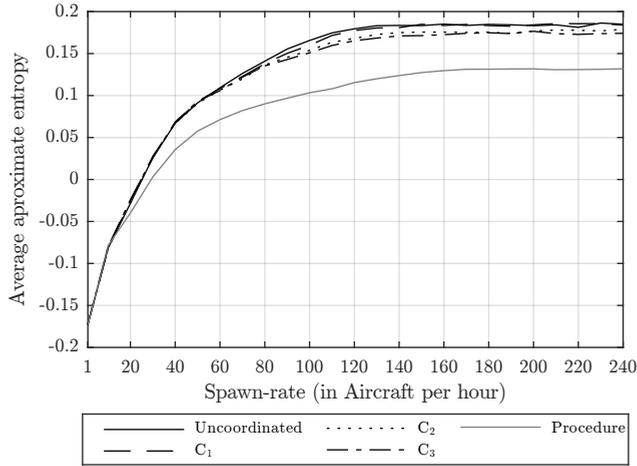


Figure 7.4: Average approximate entropy for different coordination strategies

SAMPLE ENTROPY

A similar complexity metric to characterize traffic data is sample entropy, which we introduced in Section 7.2. Figure 7.5 shows sample entropy for the different cases as a function of spawn-rate. The results are developed from averages of 500 simulation runs.

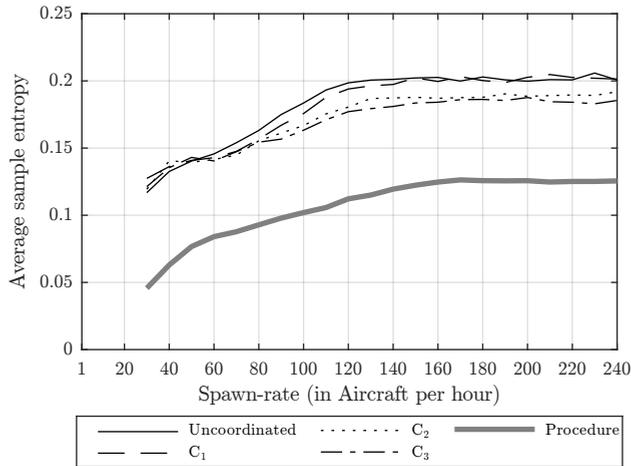


Figure 7.5: Average sample entropy for different coordination strategies

It is interesting to note that for spawn-rates of less than 30 aircraft per hour, there are no values available for the sample entropy. The sample entropy cannot be computed here since in this range there is not enough data available due to the low traffic density. For spawn rates of between 30 and 120 aircraft per hour, sample entropy increases for all

cases. In the range between 120 and 160 aircraft per hour, the sample entropies of the different cases start to converge to a maximum value. Similar to before, this maximum value occurs as the number of possible paths between gates and runway entry points is limited, and the effective spawn rate is also limited. The highest sample entropy occurs for the uncoordinated case, but for spawn-rates greater than 130 aircraft per hour there is no significant difference between the uncoordinated case and C_1 . For high spawn-rates, there is no difference in the traffic complexity of these two cases. For the Procedure, the sample entropy is lower than for any of the other cases. The procedure constrains the routes between the gates and the runway entry points, which results in traffic with less complexity. Coordination reduces traffic complexity compared to the uncoordinated case, and higher scopes of coordination results in lower traffic complexity. The coordination leads to more structured traffic. For high spawn-rates the uncoordinated case and C_1 , and C_2 and C_3 have similar sample entropy.

SUMMARY

All three complexity metrics show similar trends. These are that:

- Low spawn-rates result in low complexity.
- High spawn-rates result in high complexity.
- Coordination reduces complexity.
- Procedure results in lowest complexity.

The results of the performance metrics that we presented in Section 6.4 show the inverse trends. Also, significant differences in complexity occur at the same spawn-rates as significant differences in performance. Thus, the results indicate that there is a correlation between the entropy and the performance.

7.3.2. TIME DEPENDENT TRAFFIC COMPLEXITY

As the traffic situation changes throughout a simulation run, the traffic complexity changes throughout the simulation run as well. Areas with low complexity occur if traffic is structured and could indicate emergence of traffic patterns. There are 500 simulation runs for each simulation setup. To analyze the results in a structured way, we select individual simulation runs based on criteria for spawn rate and traffic complexity. We chose a spawn rate of 100 aircraft per hour. As seen in section 7.3.1, this was the highest spawn rate where no saturation effects occurred for any of the complexity metrics. Out of the 500 simulation runs for this spawn rate, we select one simulation run that has a complexity closest to the median complexity measured for all 500 simulation runs. Figure 7.6 shows the standard deviation of route length as a function of time for one simulation run of the uncoordinated case and the case with scope of coordination C_2 .

Figure 7.6 shows that for both the uncoordinated case and the case with scope of coordination 2, there are periods of time with 0 standard deviation of path lengths. Comparing both cases, the periods where the standard deviation of route length > 0 are longer and more frequent in the uncoordinated case. The maximum standard deviation

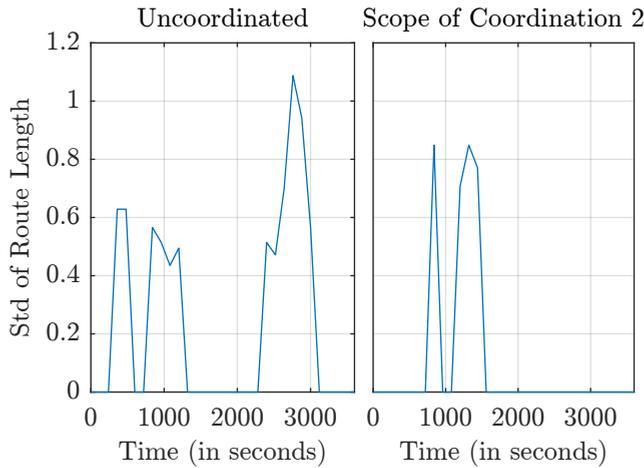


Figure 7.6: Comparison of standard deviation of path length for one representative run with spawn rate 100 aircraft per hour

of route length is higher for the uncoordinated case. The periods with low complexity indicate the emergence of stable traffic patterns.

