Master's thesis

NTNU
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Dept. of Industrial Economics and Technology Management

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Implementing Electric Aviation in Norway, the Strategic Electric Aviation Problem over Multiple Periods

Master's thesis in Industrial Economics and Technology Management
Supervisor: Carl Henrik Andersson
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Preface

This thesis concludes my Master of Science at the Department of Industrial Economics and Technology Management at the Norwegian University of Science and Technology. The thesis is within the field of Managerial Economics and Operations Research, and is a continuation of the specialization project *TIØ4500* within the same field.

I would like to thank my supervisor Professor Carl Henrik Andersson for invaluable feedback, meetings, discussions, and reflections during this work. In addition, I would like to thank my co-supervisor, Professor Tobias Andersson Granberg, for knowledge of the aviation industry, feedback and references to relevant resources. Both supervisors have been an amazing support throughout this process, both with good laughs and input. I would also acknowledge the thesis of Alan Kirene, who laid much of the foundation of the work and provided insights on electric aviation and subsidized routes in Sweden. Finally, I would like to express my gratitude to my friends and family who have been there through endless hours of strategic electric aviation talks.

Abstract

Addressing global warming demands radical shifts in high-emission sectors. This thesis focuses on the aviation industry, particularly in Norway, considering the transformation to electrical aviation. With the goal of formulating a strategic model for the implementation of electric aviation (EA), this thesis is aimed at government entities and airport infrastructure providers, with the purpose of giving advice on the optimal investments in charging station locations, EA routes, and EA airplanes over several periods.

The thesis begins by exploring the status and requirements of EA and the current situation on EA in Norway, emphasizing Norway's unique geography and emission reduction targets. The literature is then reviewed, where strategic electric aviation problems have been little explored in the existing literature, so insights are combined from conventional aviation and electric vehicles. Then, the Fixed Route Electric Aviation Problem (FREAP) is introduced, which considers electric aviation where demand per direct route is assumed to be constant. To provide more accurate solutions, this culminates in the development of a heuristic and an exact solution method to ensure feasible routes, that again guide charging station investments.

An economic analysis on the heuristic solution method is performed, which reveals insights into cost dynamics, technological scenarios, and strategic goals. Notably, the model favors southern high-demand routes, but can expand in northern regions in early periods due to range limitations of available EA models. When the FREAP model and input data are modified based on current Norwegian strategic requirements, it is highlighted that the model prefers to invest in hub-centric charging infrastructure over Public Service Obligation (PSO) routes.

The thesis concludes by recommending the building of initial charging infrastructure in the hubs rather than in the PSO network. The main contribution of the thesis is to create an optimization model for Norway's EA implementation, highlighting the advantages of early investments around hubs and exploring how optimal charging station locations are affected by range improvements and strategic goals. The FREAP is also adapted to the Norwegian strategy, to help provide insights for Norway's transition toward sustainable electric aviation.

Sammendrag

Håndteringen av global oppvarming krever radikale endringer i sektorer med høye utslipp. Denne avhandlingen fokuserer på luftfartsindustrien, spesielt i Norge, med tanke på overgangen til elektrisk luftfart (EA). Med mål om å formulere en strategisk modell for implementeringen av elfly, retter avhandlingen seg mot offentlige instanser og infrastruktureiere, med formål om å gi råd om optimale investeringer i plassering av ladestasjoner, EA-ruter og EA-modeller over flere perioder.

Avhandlingen starter med å utforske status og krav til EA samt dagens situasjon med EA i Norge, med vekt på Norges unike geografi og mål for reduserte utslipp. I litteraturgjennomgangen har strategiske problemstillinger knyttet til elektrisk luftfart vært lite utforsket, så det kombineres derfor innsikt fra både tradisjonell luftfart og elektriske fartøy. Deretter introduseres "Fixed Route Electric Aviation Problem" (FREAP), som antar at etterspørsel per direkte flyrute er konstant. For å gi mer nøyaktige løsninger, blir FREAP gjort mer presis gjennom utviklingen av en heuristisk og en nøyaktig løsningsmetode for å sikre gjennomførbare flybevegelser, som igjen veileder investeringer i ladestasjoner.

En økonomisk analyse av den heuristiske løsningsmetoden utføres, som avdekker innsikt i kostnader, teknologiske scenarier og strategiske mål. Modellen favoriserer særlig sørlige ruter med høy etterspørsel, men kan utvide seg i nordlige regioner i tidlige perioder på grunn av rekkeviddebegrensninger hos tilgjengelige modeller. Når FREAP-modellen og dataen tilpasses Norges nåværende strategiske krav, fremheves det at modellen foretrekker å investere i ladestrukturer sentrert rundt knutepunkter fremfor FOT-ruter (forpliktelser til offentlig tjenesteytelse, senere referert til som PSO).

Avhandlingen konkluderer med anbefalingen om å bygge initiell ladeinfrastruktur ved knutepunkter fremfor i PSO-nettverket. Hovedbidraget til avhandlingen er å skape en optimeringsmodell for Norges implementering av EA, der fordelene ved tidlige investeringer rundt knutepunkter belyses, samtidig som optimal plassering av ladestasjoner påvirkes av rekkeviddeforbedringer og strategiske mål. FREAP-modellen tilpasses også den norske strategien for å bidra med innsikt i Norges overgang til bærekraftig elektrisk luftfart.

Contents

List of Figures

List of Tables

1 Introduction

To limit global warming to 1.5°C, greenhouse gas emissions must peak before 2025 and decline by 43% by 2030 [United Nations Climate Change, 2023]. As a consequence, more and more countries are setting carbon neutrality targets, where zero-carbon solutions can offer possibilities where service is maintained with lower negative impacts on consumers. The aviation industry is an important contributor to global greenhouse gas emissions, accounting for approximately 2.5% of global CO_2 emissions [Ritchie, 2020]. World Economic Forum and McKinsey & Company [2023] expect that by 2050, the aviation industry will need to invest between 700 billion and 1.7 trillion dollars to provide sufficient infrastructure for hydrogen, battery electric and hybrid electric aircraft. Electric aviation is expected to arrive earlier than hydrogen aviation and be better suited for short-range routes with low demand, where the first commercially viable electric airplanes with room for 9-19-passengers are expected to arrive on the market around 2026-2028 [Avinor and Luftfartstilsynet, 2020]. However, for this implementation, we need infrastructure investments, both for zero emission energy sources and for a sufficient power grid and charging infrastructure.

Norway has the most extensive airport coverage in the Nordics, and in 2020 had planned 21 subsidized routes [Avinor and Luftfartstilsynet, 2020], most of them covering short distances with low demand. The Norwegian government has set a goal of reducing greenhouse gases by 80-95% compared to 1990 by 2050 [Ydersbond et al., 2020], and in 2019 2.4% of total greenhouse emissions in Norway were due to domestic air travel [Samferdselsdepartementet, 2023]. With high access to green energy through hydropower, Norway has been a leading player in electric cars and electric ferries and may now become a front-runner in electric aviation. Wangsness et al. [2021] point out that if there are no successful routes with electric aviation in Norway in the 2020s, a full implementation of EA in the 2030s is very optimistic. Therefore, to achieve a significant reduction in emissions from aviation, Norway should invest in early technologies with a long-term perspective.

The goal of this thesis is to provide an unbiased tool for investments in charging station locations and which routes should be electrified long-term. Additionally, the tool's results should be contrasted with Norway's existing EA strategy to identify areas for improvement. The tool should plan for multiple time periods so that early investments can have the best long-term impact, while also boosting technology development. As early investments are expected to stimulate technological development, the tool allows decision makers to establish strategic goals on how much fossil aviation should be reduced in different periods while minimizing total costs. This thesis suggests an optimization model for the long-term implementation of electric aviation, with a focus on Norway. The model can also be applied to the development of refueling infrastructure for alternative aviation fuels.

An optimization model for the Fixed Route Electric Aviation Problem (FREAP) is proposed. The FREAP plans for a multiple period implementation of EA that simultaneously makes decisions on charging station locations, where to route EA, EA airplane purchases, and where to maintain conventional aviation coverage. As electric aviation is an emerging technology, the topic of placing electric aviation charging stations has been little explored in the existing literature. Additionally, to our knowledge, a model that plans for electric aviation with fleet planning, charging location, using a hybrid fleet over multiple periods has never been done before. The model can solve real-life cases with up to 6 time periods and EA ranges up to 500 km. The model is then tested on seat data on the Norwegian air transport network to provide recommendations on Norway's optimal strategy for electric aviation.