Figure 7.7 shows the sample entropy as a function of time for one simulation run of the uncoordinated case and the case with scope of coordination C_2 :

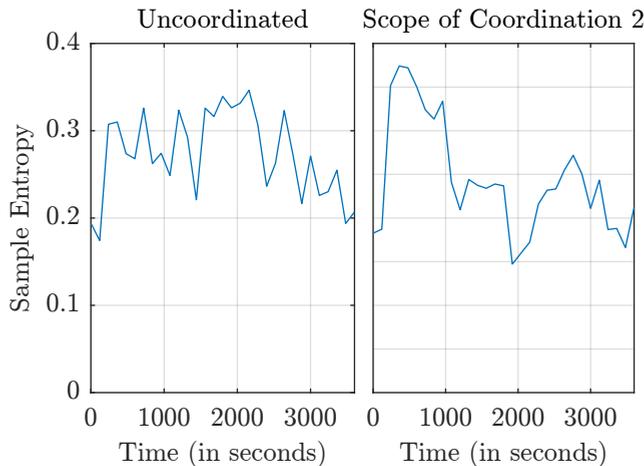


Figure 7.7: Comparison of sample entropy for one representative run with a spawn rate of 100 aircraft per hour

The results in Figure 7.7 show that both cases have similar values for entropy. Both cases start and end with low values, which is due to the moving value calculation that uses ± 10 minutes of data to calculate the value at each time. The sample entropy of the uncoordinated case oscillate irregularly, has no clear patterns emerging, and does

not show periods of time with low entropy. The case with scope of coordination 2 has an area with high sample entropy at the beginning and an area with low sample entropy at about 2000 seconds. The area of low sample entropy could indicate the emergence of traffic patterns.

Figure 7.8 shows the approximate entropy as a function of time for one simulation run. Since approximate entropy and sample entropy are very similar metrics, we selected the same specific simulation runs. Again, we compare the uncoordinated case and scope of coordination C_2 .

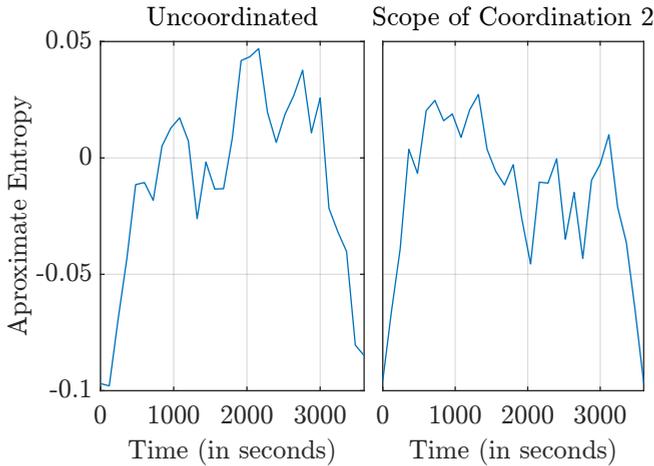


Figure 7.8: Comparison of approximate entropy for one representative run with a spawn rate of 100 aircraft per hour

As figure 7.8 shows, the approximate entropy for both cases starts and ends with low values. Similar to the sample entropy, this is due to the way the values are calculated at each time point. The uncoordinated case shows an area with lower entropy at about 1100 seconds and an area with higher entropy at about 2000 seconds. The case with scope of coordination 2 shows higher entropy at 1000 seconds and slightly lower entropy between 2000 and 3000 seconds. Overall the case with scope of coordination 2 has lower values than the uncoordinated case.

All three metrics shows that system complexity changes over time. The standard deviation of route length showed areas with 0 complexity. Sample entropy and approximate entropy did not show clear patterns. Based on the results, there is no clear indication of emergence in the system. This may be due to the homogeneous global demand distribution on the system that does not favor any specific traffic pattern.

7.3.3. TRAFFIC PATTERNS

In this section, we present and discuss the taxiway usage during the simulation runs. The Figures show the intersections of the taxiway layout as circles, and lines in the Figures that connect the intersections represent the traffic flow between intersections. The thickness of the lines and the labels next to the lines show the number of aircraft that

pass through a taxiway segment. To see if there are significant differences between control strategies we show the cumulated traffic for all simulation runs.

First, we show results for the uncoordinated case, which lead to the highest complexity in section 7.3.1. Figure 7.9 shows the taxiway usage during 500 simulation runs of the uncoordinated case for a spawn rate of 100 aircraft per hour.