The report is structured as follows. In Chapter 2, background information is presented on electric aviation, the current situation in Norway, and different key actors in the implementation of electric aviation. The existing literature on similar problems is addressed in Chapter 3. Subsequently, Chapter 4 presents the definition of the problem. The mathematical model for the Fixed Route Electric Aviation Problem (FREAP) is introduced in Chapter 5, and the model is improved with two model expansions in Chapter 6. The test instances used are described in Chapter 7. Then, a computational study is done in Chapter 8, where the performance of the model is explored, as well as managerial insights. To gain insight into the situation in Norway, Chapter 9 discusses how managerial insights differ from the situation in Norway and how to integrate strategic requirements into the model, to provide a set of final recommendations. Finally, Chapter 10 provides concluding remarks for the thesis, before possible areas of future research are presented in Chapter 11.

2 Background

This chapter sets up background information on electrical aviation and conventional aviation (CA) and presents the current situation of electric aviation in Norway. First, the fundamentals on electric aviation is introduced in Section 2.1. This report uses Norway as a case for electric aviation. An introduction to electric aviation in Norway is presented in Section 2.2. Finally, the different key actors in a long-term implementation of electric aviation are identified in Section 2.3. All sections are based on the preliminary report Voll [2023], but have been restructured and modified.

2.1 Electrical Aviation

This section presents information on electrical aviation and aviation networks. First, terminology surrounding conventional aviation is introduced in Section 2.1.1. Next, additional challenges surrounding EA are introduced in Section 2.1.2. The expected advantages of EA are presented in Section 2.1.3. Section 2.1.4 establishes the main categories of electric aviation implementations and technology implementation projects. Finally, a discussion follows in Section 2.1.5 on the current realism surrounding an EA implementation and recent changes in technology developments.

2.1.1 Conventional Aviation Networks

Conventional aviation (CA) refers to the traditional mode of air transportation based on fuel-based propulsion systems and encompasses aircraft that employ horizontal take-off and landing mechanisms. This definition excludes vertical take-off and landing (VTOL) and short take-off and landing (STOL) aircraft, such as helicopters, emphasizing extended runways or airstrips for departure and arrival. However, the definition includes airplanes that use bio-aviation fuels, since the airplane models remain, and there are no major additional infrastructure requirements. All variants of horizontal take-off and landing airplanes that use non-electric CO_2-emitting fuels are called conventional aviation (CA).

To describe the movements of flights, we refer to flight legs and flight routes. A flight leg, also called a flight arc, is a direct travel between A-B or B-C, whereas a flight route consists of one or more flight legs, like traveling A-B-C. When passengers travel, they do so between an origin and a destination [Bazargan, 2016]. While making their journey from origin O to destination D, passengers may choose to travel directly or opt for a combination of different flights using various routes. Passenger preferences have a high price elasticity [Brons et al., 2002], which means they are willing to substitute different flights according to price. Typically, passengers prioritize cost and travel time over the specific airports visited. As a result, they view combinations of routes like (O, A, D) and (O, B, D) as equal, provided they offer similar costs and duration. In this text, the term routes will be most commonly used and can refer to both a flight leg/arc and a series of flight legs flown by an airplane.

In most cases, aviation networks are structured around hubs. A hub airport is larger in size compared to its neighboring airports and serves as a major departure and arrival point for numerous aircraft [Kinene, 2022, Manuscript 1]. An example of a journey is from Trondheim, Norway, to Tokyo, Japan. A route then may involve traveling to the national hub Oslo, Gardermoen, to an international hub in Paris, Charles de Gaulle, where a long-distance flight goes directly to Tokyo.

When an airplane is in flight, there are certain activities that take up time. During a stop, passengers must disembark and new passengers must board, and there may be a need to refuel and change the crew. For smaller aircraft on short-term routes, this exchange can take as little as 15 minutes, as in Appendix B.A, but this varies based on the airplane capacity. Refueling time also varies between aircraft. For the average small plane, it can take anywhere between 10 and 40 minutes, while the average commercial plane takes between 45 and 90 minutes to refuel [Krasner, 2023].

Due to the high environmental impact of aviation, there are several initiatives to make aviation fuels more environmentally friendly, such as bio-aviation fuels [Wang et al., 2019]. Low-emission fuel options often use conventional aircraft available today and have similar ranges and passenger capacities. On the contrary, emerging technologies, such as electric aviation and hydrogen aviation, have a lower energy density, resulting in limitations in both range and capacity [Bergero et al., 2023].

2.1.2 Challenges in Electrical Aviation

EA is distinct from CA in that it is anticipated to have a much shorter range and require more frequent charging than refueling in conventional airplanes. In addition, any airplane that has a charging time greater than the stop time requires an additional charging time.

Since current charging capabilities are expected to be too slow, it is necessary to install efficient charging infrastructure in airports to minimize downtime. Currently, there are no global standards for EA charging infrastructure, but several organizations are working to establish a global standard [Smedberg et al., 2022]. The implementation of fast chargers requires investments in the infrastructure at these airports and possibly in the surrounding power grid. To ensure that aviation is zero emission, infrastructure investments also involve building renewable energy, where some suggest that airports can be power hubs. World Economic Forum and McKinsey & Company [2023] point out that although airports can be power hubs, their long-term electricity demand exceeds their ability to produce green energy. Green energy production typically requires a large amount of space, so additional electricity collaborations are expected to be essential to provide the energy production needed for the transition to zero emission aviation. Therefore, planning for charging station investments should happen as early as possible.

With current technology and regulations, short-term electric airplanes are expected to have a capacity of 9-19 seats and a range of 350-400 km (max 500 km)[Wangsness et al., 2021]. World Economic Forum and McKinsey & Company [2022] have stated that the maximum range of electric airplanes will be around 400 km by 2035 and rising to 600 km by 2050.

Currently, short routes (<200km) are best suited for the first pilot electric aviation projects [Ydersbond et al., 2020]. The maximum number of seats in the early periods is expected to be 19, due to stricter regulations on larger airplanes. Obtaining a CA aircraft certification with more than 19 seats on average takes 10 years and requires considerable financial resources [Ydersbond et al., 2020]. Due to the risk of battery drainage, models are expected to have a battery reserve required that limits the range below the maximum range [Reimers, 2018a]. Most discussions surrounding range are therefore on the "permitted range", rather than the maximum range, due to strict regulations. Currently, the only approved airplanes for use are 2-4 seats and are mainly used to train pilots [Reimers, 2018a]. In the <19 seat segment, some relevant actors are Eviation and Heart Aerospace.

2.1.3 Advantages of Electrical Aviation

For the first years of electric aviation implementation, electric airplanes are expected to have higher purchase, operating, and maintenance costs than conventional aviation. Among these costs are investments in competence, infrastructure, and other increased costs related to more extensive coordination [Wangsness et al., 2021]. However, long-term electric aviation is expected to have lower maintenance and operating costs. This is because conventional combustion engines have a high level of wear and tear, resulting in a high cost per take-off and landing. Therefore, engine maintenance can potentially be reduced by more than 50% compared to conventional aviation [Reimers, 2018b].

In addition, engine maintenance in traditional engines can be unpredictable and lead to costly downtime. On the contrary, electric systems can perform "self-checks" and have more predictable maintenance requirements [Reimers, 2018b]. Lower maintenance costs and more predictable maintenance times lead to an expected lower cost of electric aviation, with the bonus of being more reliable and environmentally friendly.

A consequence of the high maintenance per flight is that conventional flights are more incentivized to use larger airplanes on longer routes. In electric aviation, the maintenance per flight is expected to be lower, leading to a more linear relationship between distance travelled and costs [Egeli, 2023]. This also makes electric airplanes better suited for shorter-range routes with multiple stops. Another advantage is that electric motors produce significantly less noise compared with combustion engines [Egeli, 2023]. Particularly in regions where the airport is close to the city, this may increase happiness and connectivity in the area, as more people can live near the airports without being bothered by noise.

2.1.4 Technology Implementations

Several types of technologies that can be used to realize electric aviation are presented in Table 1. As mentioned, there are no standards for charging electric aviation [Smedberg et al., 2022]. The absence of infrastructure standards encourages a phased implementation of EA and early projects to test infrastructure options, rather than building extensive infrastructure with outdated requirements.

Table 1: Overview of electric aviation technologies

	Motor type
Battery electric	Electric
Serial hybrid	Electric
Parallel hybrid	Electric + conventional
Fuel cell	Electric

Source: Samferdselsdepartementet [2023]

Initiatives are being carried out in all the technology categories listed in Table 1, with the current certified models being battery electric. As stated in Section 2.1.3, fully electric airplanes are expected to have lower costs due to fewer moving parts in noncombustion engines. However, hybrid solutions are expected to perform better with respect to range, as they can utilize an additional energy source [Samferdselsdepartementet, 2023]. The distinct types of models also has separate ways to handle charging. Battery electric models will either use battery swapping or require time to charge, whereas hybrid or fuel cell models may use alternate fuel to cover the missing power if the remaining power is insufficient.