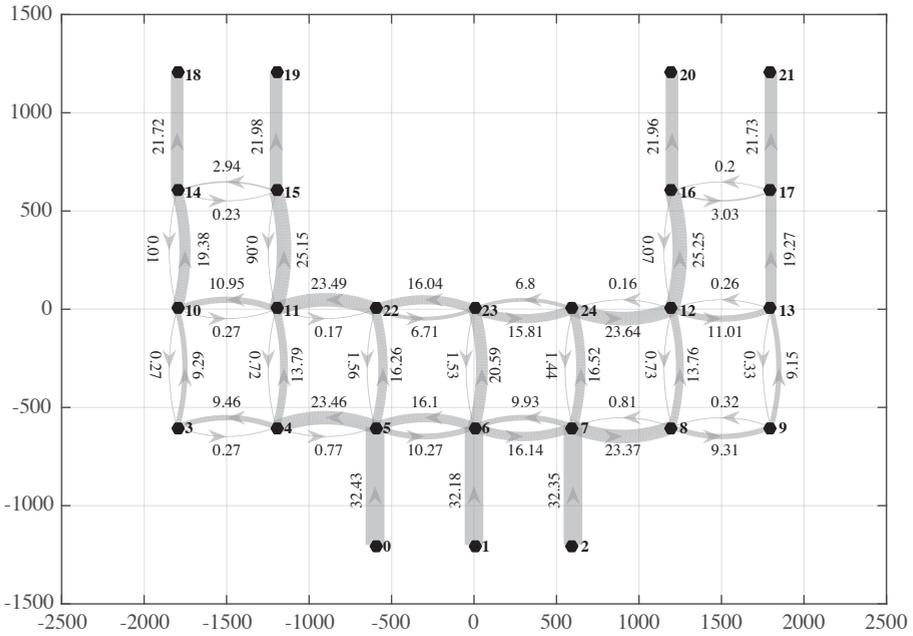


Figure 7.9: Average taxiway usage of uncoordinated decentralized controllers for 500 simulation runs with a spawnrate of 100 aircraft per hour

The traffic flow in Figure 7.9 shows balanced traffic counts from all three gates and to all four runway entry points. Most taxiway segments are dominantly used in one direction. For most segments at least ten times as much traffic is traveling in one direction than the other direction. Between nodes 5 and 6, 6 and 7, 22 and 23, and 23 and 24 traffic flows in both directions are more similar.

Figure 7.10 shows the results from the simulations of the case with scope of coordination 2. The traffic flow in Figure 7.10 is balanced between the tree gates and between the four runway entry points. Traffic on most taxiway segments is traveling in the same direction, with at least 15 times as much traffic traveling in one direction than in the opposite direction. Between nodes 5 and 6, 6 and 7, 22 and 23, and 23 and 24 traffic is traveling in both directions.

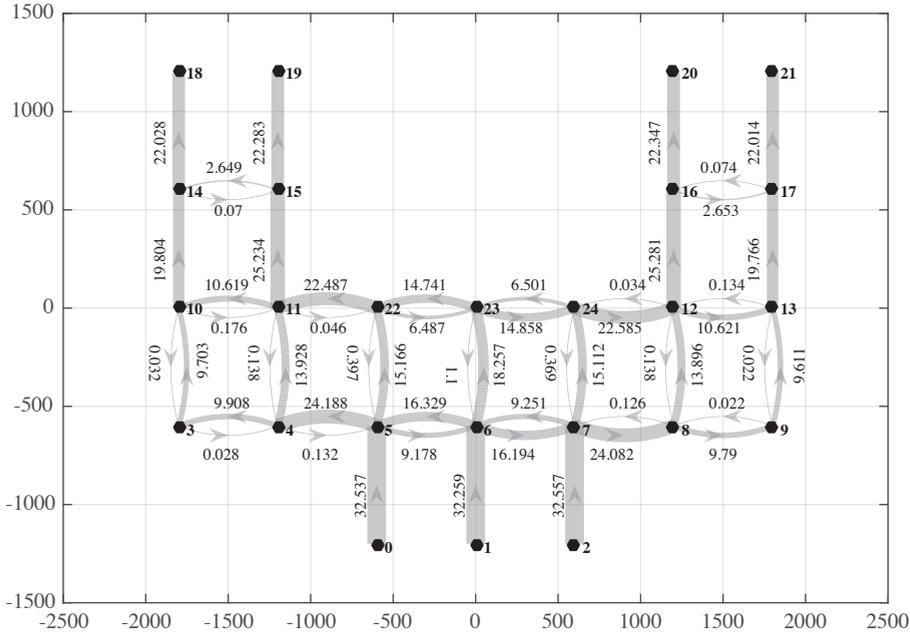


Figure 7.10: Average taxiway usage of decentralized controllers with scope of coordination 2 for 500 simulation runs with a spawnrate of 100 aircraft per hour

The taxiway usage shown in figures 7.9 and 7.10 show similarities between the decentralized control without coordination and scope of coordination 2. A clear structure of the taxiway system is visible, and the taxiway system can be divided into three main areas:

1. Taxiway segments left of waypoints 5 and 22 are primarily taxiing left towards runway entry points 18 and 19.
2. Taxiway segments right of waypoints 7 and 24 are primarily taxiing right towards runway entry points 20 and 21.
3. In the center area taxiway segments are used in both directions. This is the area where aircraft taxiing towards runway entry points 18 and 19, and 20 and 21 taxi on the same taxiway segments, where the controllers have to resolve conflicts, so aircraft do not taxi in opposite directions on the same taxiway segments.