Fully hydrogen-based airplanes are expected to arrive later than electric ones, but are better suited for longer ranges and higher capacity. Airbus and Rolls-Royce have started initiatives with the goal of entering the market with a hydrogen airplane by 2035 [Samferdselsdepartementet, 2023]. World Economic Forum and McKinsey & Company [2023] expect that in 2050 aircraft battery charging will account for 4-11% of the electric power demand in aviation, while the remaining 89-96% are used by hydrogen aviation. This corresponds to hydrogen aviation being able to cover longer ranges and capacities, and by extension covering more of the global demand. Despite hydrogen aviation being farther away than electric aviation, the first test flight of a 19-seat hydrogen electric airplane occurred recently [ZeroAvia, 2023], where ZeroAvia is aiming for certification in 2025 [GreenAir News, 2023c].

Battery technology is the primary factor driving technological development in terms of range and capacity, but it is difficult to have a significant impact on development. It is generally accepted that electric cars will be the main driver for the development of battery technology [Reimers, 2018b]. This means that governments have limited ability to influence the most important driver for improving range and capacity. Due to this, many EA providers build their models with the expectation that battery capacity will increase over time, such as the Heart Aerospace ES-30 [Aerospace, 2023]. The main job of governments is therefore to incentivize the building of the aircraft and sufficient infrastructure, while batteries over time can be swapped out to improve the range of existing airplane models.

2.1.5 Closed Projects and Transfer to Hybrid Solutions

Recently, several projects for producing electrified aircraft have been closed or postponed. Technam postponed their P-Volt program and believes that EA "can only be achieved by extremely aggressive speculation on uncertain technology developments" [Technam, 2023]. They point out that the most advanced batteries will quickly degrade after a few weeks in operation, and only a few hundred flights would drive operators to replace the entire battery. This leads them to say that the service goal for 2026-2028 is not viable [Technam, 2023]. During 2023, the Norwegian Airport owner Avinor also removed the goal of complete electrification of domestic air travel by 2040 [Avinor, 2023b][Avinor, 2023c]. This points to a general issue within EA, which is that technology development is dependent on battery development, and battery development has a great deal of uncertainty.

The limitations of fully electric aviation have been met with initiatives on hybrid-electric propulsion and hydrogen aviation. An example of transfer to hybrid-electric is Heart Aerospace, who switched their 19-seat electric aircraft to a 30-seat version with reserve-hybrid power. The aim is to create a model with a greater range and capacity that can be used commercially sooner, with less restrictions on battery technology [GreenAir News, 2023b]. Long-term, the model will have an improved range as battery technology progresses [Aerospace, 2023]. In hybrid power, Pratt & Whitney Canada and Collins Aerospace are currently cooperating on a 1MW motor that is half the weight of the most advanced electric motors currently on the market, but will deliver four times the power and double the voltage, with the Rolls-Royce turbogenerator system that allows for scaling around similar numbers [GreenAir News, 2023a]. An 8-9-seater hybrid electric Cessna Grand Caravan is also in workings with an emission decrease of up to 70% and a reduction in operating costs of 25-40% with a maximum range of 1000 miles [Pullen, 2022]. The aim is to achieve certification by 2024, and that customers can convert their existing aircraft to hybrid electric when certification is achieved [Reichmann, 2021].

It is clear that the aviation industry will eventually move towards zero- and lower-emission planes, largely due to the numerous initiatives in progress and the absence of other zero emission options. Whether the first step is taken with fully electric or hybrid-electric aircraft is yet to be seen. With current technologies, hybrid-electric solutions seem more plausible short-term, where the substitution to fully electric may become more gradual as battery technology improves. Nevertheless, transitioning to hybrid electric aviation requires the installation of charging infrastructure and the availability of zero emission energy sources. Additionally, a transformation to hydrogen aviation will require new investments in green energy to produce green hydrogen. Therefore, the implementation of electric aviation infrastructure is still relevant, but precisely which technologies will be leading is uncertain.

2.2 Electric Aviation in Norway

This thesis uses Norway as a case study for the long-term implementation of electric aviation. This section presents an introduction to the current situation of electric aviation and the requirements of electric aviation that are specific to Norway. First, in Section 2.2.1 a foundation is made on the situation surrounding electrification in Norway. Norway's unique geography and regional transportation network is introduced in Section 2.2.2. Section 2.2.3 elaborates on the network and regulations for subsidized air travel. Finally, the current initiatives to implement electric aviation are presented in Section 2.2.4.

2.2.1 Electrification in Norway

Norway is a country well suited for electric aviation due to its many short-range routes, high access to green energy through waterpower, and wide political support for efforts to make aviation more environmentally friendly [Samferdselsdepartementet, 2023].

Due to Norway's access to waterpower, the country has 98% renewable electricity [Egeli, 2023] and has over time had low electricity costs. As a result of low costs and several political incentives, Norway has the largest share of electric cars and ferries in the world [Ydersbond et al., 2020], and a population that traditionally has been positive toward climate efforts through electrification. However, a combination of events has led to a recent increase in power prices, with prices expected to remain high in the near future [Regjeringen, 2023]. This increase in power prices may decrease optimism related to electrification efforts.

Many draw parallels between the development of electric aviation and the development of electric cars. One of these parallels is that Norway was thought to be a small market for electric cars due to its small population, but ended up being one of the largest initial markets. 12% of the car fleet in Norway was electric in 2021 [Wangsness et al., 2021]. In contrast, the Norwegian market for short-range flights is large on an international scale. One of the main reasons for early investments in electric cars was the economic incentives that lowered the cost. To encourage early investment in electric aviation, similar solutions have been suggested, such as those outlined in Wangsness et al. [2021].

2.2.2 Geography and Regional Transportation

Norway has a challenging geography with fjords and mountains, creating difficulties in surface transport [Ydersbond et al., 2020]. Despite this, more than 90% of the population has access to an airport less than a 90-minute drive away [Samferdselsdepartementet, 2023], which is due to extensive airport coverage. 85% of the flight routes are less than 500 km and 75% of the flight routes of the dominant player on the regional routes, Widerøe, are shorter than 300 km. When looking at all airports, Norway has 100 Origin-Destination pairs of airports that are less than 200 km apart. In contrast, the Nordic nation with the second highest number is Sweden, with 15 $\leq$ 200 km Origin-Destination pairs [Ydersbond et al., 2020].

The Norwegian government has set a goal to reduce greenhouse gases by 80-95% compared to 1990 by 2050 [Ydersbond et al., 2020]. To achieve this, regional transportation must also become zero emission. Due to the difficulties in surface transport surrounding mountains and large bodies of water, the main way to achieve zero emissions is by building roads, bridges, tunnels, railway structures, or by air. However, there is a political consensus that it is too costly to build a sufficient train capacity to cover all the demand in Northern Norway that is currently covered by aviation. The result is that the only realistic option to maintain long-term connectivity in these regions is to build a zero emission airplane fleet.

Some potential problems with Norway for electric aviation are low temperatures and weather conditions with snow and ice. To ensure that electric aviation is possible despite this, the weather conditions have been used as an argument to be one of the first investors in electric aviation, as early investments can incentivize the first models to be adapted to the Norwegian climate [Wangsness et al., 2021].

The regional hubs in Norway are Oslo, Bergen, Trondheim and Tromsø [Samferdselsdepartementet, 2023]. The gaps between all the hubs are more than 300 km, which makes hub-routes unsuitable for the early stages of electric aviation. As most flights are between these hubs, routes that can be replaced with a range below 300 km are only about 24% of total demand, using data from Statistics Norway [2023] and the Vincenty distance between airport coordinates. Consequently, early implementation involves either setting goals that only consider short-range routes in early periods or creating shorter routes for the EA to be able to cover more of the demand. However, if the aviation network were significantly rerouted with EA, this would involve adding additional stops and charging stops to existing routes. The result of this would be that the amount of time it takes to travel would be longer, making options like trains or buses more appealing.

2.2.3 PSO / FOT Routes

Norway has achieved a wide range of airport access for its population by providing subsidized routes. Subsidized routes in Norway are called FOT routes (forpliktelser til offentlig tjenesteytelse), but are here referred to as PSO routes (Public Service Obligations), as that is more commonly used internationally. PSO routes are subsidized routes that ensure satisfactory plane coverage in areas with a market that is not sufficiently competitive [Avinor and Luftfartstilsynet, 2020]. Most of the traffic from smaller regional airports is PSO routes [Samferdselsdepartementet, 2023]. In 2020, there were PSO routes serving 29 airports, distributed among 21 routes [Avinor and Luftfartstilsynet, 2020]. A map of the PSO routes in Norway in 2022 can be seen in Figure 1.