When closely comparing the taxiway usage in figures 7.9 and 7.10 we observe that while the global structure is similar there are small but noticeable differences. With scope of coordination 2, there are less aircraft taxiing in the opposite direction from the main traffic flows, for example between waypoints 10 and 3, 13 and 19, 4 and 5, and 8 and 7. With scope of coordination 2, less aircraft use taxiway segments between waypoints 14 and 15, and 16 and 17 to switch between runway entry points. With scope of coordination

2, the traffic is separated earlier during the taxiing. The total number of aircraft movements in Area 3 (see above) in the center of the taxiway system where traffic streams mix, is lower with scope of coordination 2 than for the uncoordinated case. This shows that there are unnecessary aircraft movements in the uncoordinated case. The controller in the case with coordination can hold aircraft and wait for a taxiway segment to become available to utilize a shorter and more efficient route. These small differences between the two cases lead to the overall smaller complexity and higher performance of the case with scope of coordination 2 compared to the uncoordinated case, which we discussed in Section 7.3.1 and Section 6.4.

7.3.4. DISRUPTION RESPONSE

We ran simulations for 1000 runway configuration changes, as described in Section 7.2. We compared the uncoordinated case to decentralized controllers with scope of coordination C_1 , C_2 , and C_3 . The spawn-rate is 120 aircraft per hour. Figure 7.11 shows a boxplot of the bleed times for the different simulation cases.

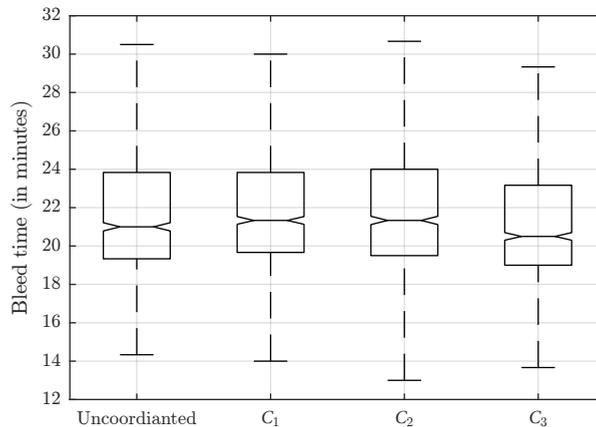


Figure 7.11: Boxplot of bleed times after runway configuration changes for different coordination cases

The results in Figure 7.11 show no significant difference between the four different cases. Scope of coordination C_3 has a 2% lower median than the uncoordinated case, lower upper and lower adjacents, and lower 25th and 75th percentiles.

Figure 7.12 shows a boxplot of the lead times for the different simulation cases. As can be seen in Figure 7.12, the differences in lead time between the four cases are small. The median lead time for the uncoordinated case is smallest for the uncoordinated case and about 0.5% smaller than the median lead time of the case C_3 .

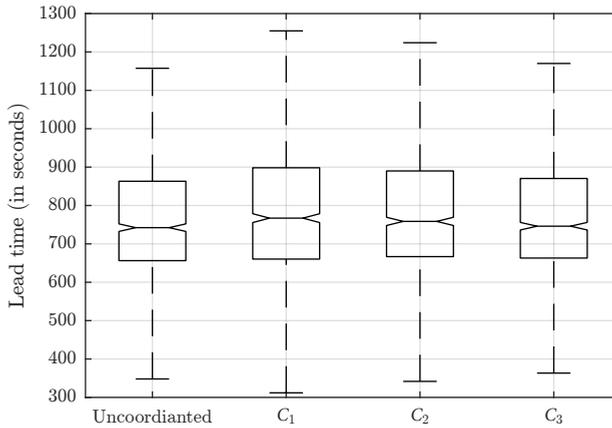


Figure 7.12: Boxplot of lead times after runway configuration changes for different coordination cases

7.4. CONCLUSION

In this Chapter, we investigated the traffic complexity, emerging traffic patterns, and the disruption response of the decentralized controllers. We used observations that were recorded during experiments for Chapter 6 for the analysis of traffic complexity and emerging traffic patterns, and simulated runway configuration changes to study the disruptions response of the decentralized control system.

Our results show differences in traffic complexity for the varying coordination strategies of the decentralized controllers. The uncoordinated case resulted in the highest complexity. With higher scopes of coordination complexity decreased, and the procedure resulted in the lowest traffic complexity. An interesting observation is that changes in the standard deviation of path length correspond to changes in performance that we discussed in Section 6.4.

Although the traffic complexity changes over time, we could not distinguish phases with different levels of complexity within individual simulation runs. This indicates that no traffic patterns are emerging during the simulation runs. This finding can be explained, as we are studying a symmetric taxiway layout with homogeneous demand and thus, there is no single preferred solution to handle traffic.

There is a global structure visible in the average taxiway usage of all simulation runs. Most taxiway segments are primarily used in one direction. Only in the area where different traffic streams are meeting are taxiway segments used for traffic in both directions. There are small differences in the average taxiway usage between the uncoordinated case and the case with scope of coordination 2. The total traffic count in the center area of the taxiway layout is higher for the uncoordinated case, which shows that without coordination there are unnecessary aircraft movements during taxiing.

The disruption study showed that all decentralized controllers could handle runway configuration changes. The differences in lead time and bleed time between the different coordination strategies are not significant.

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8

CONCLUSION

In this work, we motivated and presented a decentralized approach to control taxiing aircraft at an airport as an example of the applicability for the Air Transport Systems. We demonstrated that decentralized controllers at the intersections could successfully handle the traffic with local knowledge. We have shown that coordination between agents improves system performance. In this Chapter, we summarize the results, discuss implications of this work for current operations, and suggest future research on decentralization that could further benefit the air transportation system, as well as other infrastructure networks. At the end of this Chapter, we propose a methodology to evaluate if tasks can be decentralized.

THE goal of the Thesis was to demonstrate the applicability of decentralized control in the air transportation context. Specifically, that there are tasks in the context of Air Traffic Control (ATC) where decentralization can be applied to ensure viable operations without significant performance penalties. We selected a relevant sub-area of the vast and complex field of ATC: Aircraft taxiing operations at an airport. This area is the focus of ongoing research since the efficiency of aircraft taxiing impacts performance, capacity, and the environmental impact of flight and airport operations. The following core objectives that we defined in Section 1.2 of the thesis were addressed for decentralization in the context of aircraft taxiing:

- To highlight the challenges and limitations of current centralized approaches for planning and control of air traffic control
- Specify and discuss relevant performance indicators for ATC
- Implement a decentralized control approach in a relevant ATC context
- Explore the impact of critical parameters for decentralized control, specifically, demand, information, and coordination, on system stability and performance

This Chapter summarizes and discusses how these objectives were met in this thesis. We first highlight the main contributions of this work to the body of knowledge, some of which we introduced in Section 2.6. Then we discuss the main findings of the thesis. We close this Chapter with recommendations for future research and propose a methodology to assess the viability of decentralization.

8.1. CONTRIBUTIONS

To sustain the growing demand for air transportation, Air Traffic Control must provide the capacity to process and guide flights through the air transportation system. With a limited ability to expand existing infrastructure, the effort of research and industry is focussed on improving the operation of the existing infrastructure. The mental capacity of the human air traffic controller has been identified as one capacity bottleneck in the system. Several current developments focus on reducing the workload of each controller through automation or on balancing the load between controllers through restructuring. Both of these approaches follow a centralized control paradigm, which is constrained by the capacity of a central actor in the system, and vulnerable to failure of a few central actors of the system. A scalable, agile, and robust system is desirable for Air Traffic Control operations to meet future requirements for capacity and safety. In this Thesis, we proposed and demonstrated the application of decentralization in the context of Air Traffic Control. Specifically, we implemented a decentralized control infrastructure to handle aircraft taxiing operations at an airport. This infrastructure autonomously and dynamically adapts to changing conditions in the system. We do not believe it is feasible or desirable to decentralize the entire air transportation system. Instead, we propose to identify tasks that can be decentralized without compromising system stability and to utilize decentralization to increase the capacity and performance of the system.

We presented the core results of this work in three independent Chapters. In Chapter 4 we presented an analytical solution for aircraft push-back scheduling, which is a key

part of the planning of taxiing operations. We explicitly took into account uncertainty in aircraft taxiing using Cumulative Density Functions. This Chapter motivated splitting up the taxiing process into smaller, local problems with less uncertainty, that can be solved by decentralized controllers. In Chapter 5 we implemented a decentralized control for aircraft taxiing, and evaluated the impact of scope of information on system stability and performance, using an arbitrary airport layout. In Chapter 6 we compared different coordination strategies between decentralized controllers. In that Chapter, we showed how coordination could improve system performance. While these Chapters are self-contained, they motivate and demonstrate the implementation of decentralization in the context of air traffic control, with a focus on aircraft taxiing operations.

The primary contributions of this thesis were:

- **The feasibility of decentralization was demonstrated in the context of Air Traffic Control**

In Chapters 5 and 6, we implemented a decentralized control of aircraft taxiing for an arbitrary airport layout. We demonstrated that the decentralized controllers could successfully guide traffic through the taxiway system at various demand levels. They were able to avoid forbidden or unsafe states, specifically aircraft taxiing in opposite directions on the same taxiway segment. In Chapter 2 we highlighted that the current ATC follows a centralized paradigm, highlighted the limitations of centralization, and discussed that decentralization could help to increase the capacity and performance of the Air Transportation System. We demonstrated that decentralization could provide a viable approach to control aircraft taxiing operations during the tactical phase that responds to changing traffic conditions and results in stable operations.

- **A distributed and autonomous control infrastructure that commands traffic agents was developed**

In Chapters 5 and 6 we decentralized the control of aircraft taxiing operations. In current operations, centralized human controllers give commands to aircraft to guide them through the taxiway system. Compared to other work that let aircraft choose their own routes, our approach was to implement autonomous controllers at each intersection. These controllers observe the state of the taxiway system and provide routing commands to approaching aircraft. Aircraft autonomously kept safe separation distances from other aircraft and adjusted their speed in accordance with the commands of the controllers - as pilots are doing today.

- **The impact on scope of information of decentralized controllers was investigated**

In Chapter 5 we explored how little information is sufficient to control aircraft taxiing. We varied the scope of information, which is the geodesic distance at which a controller at an intersection can observe traffic, from only the adjacent taxiway segments to all taxiway segments in the taxiway system. These experiments allowed us to determine the minimum required information to successfully control aircraft taxiing, and to investigate if there is a performance benefit from having more information available.

- **Different coordination mechanisms were implemented and compared for the decentralized controllers**

In Chapter 6 we implemented and compared different coordination strategies. We implemented an auction mechanism where the decentralized controllers compete for using taxiway segments. The controllers based their bids on the shortest routing of aircraft through the taxiway system. As a performance reference, we designed a static procedure specific to the taxiway layout and demand situation that effectively decoupled the major traffic streams in the system. We compared the performance of this procedure to varying scopes of coordination, which is the geodesic distance how far a bid of an agent can be propagated through the system.