When discussing which routes to electrify, PSO routes strike out, as they often cover short distances with low demand. For many of the PSO routes, a range of below 200 km and a capacity of 9-19 seats is sufficient [Wangsness et al., 2021]. There, early models with 9-19 seats may be usable to cover existing demand long-term. In Norway, 80% of the PSO compensation is for scheduled operations in Northern Norway [Solvoll and Hanssen, 2022]. As the operation of PSO routes is costly, many of these also may contain several stops before reaching a hub, such as the routes (Kirkenes, Vadsø, Båtsfjord, ..., Alta), shown in the upper right corner of Figure 1.

Figure 1: Map over PSO routes in Norway from 2022
Source: Samferdselsdepartementet [2023]

As the most relevant routes for electrification are PSO routes, PSO revision times are relevant for electric aviation investments. In Northern Norway, PSO routes are given as contracts of up to 5 years duration, starting in 2022, 2027, etc. [Avinor and Luftfartstilsynet, 2020]. The different airlines may then each provide an offer. Generally, the offer that requires the lowest amount of subsidy should win the competition [Regjeringen, 2022]. The recently published National Aviation Strategy states that the government wants to start implementing zero- and low-emission airplanes on PSO routes by latest 2028 and 2029, if technology is available [Samferdselsdepartementet, 2023]. The government will also consider opening contracts in the 2024-2028 time frame if relevant aircraft become available on the planning horizon [Samferdselsdepartementet, 2023].

As PSO routes and transportation are considered critical infrastructure, PSO routes must be reliable. When investing in charging infrastructure for electric aviation, it is therefore likely that slow chargers are available at all airports. The cost of constructing faster charging stations is expected to be more expensive and it is not clear if all airports require this. Furthermore, it should be noted that severe weather conditions often have an impact on the dependability of PSO routes, increasing the probability that airplanes will charge at airports without fast chargers. Due to the need for reliability, this may require that fast chargers be built in all airports with an EA route. There are also many political forces and incentives that participate in the planning of PSO routes, making it difficult to make changes to existing PSO routes. This makes it even more important that, when a route is electrified, the route stays in operation.

2.2.4 Ongoing initiatives

Currently, there are several initiatives regarding the infrastructure required for electric aviation. Elnett is a project in the Stavanger region in Norway that seeks to explore how smart energy control, power production, and optimal use of the power grid can ensure the charging of electric aircraft, ships, and buses without having to make significant investments in the existing power grid [Reimers, 2018a]. The project's goal is to have scheduled traffic for electric aviation by 2026 [Avinor, 2022]. Closely related, there is a cooperation between Avinor, Sparebanken Vest, Berg-Hansen, Aircontact Group, and the Business organization in the Stavanger region to establish the world's first fully electric passenger route between Stavanger and Bergen [Ydersbond et al., 2020]. The Bergen-Stavanger route is expected to become Norway's first commercial EA route [Hollund, 2022].

Recently, the Nordic Network for Electric Aviation published a report on the implementation of electric aviation in the Nordic countries. This report presents an example of the Elfly Group, which proposes an electric seaplane that can travel between city centers by using sea terminals. Potential airports have been identified to be Stryn, Florø, Bergen, Haugesund, Odda, Leirvik and Stavanger [Egeli, 2023].

The Green Flyway project has created a testing arena for electric aviation, drones, and other autonomous air vehicles between Røros and Østersund. This initiative is designed to facilitate the testing of these technologies in the airspace between Sweden and Norway. One of the main functions of the flyway is to test the charging infrastructure required to enable technologies to become operational in a commercial setting [Green Flyway, 2023].

2.3 Key Actors

In this section, several key actors are identified for the implementation of electric aviation in Norway. For each actor, a simplified version of their objectives and which parts of electric aviation they have a direct influence over are presented. Then, we highlight how these actors are represented in Norway. The key actors have been identified as government entities, airport infrastructure providers, flight operators, airplane producers and aviation customers. Finally, it is concluded that government entities is the most relevant actor to focus on in Norway.

Government Entities

Government entities refer to national and regional governments and relevant aviation organizations controlled by the government. The government wishes to achieve political goals, keep the population satisfied and spend a minimum amount of money, which can often lead to a clash between the objectives. In this case, it is most relevant to talk about strategic goals regarding reduced emissions, in which many countries have tied themselves to emission reductions, such as those in the Paris Agreement [United Nations, 2015]. Government entities have regulatory and economic control over aviation, with the opportunity to create regulations and establish economic penalties or subsidies. They can also initiate pilot projects to test out recent technologies, and very high-level government organizations can help establish standards for charging infrastructure.

In Norway, three key actors in electric aviation are the state department Samferdselsdepartementet, the Norwegian Civil Aviation Authority (Luftfartstilsynet) and the airport operator and owner Avinor [Reimers, 2018b] [Samferdselsdepartementet, 2021]. Samferdselsdepartementet makes the decision on allocation of PSO routes, Luftfartstilsynet enforces security, regulation and training of crew, and Avinor owns, runs, and develops airports [Samferdselsdepartementet, 2021]. Due to this division of responsibility, there is a fleeting transition between the state and airport operators in Norway, where the state has a large control over the airport infrastructure providers. Increased control of airport infrastructure is part of the reasons why Norway is a good starting point for electrical aviation.

Airport Infrastructure Providers

Airport infrastructure providers refer to the owners and staff of airports that will enable the operation of EA. Airport infrastructure providers need to know from government entities or flight operators where and when to build the necessary infrastructure and how to build it from governing entities or airplane producers. The "how" refers to standardization, where standardization of chargers leads to a lower risk of building infrastructure that will have to be replaced. In addition, infrastructure providers need to have sufficient expertise to serve the new infrastructure. This can involve technicians on battery power and electric aircraft, and staff operating charging stations.

In Norway, airport infrastructure providers are mainly Avinor and Avinor employees. Avinor is a state-owned company that owns and operates 44 airports in Norway. In addition to these, there are two airports in Norway with scheduled traffic that is not owned by Avinor [Solvoll and Hanssen, 2022]. In the shift towards electric aviation, the role of Avinor is to facilitate the necessary infrastructure, while the flight operators purchase the airplanes. Avinor has stated that when the infrastructure for electric aviation is required, Avinor will also have that infrastructure available. Together with Luftfartstilsynet, Avinor has been asked to develop a program for the introduction of electric airplanes in Norway. To achieve this, they are currently cooperating with Norges Luftsportsforbund (NLF), SAS, Widerøe, and Klimastiftelsen ZERO [Avinor, 2023b]. Avinor currently has a Pipistrel Velis Electro 600, which is the first electric aircraft model approved by EASA. Some intended uses are to test different charging concepts and acquire operational experience.

Flight Operators

Flight operators is a broad category that includes both airlines and other air mobility providers. Flight operators will have one of the main costs of electric aircraft implementations [Le Bris et al., 2022], as they often purchase airplane models and pay the cost of operating the airplanes. Airlines are expected to maximize their revenue, and are therefore unlikely to invest large sums in EA unless there is an expected economic gain in it or a guarantee that they can utilize their investments. For profit to be possible, they need the guarantee from the state and airports operators that the required infrastructure is available when an EA airplane is acquired and that it can be run with a profit, through subsidies in either operational costs or aircraft purchasing costs. An additional incentive for flight operators in that CA is receiving more CO_2 penalties and is expected to decrease in market size long-term due to climate requirements. The only long-term way to counter this effect is to replace the fleet with zero- to low-emission airplanes, making zero emission aviation a long-term strategic goal. To be available, flight operators are dependent on airplane producers to produce functional EA technology. They also depend on available pilots with the relevant competence to operate EA.

In Norway, the main flight operators are SAS, Widerøe and Norwegian, where Widerøe currently operates 75% of the flight routes shorter than 300 km [Ydersbond et al., 2020]. The education of pilots can be affected by government regulations, and actors such as Avinor and the Flight School at the University of Tromsø currently own electric airplanes for the education of new pilots and testing of technology implementations [Löfving et al., 2023]. Many flight operators partner with airplane producers, providing funding and signals to investors. Examples are Finnair with Heart Aerospace and Widerøe with Technam and Rolls-Royce [Le Bris et al., 2022].

Airplane Producers

Airplane producers refer to companies that develop or manufacture electric aircraft, parts, and accessories. An important part of EA is the battery technology, which involves several additional stakeholders. Despite the main limitations of electric aviation being battery technology, it is still assumed that electric cars will be the main driver of battery development [Reimers, 2018b]. This makes it difficult to affect technological developments directly through incentives. But organizations can shorten the authorization period of new aircraft. The airplane producers are also dependent on sufficient funding and expectations of a future market to sell their products. Therefore, they are dependent on flight operators making deals to buy their products, investors, and signals from governing entities that EA is wanted. Examples of airplane producers are Rolls-Royce, Heart Aerospace, Ampaire, and MagniX [Le Bris et al., 2022]. Some currently upcoming technologies and airplane producers are mentioned in Section 2.1.5.