- **An analytical solution for part of the planning of aircraft taxiing operations was developed**

In Chapter 4 we presented an analytical solution for the push-back scheduling of taxiing operations. Our solution explicitly took into account the uncertainty of aircraft taxi times. We use the Cumulative Density Function of aircraft taxi time to determine aircraft availability at the runway, and propagate uncertainty to consecutive departures. Compared to other work that uses computational methods to optimize push-back times, our solution can reduce computational effort for part of the planning problem for aircraft taxiing.

- **A flexible agent-based simulation environment for air traffic was developed**

For the experiment in Chapters 5 and 6 we developed an agent-based air traffic simulator. This air traffic simulator provided a modular, open-source environment to conduct experiments and test new concepts for Air Traffic Control. In other work, this simulator was used to simulate mid-air encounters between air traffic. In on-going work, this simulator is being used to simulate aircraft taxiing operations at Amsterdam Schiphol Airport.

8

8.2. MAIN FINDINGS

Based on the results of this work, we would like to highlight the following findings:

- **Given that a minimum amount of information is available, decentralized control of aircraft taxiing results in viable operations**

Chapter 5 showed that the decentralized controllers could successfully handle aircraft taxiing operations at an airport. If the controllers only had information about the adjacent links available, then unsafe states occurred during the simulation. In the specific case that was simulated, providing information about two consecutive taxiway segments to each decentralized controller was enough to avoid unsafe states in the system. We expect that the value for this threshold is different for other taxiway layouts. This finding means that global information about the system is not required for successful decentralized control, and local information about the system is sufficient to ensure valid decentralized control.

- **Limited information about the state of the system is sufficient to achieve good performance**

The results in Chapter 5 showed that the scope of information has an impact on performance and that there is a threshold scope of information, at which the performance is similar to the global scope of information. Adding more information did not result in better performance for decentralized control. The performance was measured by taxi-time, average taxi speed, number of stops, and system throughput. This finding is important since it can motivate avoiding the cost associated with gathering and processing global information at each controller.

- **Coordination can improve the performance of decentralized control and outperform a pre-defined, static procedure**

In Chapter 6 we implemented different coordination strategies. We compared the performance of decentralized controllers without coordination to controllers that used an auction-based coordination with varying scopes of coordination to a procedure that was designed specifically to the airport layout. The results show that higher scopes of coordination improve any of the tested performance metrics. For high spawn rates scope of coordination 2 achieved even higher performance than the controllers following procedure, while keeping the flexibility of the decentralized control.

- **Uncertainty constrains performance**

In Chapter 4 we determined the trade-off between flight delay and runway utilization using an analytical approach. For lower uncertainty in aircraft taxi times, the desired runway utilization could be achieved with lower cumulated expected flight delays. This result highlighted that uncertainty constrains the achievable system performance. This finding motivated splitting of the taxiing process into smaller problems with less uncertainty, which lead to the decentralized approach.

- **A 100% runway utilization is not achievable in real airport operations**

The analytical approach in Chapter 4 showed that a 100% runway utilization could only be achieved if aircraft are guaranteed to arrive at the runway before it becomes available. In a theoretical model, aircraft taxi times can reach infinitely high values, which means aircraft would have to leave the gate infinitely early before the flight and then accumulate delay as they wait for the runway to become available. In reality, a 100% runway utilization cannot be guaranteed, as flights would have unacceptable waiting times at the runway.

8.3. FUTURE WORK

- **Test the algorithm with realistic airport layout**

A major limitation of the results in Chapter 5 and Chapter 6 is that an arbitrary airport layout was used in the experiments. Potentially, our control approach could be used to enable autonomous control of new aircraft guidance systems such as "follow-the-greens" [1]. The first step towards an implementation of such a system is to validate our decentralized controller with a real airport layout. It might be necessary to expand the control agent behavior to support more complex airport layouts, and as mentioned in the previous Section, some of the main findings may differ for a real airport layout.

- **Elaborate the disruption response survey**

In Chapter 7 we presented the results of disruption response experiments. In these experiments, we switched the runway configuration of the airport and measured the time it takes the system to return to the performance levels before the switch. In future work, it shall be explored, how the decentralized controller responds to other types of disruption, for instance, the closure of one or several taxiway segments. The goal of this disruption study would be to demonstrate the robustness and resilience of the decentralized control.

- **Implement more advanced methods to improve the agent behavior**

The decentralized control that we used in Chapters 5 and 6 used agents at each intersection that control traffic that approaches the intersection. Aircraft are handled individually by the controller and are processed in the order of their individual priority. In future work aircraft that are approaching from the same link could be grouped together and processed as a single unit by the controller. Such a platooning logic can improve traffic flow and reduce the amount of communication between controllers and aircraft.

In Chapter 6 we demonstrated that the performance of the decentralized control could be improved by using coordination. The results in Chapter 7 showed that the performance increase was correlated to lower system complexity, but coordination did not lead to the emergence of traffic patterns. In a next step, agent-based learning mechanisms could be employed to improve the performance of the decentralized control further. A learning mechanism could lead to the emergence of stable traffic patterns, which would reduce the complexity of traffic and improve performance, similarly to the procedure in Chapter 6.

In Chapters 5 and 6 the routing decision of the agents is based on the current traffic situation, which implicitly assumes that the current traffic situation of a certain part of the system is still present by the time an aircraft reaches that part of the system. While this assumption is acceptable for areas close to the current aircraft position, for areas that are far away, we expect the traffic situation to have changed in the future. In future work, the routing decision of the agents should take into account the future states of the system using anticipatory routing.