Aviation Customers

Aviation customers are the last category and refer to passengers, businesses using aviation for transport, and other customers of aviation services. This category has a general impact on state actors through voting or lobbying and controls the demand of flight operators. As mentioned in Section 2.1.1 the price elasticity of customers is high, so it is uncertain to what extent customers will prioritize flying with zero emission options. However, it is likely that the implementation of zero emission aviation can increase demand due to environmental impact. Businesses may also be interested in using EA for the transportation of goods, as it reduces climate impact, which again can affect consumers, lower emission taxes, or increase morale in employees.

2.3.1 Connection Between Key Actors

As presented, the different key actors are intertwined with each other, but the one that has the most power and is the least dependent on others to act is government entities. The aim of all stakeholders is an increase of electric aviation; however, this is dependent on prices, costs, technological advances, and the behavior of other key players. Governments have the capacity to make electric aviation profitable for airlines through subsidies and can also make early investments in airport infrastructure, such as Avinor in Norway. A combination of government investments and signals boosts a positive outlook for airplane producers to gain more funding and incentivizes flight operators to continue cooperating with airplane producers. Especially in Norway where the state controls the airport infrastructure providers, government entities have a large control over what happens and can send out signals that can speed up the development and deployment of EA.

Norwegian government entities have the power to subsidize purchases of EA models and EA routes and initiate investments in charging infrastructure. Of these, the most important decision is investing in charging stations, as it requires the most planning and additional potential investments in the power grid. To know where to place charging stations, possible routes must be considered, and to know which routes can be considered, we must consider available EA models. As there are many uncertainties about the costs, charging times, ranges, and capacities of the first EA models, it is difficult to make accurate estimates on the exact number of airplanes needed for the transition. However, we can assume that once an investment in airplanes has been made, those airplanes should be reused. When the specific aircraft that are available are not known, the primary focus shifts to the amount of total EA capacity that is invested in with different ranges, as this affects the ability to construct EA routes. Subsequently, the combined decisions of charging station investments, electrification routes, and investments in EA models can be used to boost technology developments in EA and contribute to a long-term implementation of EA.

3 Litterature Review

This chapter presents relevant literature on the Fixed Route Electric Aviation Problem (FREAP). Electric aviation (EA) can be divided into different parts that are covered by different professional fields: The literature on general aviation and the literature on electric vehicles. Both contain literature that spans several fields, such as the physics behind travel and flight, chemistry behind battery/fuel usage, logistics surrounding on-site infrastructure, short-term route planning, and strategic long-term investments. This report explores strategic electric aviation planning within the field of operations research. There is extensive literature on conventional aviation and electric vehicles, but the strategic aspect of electric aviation has not been explored as extensively [Voll, 2023]. This report seeks to combine strategic planning of aviation with mobility planning of electric vehicles and to create a model for a long-term strategic implementation of electric aviation.

As there is little literature on strategic electric aviation problems, the search strategy is influenced by finding similarities with other problems that have been covered in the literature. First, the search strategy is presented in Section 3.1. Next, the FREAP is presented in Section 3.2. Solution methods used in existing literature are presented in Section 3.3. To conclude, Section 3.4 presents how the FREAP contributes to the existing literature. As the FREAP builds on the preliminary report Voll [2023], much of the literature and text is reused. Sections 3.1, 3.2 and 3.4 are rewritten versions of the preliminary report Voll [2023].

3.1 Search Strategy

This section discusses the search method for the relevant literature. The search strategy builds on the literature review from the preliminary report Voll [2023], and has added some parts to cover new aspects of the problem. A new search was conducted, leading to the removal of Jaillet et al. [1996] and an addition of two new articles Wang et al. [2016] and Bazargan [2016]. Similar problems to strategic electric aviation problems are introduced in Section 3.1.1. Furthermore, the search matrix is presented in Section 3.1.2. Finally, articles that have been identified and researched more thoroughly are provided in Section 3.1.3.

3.1.1 Similar Problems

A preliminary search was carried out on the background of electric aviation, to identify the different requirements for strategic aviation problems. Then, searches were made on electric aviation problems that are field-specific to optimization. Based on the search strategy, few articles that combine strategic planning over several airports with electric aviation were identified.

A preliminary search for electric aviation reports was conducted to determine the various needs for strategic electric aviation problems. Subsequently, searches were made for electric aviation problems that are field specific to optimization. Despite extensive research on the physical features and qualities of electric vehicles and the design of charging infrastructure, there is still a scarcity of literature on the modeling of electric vehicle networks [Baykasoğlu et al., 2019], and even less on the strategic implementation of electric aviation. Therefore, the FREAP combines concepts from the problems of conventional aviation and electric vehicles.

Electric aviation was divided into two groups of similar problems. The first is electric vehicle problems (EVPs), which focus on the requirements and limitations of a vehicle being electric. Then, there are aviation problems, which tend to have a better presentation of strategic requirements concerning aviation. There is little overlap between EVPs and aviation problems, but together they cover many of the challenges faced by a strategic model for electric aviation. Similar problems have been found to be:

- Electric vehicle planning (EVP) (Buses, cars, trucks). Usually involves:
  - Investments in Charging Stations
  - Range and Charging Restrictions
  - Vehicle Investments and Hybrid Fleet Planning
- Aviation subsidized route planning. Usually involves:
  - Strategic Planning and Requirements
  - Multi Commodity Flow or Fixed Routes
  - Customer Satisfaction from Travel Times and Schedules

3.1.2 Search Matrix

Initial searches involved searching for background information regarding electric aviation in Norway and Sweden, and the thesis of Alan Kirene, "Models for the Procurement of Subsidized Air Services: Conventional Aircraft and the Adoption of Electric Aircraft" [Kinene, 2022], which looks at a PSO planning with electric aviation in Sweden. From the identification of similar problems in Section 3.1.1, a search matrix was created.

The search matrix is presented in Table 2. Additionally, the identified articles from the preliminary report Voll [2023] were re-considered. The search was conducted in Google Scholar. Each search combined an area word with one or more optimization-specific words and one or more relevance words. Examples are "Aviation Network Design problem" and "Electric aviation charging location multi-stage investment optimization".

Search results were initially evaluated by checking the titles of the first 1-3 result pages of each search in Google Scholar. As the task does not consider the power grid, on-site queueing and infrastructure, or the technical construction of electrical airplanes, these results were not explored. The non-optimization literature was

Table 2: Search matrix used for literature study

Area	Optimization specific	Relevance
Electric aviation Electric vehicle Aviation/Airplane/Airline	Charging station/location/facility Network design Multi-period/-stage investment Hybrid/Mixed Fleet Fixed Route	Optimization Problem Strategic

also not explored, outside of providing context for Chapter 2. For those that fit the problem, the abstract was read, and the most relevant articles were read more thoroughly. For the most relevant articles, the reference list was checked to find more relevant literature. Literature with many citations or that had a lot of overlap with the problem definition was prioritized. There was no filtration on the date, but much of the literature was from recent years, due to the nature of the problem.

3.1.3 Identified Articles

The following literature was identified and is believed to provide sufficient coverage of the field. The literature is mapped to different relevant terms in Table 3, and important terms are explored further in Section 3.2. Baykasoğlu et al. [2019] presents a review of the literature on conventional vehicles, while Bazargan [2016] is a book that elaborates on conventional aviation operations and scheduling.

1. Lu et al. [2018]
2. Alp et al. [2022]
3. Wang et al. [2016]
4. Lu et al. [2019]
5. Worley et al. [2012]
6. Erdoğan and Miller-Hooks [2012]
7. Kinene [2022, Manuscript 5]
8. Birolini et al. [2021]
9. Kadri et al. [2020]
10. Cheng et al. [2016]
11. Baykasoğlu et al. [2019]
12. Bazargan [2016]

Table 3 presents the different literature in relation to each other. Fixed demand (FixD) refers to if demand is perceived per arc or between endpoints. Time-dependent demand (TDD) refers to demand being linked to time windows, so that airplanes must travel at specific times to serve demand. Investment decisions in charging stations (CInv) and vehicles (VInv) refer to whether there is a decision to invest. The opposite is the case if there are no investments in charging stations or vehicles, or if the investments are fixed. Mixed fleet (MixF) is if the model allows for a combination of conventional vehicles and electric vehicles/alternate fuel vehicles. Individual vehicles (IV) are the tracking of each individual vehicle, or if vehicles are routed on a more general level. Individual vehicles are necessary to keep track of a state of charge (SoC). Furthermore, multiple period planning (MPP) refers to a problem that involves planning over several periods. Finally, the method refers to whether a model is solved via a heuristic or an exact solution. If a letter is in parentheses, it means that the article uses both, but the non-parentheses method is the main solution method.

Table 3: Comparison of reviewed literature*

Nr	Area	FixD	TDD	CInv	VInv	MixF	IV	MPP	Objective	Method
1	E-taxis	No	Yes	No	No	Yes	Yes	No	Min costs	H
2	E-trucks	Yes	No	Partly	Yes	Yes	No	Yes	Min costs	E
3	E-buses	Yes	No	Yes	No	No	Yes	No	Min costs CInv	H(E)
4	Railway	Partly	Yes	No	No	No	No	No	Min costs travel	E
5	EV general	G-VRP	No	Yes	No	No	Yes	No	Min costs	E(H)
6	EV general	G-VRP	Yes	No	No	Partly	No	No	Min costs travel	H
7	EA	Yes	Yes	Yes	Yes	Yes	Yes	No	Max passengers	E
8	CA general	No	Yes	No	No	No	No	No	Max profit	E
9	EV general	Yes	No	Yes	No	No	No	Yes	Max passengers	E+H
10	CV general	No	Yes	No	No	No	Yes	Yes	Min costs	H
11	CV review	Mix	Mix	No	Mix	No	Mix	Mix	Mix	E+H
12	CA review	Mix	Mix	No	Mix	No	Mix	Mix	Mix	E+H
FREAP	EA	Yes	No	Yes	Yes	Yes	No	Yes	Min costs	E+H

*Abbreviations: FixD (Fixed demand), TDD (Time-dependent demand), CInv (Charging station investments), VInv (Vehicle investments), MixF (Mixed/Hybrid fleet), IV (Individual tracking of vehicles), MPP (Multiple period planning), E (Exact), H (Heuristic)

3.2 The Fixed Route Electric Aviation Problem

This section presents the different aspects of the Fixed Route Electric Aviation Problem (FREAP) and how these are handled by the existing literature. The FREAP considers the strategic planning of electric aviation charging infrastructure, routes, and airplane investments, across several airports over multiple periods.

The problem is broken down into different parts. Section 3.2.1 explains the differences between assuming demand per arc (Fixed Demand) or demand between endpoints (i.e., multi-commodity flow or vehicle routing). Section 3.2.2 explains the issue of using fixed charging station locations or using the model to determine the charging station locations. Next, Section 3.2.3 presents the literature on fleet investments, as well as models on fleet transition to hybrid fleets. Furthermore, Section 3.2.4 elaborates on how time is represented in different literature. Here, the planning horizon, repeatability, and tying demand to time windows is discussed. Finally, different approaches to the objective function are introduced in Section 3.2.5.

3.2.1 Fixed Route Demand

In aviation networks, demand can be considered 1) as fixed along direct routes (arcs) or 2) as a flow of demand between endpoints (origins to destinations). The difference can be exemplified using buses. In bus networks, passengers can both enter and leave buses at all stations and may take several buses to travel from an origin to a destination. If demand is assumed to be fixed, the demand on each bus is viewed per direct trip. So if a passenger travels A-B, B-C and C-D with different buses, this corresponds to a demand of 1 along each of these arcs A-B, B-C and C-D. In the case of endpoint demand, demand is registered as 1 from A to D. The model can then choose to route the demand along arcs A-B, B-C, and C-D. In this report, the most relevant versions of endpoint demand are vehicle routing, which is routing demand between endpoints through vehicles, or multi-commodity flow, which is when there is demand between multiple origins and destinations, and this is routed as a combination of flows.

The difference between endpoint demand and fixed route demand also affects the data used. In the fixed route case, it is necessary to use fixed route demand. In aviation, fixed route demand refers to demand from existing airplane routes and purchases of airplane tickets along direct flights. Using endpoint demand, it becomes necessary to estimate the demand between endpoints, as customers may transfer airplanes or consider different modes of transportation. Endpoint demand tends to have more uncertain data, whereas fixed route demand often can be distilled from sales data. The endpoint demand option enables the redirection of demand, whereas the fixed demand option does not, but is quicker to solve. Therefore, by selecting the fixed route demand, the model loses the opportunity to discover more suitable routes. The FREAP assumes fixed routing due to a combination of large uncertainty in endpoint demand and the significant increase in complexity that is introduced by using multi-commodity flow or vehicle routing.

Fixed demand leads to a considerable decrease in complexity and is often easy to retrieve data on. The least complex way to consider demand is to assume that all flights are fixed to airplanes [Bazargan, 2016], but this is not applicable to EA implementations, as new EA airplanes will have a different range and will replace existing flights. Wang et al. [2016] present a model electric vehicle charging station placement for public buses where charging stations are located at different bus stops, in a network with fixed bus routes. As the bus routes are fixed, there is no vehicle routing along the routes. On a more strategic level, Alp et al. [2022] propose a model for fleet truck planning that considers total fixed demand. The number of trucks bought must then cover the total demand. In Kadri et al. [2020], demand is represented as a set of predetermined trips to be taken by electric vehicles. The focus of the model is the location of charging stations over multiple periods, where demand is stochastic. Kinene [2022, Manuscript 4] does not require demand to be covered, but maximizes the connectivity of the charging stations. Connectivity is then defined from the population in an area and becomes another way to consider demand.

Vehicle routing problems become a form of endpoint demand as demand can be routed through vehicles using different routes. Cheng et al. [2016] solves the inventory routing problem, in which inventory is routed from one assembly plant to several suppliers using a fleet of capacitated vehicles. The demand from the suppliers is then fixed, but each vehicle is routed from the source to the suppliers. In Worley et al. [2012] vehicle routing is used to identify a mix of EV fleets and where to place EV routes and charging stations. The Green Vehicle Routing Problem (G-VRP) was introduced by Erdoğan and Miller-Hooks [2012], which addresses additional problems with alternative fuel-powered vehicle fleets with respect to limited range and refueling infrastructure. This implementation also requires that each customer is visited only once and that each vehicle returns to a charging station.

Using multi-commodity flow yields more flexible solutions, which can be useful when dealing with new technologies. However, it is more time-consuming, so most of the literature identified uses heuristics for larger-scale data. Lu et al. [2018] have formulated a model on the scheduling of taxi fleets with hybrid fleets, which is formulated as an integer multi-commodity flow problem. A problem with a scale more similar to that of aviation is presented by Lu et al. [2019], which considers railway locomotive by turning the resource-recharging station location and routing problem (RSS-LRP) into a multi-commodity flow problem, using linking constraints to ensure that all transportation demands and recharging requirements are satisfied. The flow from origin to destination can then be spread among many arcs and is limited by an upper bound by the vehicles traversing that arc in that time frame. However, the origin and destination of each train is fixed, so there is little vehicle routing and more resource and time planning [Lu et al., 2019]. In Kinene [2022, Manuscript 5], the demand for multi-commodity flow is estimated, and an integer number of airplanes are placed along different arcs in a time-space-energy network. Birolini et al. [2021] have extended the use of multi-commodity flow and heterogeneous airplanes, by combining a time network with a location network. Multi-commodity flow is commonly used when considering CA [Bazargan, 2016].

3.2.2 Locating Charging Stations

Locating charging stations involves the decision on where to build charging stations, rather than assuming charging station locations and investments are fixed. A differentiation from a conventional vehicle or aviation problem is that electric aviation requires additional infrastructure for charging, where the route is limited by range and possible stops at charging facilities [Erdoğan and Miller-Hooks, 2012]. In the case of EA, it is reasonable to assume that charging station investments will be made on locations with existing airports, leading to a finite discrete set of possible charging station locations.

Much of the literature that does not involve the location of charging stations, instead focuses on the scaling of charging infrastructure or has a large set of possible charging station locations. It is more common in EV literature on cars or buses that the charging facility locations are fixed, as this is handled by the state, or the set of possible charging station locations is very large. Erdoğan and Miller-Hooks [2012] assume a fixed location of charging stations and addresses additional issues with alternative fuel-powered vehicle fleets, with respect to limited range and refueling infrastructure. Lu et al. [2019] also use a fixed set of recharging stations, but has added a maximum capacity to each recharging station. Moreover, Alp et al. [2022] consider fleet planning at a more general level, with a number of trucks with a given range and ability to operate, and related costs for purchasing charging instruments. The model then does not make a decision on where to locate charging stations, but determines the relevant capacity of chargers to be used. A more general approach is taken by Baykasoğlu et al. [2019], which present a literature study on Green Vehicle Routing problems.