- **Explore decentralization in other areas of Air Transportation**

As we discussed in Chapter 2, decentralization could help in addressing several of the current challenges of the Air Transportation System. While in this work we focused specifically on the aircraft taxiing operation at an airport, operations at areas that are currently managed by a centralized control could benefit from decentralization, for example:

- Flow control ensures that capacity constraints of Air Traffic Control resources are not exceeded. In a decentralized approach, each resource could be an autonomous controller that communicates its current and forecast capacity in order to manage utilization collaboratively with other resources.
- Another interesting area could be maintenance decision making. Currently, maintenance technicians that discover a fault will communicate with a cen-

tral maintenance department and wait for a work order to conduct a repair. For some of these maintenance jobs, technicians might have all relevant information locally available and would come to the same decision as the central maintenance department. In a decentralized approach, more autonomy would be given to technicians to decide if and how to repair a fault. This approach could save time and capacity for the central department, and thus, reduce the cost of maintenance.

- Another application could be the prioritization of flights in the case where there are conflicting flight plans that want to utilize the same slot. Currently, a central authority decides which flight gets priority without explicit information about the importance of a flight for the airline. In a decentralized solution, airlines would compete to decide which flight gets priority. For this approach, an auction mechanism could be employed where airlines use their knowledge about the value of a flight for their operations to bid for a specific slot.

- **Apply decentralization to other domains with smart infrastructures (road traffic, electric power grids, etc.)**

In the area of road transportation developments are moving towards autonomous and sensor-rich cars that can communicate with each other and the road infrastructure, to improve the efficiency of the road network. To implement a centralized control, the size, complexity, and amount of uncertainty of the road network requires significant data processing and transmission capacity. To reduce system cost, much of the system could use decentralized control, and only crucial tasks in the system should be centralized. This would follow the approach that is already being implemented in computer networks, where Big-Data applications decentralize much of the computational load. As a first case study, the algorithms we developed in Chapters 5 and 6 could be adapted to be used for smart traffic lights. In the electric power grid, the demand side is highly decentralized, as the consumption behavior of individual customers determines global demand. The push towards renewable energy results in decentralization on the generation side as well. Local knowledge can help reduce uncertainty in demand and utilize volatile energy sources more efficiently. Studying emerging effects can motivate smart grids, where local control of demand and supply can reduce the need for energy storage and transportation.

8.4. PROPOSED FRAMEWORK FOR DECENTRALIZATION

The premise of this work was that decentralization can help to solve some of the current challenges in the Air Transportation System (ATS). We demonstrated that a decentralized control can successfully handle aircraft taxiing operations at an airport. This case is just one specific task in the air transportation system. We do not expect that it is feasible or desirable to decentralize every task or component of the ATS. As we discussed in Chapter 2, a framework is needed to assess if a task in the Air Transportation System can be decentralized. These criteria should provide an estimate of the system-wide impact of decentralization of individual tasks. As a final contribution from the insight gained

in this work, we propose such a framework that classifies tasks within the system and allows the estimation of which tasks can be decentralized.

8.4.1. CONTEXT

The Air Transportation System (ATS) is a complex socio-technical system. It has human and technical components that interact within an environment. Each of these components responds to changes in the system, the environment, the state of each component, and the system changes over time. The ideal state of technical components, as well as the goals and objectives of humans in the system, are diverse and can contradict each other.

The ATS is subject to system-level constraints. These constraints may not be violated or exceeded to achieve a stable system. They can relate to macroscopic properties, such as the rate of people and goods transported in the system, mesoscopic properties, such as the required capacity of an airport, and on a microscopic level such as keeping a safe separation between aircraft.

The performance of the ATS is measured using global performance indicators. Typically, these indicators capture the capacity, efficiency, and environmental impact of the system. While they are used to measure performance on a system-wide level, these indicators commonly are measured on a local level and accumulated across the entire system. One example of such an indicator is the capacity of the ATS, which is determined by the sum of the capacities of individual airports and airspaces.

The global properties of the ATS emerge from local interactions of actors within the ATS. Actors in the ATS use information from their local environment, other agents, and global rules to make decisions. Based on their decisions, actors take actions. These actions change the state of the actor and can affect other actors in the system. These interactions between actors propagate through the systems and thus, can affect the system on a global level. The globally-perceived state of the system is based on the state of all individual actors.

Depending on the mechanism of how the actors in the system interact, we can identify different types of interdependencies between parts of the system. Rinaldi et al. [2] introduce a classification that distinguishes “physical, cyber, geographic, and logical” interdependencies. This classification of interdependencies helps to understand how actors within a complex system affect each other. Understanding the interdependencies in the system is critical to ensuring that the actions of individual actors in the system do not lead to a violation of system level constraints or an undesired impact on performance.

8.4.2. FRAMEWORK

Using a MAS model, each actor in the ATS can be represented by an individual decision unit. MASs are distributed control systems where decision units can directly or indirectly affect each other. We can represent a decision unit with a simplified model using the Structured Analysis and Design Technique (SADT) notation that was introduced by Ross [3]:

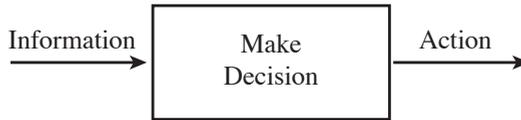


Figure 8.1: Simplified representation of decision unit using SADT notation [3]

As shown in Figure 8.1, a decision unit in the MAS receives information by observing its environment, makes a decision, and takes an action. To be able to decentralize a decision or control task we need to understand existing interdependencies, assess their relevance to the state of the system, and need to ensure that constraints of interdependency are sufficiently addressed to satisfy higher-level system properties.