Much previous literature has focused on the set-covering problem, where vehicle flows are known, to optimize the placement of charging stations. This is the approach used by Kinene [2022, Manuscript 4], which considers the building of a charging station as a one-time investment that covers a given area with electric aviation. If all possible routes are known, the location of charging stations can be seen as a maximum cover problem. Kadri et al. [2020] use the same approach as Kinene [2022, Manuscript 4] of maximizing coverage.

The Vehicle Routing Problem with Recharging (RVRP) is a version of the Vehicle Routing Problem (VRP) that considers the routing of vehicles and the installment of charging stations simultaneously. The need for charging stations and the limited range of electric aircraft has a major impact on which routes are feasible, so finding alternative routes may be important in the early stages of electric aviation. The first presentation of the RVRP was presented by Worley et al. [2012]. Kadri et al. [2020] decide charging station locations based on covered EV flows. This implementation also assumes that one charging station covers all the demand and that a vehicle always charges fully when arriving at a charging station. Both Kadri et al. [2020] and Worley et al. [2012] consider vehicle routing and the location of charging stations simultaneously, but this also has a large impact on solution time.

In electric aviation or bus networks, there is a limited number of potential charging station sites, as well as a noteworthy connection between routes and charging station locations. An approach is proposed by Kinene [2022, Manuscript 5], which combines a time-space scheduling problem with the decision of investing in charging stations. In Kinene [2022, Manuscript 5] a decision is also made on the relevant number of airplane chargers, rather than assuming that the investment in a charger is sufficient to cover all demand. The location of charging stations in Wang et al. [2016] is rather similar to the FREAP, in that there is a fixed number of locations for charging stations (bus stops) and routes moving in and out of these. The location of charging stations is decided by that the different buses need charging stations to allow movement. Wang et al. [2016] present two models. In one of the models, a density of charging stations is required along a route, while the other ensures that each bus has a sufficient charging level at all times.

3.2.3 Fleet Investments and Hybrid Fleets

Fleet investments refer to whether the model tracks vehicle purchases, assumes a fixed fleet, or does not track the fleet. If there are investments in vehicles, there is also the question of whether the model tracks only electric vehicles or a combination of electric and conventional vehicles. As described in Section 2.1, current technology within electric aviation is not sufficient to replace all conventional aviation. A consequence is that any realistic solution that implements EA and requires all demand to be met will also contain CA. A fleet that combines CA and EA is called a hybrid fleet or a mixed fleet.

A hybrid fleet in combination with vehicle investments usually involves planning for the EV fleet to replace the CVs over time. Kinene [2022, Manuscript 5] is an implementation of a strategic electric aviation problem that has constructed a model that uses a network of time, space and energy to optimize both flight schedules and the number of charging stations. The model can be extended to contain hybrid fleets by adding CA types with unlimited range. Since the model allows for heterogeneous airplanes, CA and EA can be modeled in the same way. Many CA models also involve heterogeneous airplanes and fleet allocation [Bazargan, 2016], but lack the range restrictions and infrastructure requirements of EA and are therefore not considered hybrid fleets. Alp et al. [2022] consider the multiple period transition to a hybrid fleet without involving route planning, but considering a fleet as a whole. The model limits and requires investments by proposing a budget constraint that ensures that the budget is not exceeded. Furthermore, the model uses a green ratio that increases the target level of demand satisfied by e-trucks relative to the total demand covered, and an emission restriction that progressively decreases the allowed emissions [Alp et al., 2022].

A fixed set of vehicles can also involve a hybrid fleet, but then focuses more on how to utilize EVs and GVs in an optimal way. Lu et al. [2018] have built on the G-VRP of Erdoğan and Miller-Hooks [2012] and present a model for taxi routing that uses a combination of EVs and GVs for fleet planning, but where the number of EVs is fixed. Here, each individual EV is modeled on a unique EV network to ensure charging constraints for each EV are upheld, while all GVs are modeled on the same flow-time-space network. The combination of EV and GV service should cover all travel requests between the endpoints. Lu et al. [2018] also assume a fixed set of EVs, GVs, and charging stations, where taxis cover demand by traveling directly between different endpoints. Wang et al. [2016] do not contain fleet planning and assumes a fixed set of bus routes that are covered by E-buses. Lu et al. [2019] also assume a fixed set of homogeneous trains and therefore does not involve vehicle investments. Cheng et al. [2016] do not consider hybrid fleets, but has formulated a multiple period routing problem under carbon emission regulations. The model uses a carbon cap to limit carbon emissions, but allows for the purchase of additional carbon quotas.

3.2.4 Time

Time is a central factor in the problem, and the identified literature covers 3 relevant aspects of time: Time-dependent demand (requests, trip planning, and travel are restricted to time windows), planning horizon of one model run, and the use of multiple period planning.

The coverage of time-dependent demand varies from model to model. Some models tie all requests and movements to a time window, whereas others assume time independence. Much of the literature requires that demand is related to a time window and must be met in that window [Lu et al., 2018] [Lu et al., 2019] [Erdoğan and Miller-Hooks, 2012] [Kinene, 2022, Manuscript 5] [Birolini et al., 2021]. This is usually solved by using a time-location network. Other implementations do not consider time when routing vehicles [Worley et al., 2012] [Wang et al., 2016].

Many EV models are solved per day or at the beginning of each day [Lu et al., 2018], while others plan for one day and assume that day is repeated. In the strategic planning of electric aviation, we consider the strategic decisions taken by government entities. Due to the minor changes in logistics, personnel, available models, demand, etc., a detailed solution for each day is not necessary, as many of these decisions and facts will be determined on a daily basis. One way to do strategic planning is then to assume repeatability of periods and that fossil aviation will cover necessary changes that may occur on a day-to-day basis. To ensure repeatability, it is possible to use a wrap-around arc which connects the last arrival to the next day departure flight [Bazargan, 2016]. Birolini et al. [2021] have used one single day of operations and assumed repeatability by connecting the last and first events at each airport, which ensures that the number of airplanes on each airport are the same each day. As Wang et al. [2016] plan for bus routes that are repeated, this becomes a similar case to repeating one standard day.

Using multiple periods for strategic deployment plans can be very useful to decision makers [Kadri et al., 2020]. Alp et al. [2022] have looked at the transition to an electric fleet and formulated it as a multiple period fleet planning problem. This solution does not review the movement of single trucks, but plans for the purchase of charging instruments, fossil trucks, and electric trucks, and adds the opportunity to salvage all trucks and charging instruments in the time period. It is necessary that the trucks have sufficient operating hours to cover demand, and that there is a sufficient number of charging instruments to keep the e-trucks in operation. However, this model does not consider routes, but has more of a strategic look at fleet replacement to a hybrid fleet. Cheng et al. [2016] present an inventory routing problem with different carbon emission costs and limits for each period. Each period has an inventory that is updated based on the used demand and the new quantity collected. Kadri et al. [2020] present a multi-stage stochastic approach to locating charging stations. The model utilizes a maximum number of charging stations to be built in each period and states that the built charging stations are preserved over time.

3.2.5 Objective

The problem of electric aviation can be seen as a multiple objective problem, with the goals of maximizing utility (i.e. degree of electrification, customer satisfaction, geographical coverage) and minimizing costs (i.e. investing in charging stations or airplane models, running airplanes, time spent in air). These usually stand in contrast to each other, since increased utility in most cases will lead to increased costs. In the identified articles on EV planning or aviation, there are usually two approaches: 1) maximizing utility while using a constraint that sets an upper limit on how much investments can be made (pre-defined set of vehicles or charging stations, or a budget constraint on investments) and 2) minimizing costs (minimize costs while having constraints that requires a minimum of investments, like all demand must be covered or a given green ratio). Kinene [2022] and Birolini et al. [2021] are in the first group. Kirene (2022) maximizes connectivity while increased costs affects the objective value negatively, and Birolini et al. [2021] maximize operating profits for an airline. Both maximizes while there is limited demand, and therefore have a finite possible profit.

Lu et al. [2018], Worley et al. [2012] and Alp et al. [2022] minimize operational costs. Lu et al. [2018] have a fixed number of EVs and GVs, and demand in the EV and GV network. Worley et al. [2012] use a similar approach and minimizes the cost of charging, driving, and building charging stations. All customers have to be visited, demand must be met, and each vehicle has limited capacity. The factor pushing the number of vehicles up is then the capacity, as each vehicle can only enter and exit the depot once. Alp et al. [2022] minimize operational costs for driving, running the charging facilities and paying workers, as well as the costs of purchasing and salvaging vehicles, carbon emissions, and installing charging facilities. The model minimizes costs, but costs are pushed upwards by 1) requiring that new investments do not exceed a given budget and 2) requiring a minimum "green ratio" for each period, defined as the ratio of demand satisfied by e-trucks. Alp et al. [2022] also propose possible emission constraints set by governments on a required percentage of CO_2-savings or a maximum level of CO_2-emissions. Lu et al. [2019] and Erdoğan and Miller-Hooks [2012] minimize travel time. Both Erdoğan and Miller-Hooks [2012] and Lu et al. [2019] assume that the location of refueling stations is known, which provides an upper limit to the possible travel time. As Wang et al. [2016] have a main focus on where to locate charging stations, the model only minimizes the costs of charging stations invested. The cost is pushed upwards, by the fact that the entire network should be covered with e-buses.