We propose to classify the information and actions associated with a decision task to determine if it can be decentralized. We introduce four dimensions. For the information and action of the task, we each distinguish the temporal and spatial dimensions.

1. The temporal dimension of the information refers to the time period during which information that is used in the decision task is observed and collected. For some tasks, only information that is available instantaneously is used, while other tasks require accumulating information over a long period of time.
2. The spatial dimension of the information refers to the location where the information originates. For some tasks, information that is used may be available locally, while for other tasks the information is collected globally.
3. The temporal dimension of the action refers to the duration for which an action has a primary effect on the system. Some actions may change the state of the system forever or irreversibly, while other actions only affect the system temporarily.
4. The spatial dimension of the action refers to how much of the system is affected by an action. Specifically, the distance, e.g. geodesic or geographic distance, of parts of the system that are affected by an action. An action may impact the entire system, or only impact the decision unit itself.

To determine candidate tasks that can be decentralized, we define limits for each of the four dimensions. Figure 8.2 shows two plots with the dimensions for information and action, as well as boundaries that demarcate the limit for each dimension.

The boundaries in Figure 8.2 separate the plot into four quadrants, each for inputs and outputs. These quadrants can be characterized as:

I-1: Tasks require only local information that is available instantaneously.

I-2: Tasks require information from other locations that are not accessible locally to the controller, and the information is available instantaneously.

I-3: Tasks require information that is available locally to the controller, but needs to be observed over a period of time

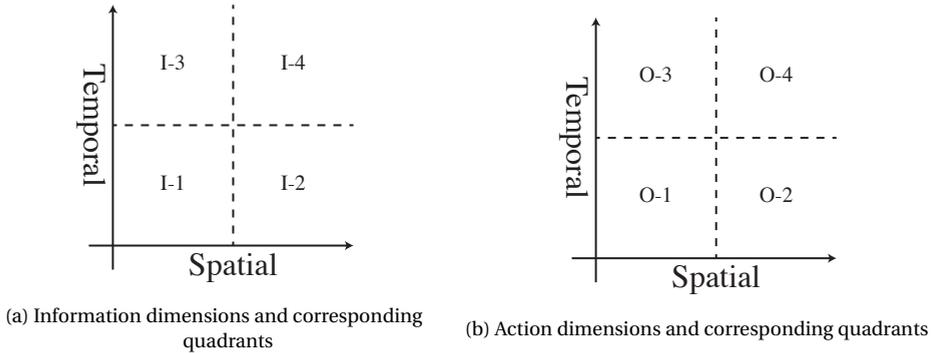


Figure 8.2: Proposed dimensions for classification of decision tasks

I-4: Tasks require information that is not available locally, and that must be collected over a period of time

O-1: Tasks affect other controllers only locally, and direct consequences from an action persist only for a short period of time

O-2: Tasks directly affect other controllers globally, and direct consequences only persist for a short period if time

O-3: Tasks only affect other controllers locally, but consequences persist for a long period of time

O-4: Tasks affect other controllers globally, and consequences persist for a long period of time.

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We suggest that any task that falls into the quadrants I-1 / A-1 can be decentralized without having a significant effect on the system, as their execution has little interdependency with other parts of the system. Tasks in other quadrants will require that some mechanism is in place to address interdependencies with other parts of the system. For quadrant I-2, communication would be a means to ensure that global information is accessible by the controller. To satisfy the interdependencies for quadrant I-3, data can be locally aggregated and analyzed over a time period. For quadrants O-2 and O-3 coordination mechanisms can be employed to address interdependencies with other parts of the system and to ensure that decisions do not have adverse long-term effects on the system.

This work made a first step to support our proposed framework. In Chapter 5 we decentralized routing decision for aircraft taxiing and carried out experiments with varying spatial scope of information. We can map these experiments onto our proposed framework: In Chapter 5 we elaborated the spatial information dimension and found the minimum required spatial information to make routing decisions for aircraft taxiing.

This framework is a proposal to identify decision tasks that can be decentralized without compromising global system properties. We propose to split the required information for a decision and the actions that result from a decision into temporal and

spatial dimensions. We hypothesize that decisions which require only local and immediately available information and have local and short-term effects can be decentralized. To make this framework viable, a methodology must be developed that determines the values of each dimension of a task, and that defines limits for each of these dimensions.

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CURRICULUM VITAE

Heiko UDLUFT

Heiko Udluft was born December 20th, 1983 in Frankfurt a. Main, Germany. After completing his high school (Abitur) in Königswinter in 2003, and civil service in Bad Godesberg in 2004, he pursued a degree in mechanical and process engineering at Technische Universität Darmstadt. He completed his B.Sc. in 2010 and his M.Sc. in 2012. Starting in his first year studies, he worked as a research assistant at the wind tunnel in the department for fluid dynamics, supporting and conducting research in Peniche design and PIV measurements. He was awarded the Lufthansa Technics Students fellowship, as part of which he completed internships in the aircraft- and component-maintenance groups, as well as the avionics systems engineering group. He studied abroad at Lund University as part of the Erasmus exchange program and completed his master thesis research at the Massachusetts Institute of Technology.

Since October 2012 Heiko Udluft has been a PhD Candidate in the Air Transport and Operations Section at the Aerospace Engineering Faculty at the Delft University of Technology. He has been teaching and supervising several bachelor and master students, some of which were able to publish and present their work at international research outlets. His main research interest is using decentralization and distributed control to improve the performance of infrastructure networks, specifically, in air transportation.

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