3.3 Solution Methods

All articles in Section 3.1.3 present mixed integer linear problems that contain NP-hard subproblems, making it necessary to implement algorithms or heuristics to improve efficiency. Due to the limited range of EA, there are different approaches to handling charging and what routes are allowed. The problem of keeping track of charge and using path generation is presented in Section 3.3.1. Next, the solution methods of the identified literature are presented. Exact methods are presented in Section 3.3.2 and heuristic methods are presented in Section 3.3.3.

3.3.1 Path Generation and Individual Routing with State of Charge

Due to the limited range, an EV or EA model requires limitations on recharging. In the identified literature, the requirement of charging is done by either restricting allowed routes via paths and assuming charging is always done at a charging station or keeping track of a State of Charge (SoC). A SoC involves updating the remaining battery capacity whenever charging is done and in-between journeys. This requires that each unique electric vehicle route is modeled and has a charge that is updated based on the chosen travel. When SoC is used, it is possible to make charging an active decision, rather than an automatic effect, when reaching a charging station. An advantage of using charging as a variable is that it provides more accurate charging tracking, which can be used to evaluate charging time, battery life, and power consumption [Kinene, 2022, Manuscript 5]. The advantages with pre-generating paths are primarily related to speed, as both keeping track of charge and having to model each individual airplane leads to an extensive increase in complexity.

Defining paths by routes shorter than the range can significantly improve performance, but the number of possible paths will also scale exponentially. In Worley et al. [2012], recharging is included by requiring that a path cannot be included unless it involves a charging station or the depot at the start and the end. Additionally, a path is restricted by never exceeding the possible range of the vehicle. Kinene [2022, Manuscript 5] presents possible combinations of allowed charging and travel with different aircraft movements across a time-space-energy network. Charging is then not made as a decision, but as a passive part of an energy network. In Kinene [2022, Manuscript 5], demand is given by a direction, where pre-generated paths provide different options on how to travel between endpoints. Wang et al. [2016] present two models, one with a battery size constraint and one without. In the battery constraint model, the State of Charge (SoC) is used to ensure sufficient coverage of charging stations. In the second case, the model assumes that if there are enough charging stations on a route to cover demand, this is sufficient. However, Wang et al. [2016] also point out that the second case will not be realistic in an implementation, as close-coupled charging stations can lead to longer stretches where an E-bus will run out of battery. Wang et al. [2016] do an individual routing of each bus route, to ensure that the bus has enough access to charging station.

State of charge involves updating the charge as a vehicle uses battery capacity. Erdoğan and Miller-Hooks [2012], Lu et al. [2018] and Lu et al. [2019] use a SoC. In Lu et al. [2018] taxi movements are modeled, where a taxi travels back to a charging station when the remaining battery is too low. If charging is not done, the state of charge is equal to the previous charge minus the extended charge of the previous trip. Erdoğan and Miller-Hooks [2012] present a Green Vehicle Routing Problem (G-VRP), which can be extended to EVs, where the limited fuel is electricity, and the resulting model includes an additional charging time. However, in Erdoğan and Miller-Hooks [2012], there is no active decision to refuel when at a fuel station. This may be because alternative fuels, such as hydrogen, do not have as much additional time associated with charging, so there is little reason not to refuel in a refueling facility. Lu et al. [2019] model the movements of trains with limited charge. In this implementation, the remaining charge is part of a train's state. If a charging station is full, the train may wait for an available spot or move to another station if it has a sufficient charging level.

3.3.2 Exact Methods

Wang et al. [2016] present an optimal tracking algorithm to solve the problem with one bus, but implement heuristic methods for all larger instances of the problem.

Alp et al. [2022] solve their problem on E-truck fleet planning to optimality, as they have presented a linear integer program. A step taken to minimize complexity is that the demand is considered on a general level, rather than between origins to destinations. This enables planning for the number of vehicles and charging stations on a general level. Lu et al. [2019] solves the resource recharging problem with an algorithm that combines column generation and Lagrangian relaxation. The problem has been broken down into a knapsack subproblem and a vehicle routing subproblem, where both subproblems are solved with dynamic programming to achieve an optimal solution. In Worley et al. [2012], the model is solved to optimality, but only for smaller instances where solution methodologies are needed for larger instances. Birolini et al. [2021] solve their aviation model using piecewise linearization, but points out that heuristic methods should be explored to further increase the problem size used. Kadri et al. [2020] use an exact Benders decomposition approach to a single-period deterministic case of their multiple period stochastic model. This solution divides the problem into a master problem concerning station deployment and a subproblem that evaluates demand coverage for each path. The subproblem utilizes the fact that a binary variable can be relaxed to be continuous in the range [0,1] without changing the optimal solution.

3.3.3 Heuristic Methods

Most of the implementations involving multi-commodity flow or vehicle routing require the use of heuristics. Lu et al. [2018] formulate two decomposition-based heuristics, which results in an optimality gap less than 3%. First, a number of EVs are allocated to schedules. Next, the remaining EVs are grouped with the allocated EVs and schedules are provided to the remaining EVs within each group. Then, CVs are given requests, and if all requests are serviced, the model is done. If not, a submodel is solved. Erdoğan and Miller-Hooks [2012] point out that VRP heuristics for the classical VRP do not work for the G-VRP, and proposes two heuristics. The first involves generating tours from combinations of arcs, merge feasible tours, and terminate when a feasible solution is obtained. The other is a density-based clustering algorithm, where neighborhoods are formed by considering where there is most likely a node that can charge the surrounding neighborhood. Kinene [2022, Manuscript 4] uses a Kernel Search heuristic to scale for larger instances, which achieves near-optimal instances faster than proposed branch-and-cut algorithms. Both Cheng et al. [2016] and the second method by Kadri et al. [2020] solve by using genetic algorithm-based heuristics. Wang et al. [2016] use a heuristic algorithm to solve both models in their general form. Both heuristic solutions are based on linear programming relaxation.

3.4 The Contribution

As presented in this chapter, there is little literature on the strategic planning of electric aviation across several airports. However, there is much literature covering strategic aviation planning and electric vehicle planning, which this thesis seeks to combine. A key consideration for the planning of vehicles that require additional infrastructure is whether the locations of the routes and charging stations are known. Both fixing charging station locations and demand through routes improve solution time, but simultaneously make the solution less precise. FREAP allocates vehicles to fixed route demand and considers the installment of charging stations simultaneously.

EV planning commonly focuses on limited range and necessary charging infrastructure to enable routes. Strategies to address these restrictions can involve either using paths, prohibiting routes that are too long or do not have charging facilities at the beginning and end, or having a State of Charge (SoC) that updates the remaining battery power based on movement and charging decisions. FREAP utilizes pre-generated paths to restrict allowed routes for improved efficiency.

There are multiple aspects of time in EV and aviation problems. For strategic problems, the time horizon is in most cases longer. The FREAP uses multiple period planning to provide strategic insights for decision makers. To ensure repeatability in a day, a solution is to secure repeatability in the model by requiring that the state at the end of the day is equal to the state at the start of the day. Another aspect is whether demand is tied to time windows. This thesis does not consider time-dependent demand, as this is considered a part of operational decisions that will be determined on a daily basis by flight operators. However, the thesis seeks to identify the best locations for routes of electric aviation and charging stations, considering a long-term perspective.

To increase the accuracy of FREAP, solution methods IRM (Individual Routing Method) and RDM (Regional Division Method) are later introduced. The IRM uses individual routing, which ensures feasibility by tracking each individual vehicle, and is common in the implementations that uses State of Charge. The RDM uses a heuristic that first solves the FREAP, and then uses the FREAP solution to generate regions that add additional airplane movement constraints. The problem is then re-optimized until a valid solution is achieved. This is similar to Lu et al. [2018] which use previous solutions to create groups and solve the subproblem for these groups.

This report seeks to fill in the gap within strategic electric aviation problems and provide a strategic model for a long-term implementation of electric aviation. The FREAP is a multiple period charging location capacitated hybrid fleet planning problem. Combining electric aviation with fleet planning, charging location, using a hybrid fleet over multiple periods has to our knowledge never been done before.

4 Problem Description

This chapter describes the Fixed Route Electric Aviation Problem (FREAP). The purpose of the FREAP is to be a tool for government decision makers to determine the locations of electric aviation charging stations over time, considering electric aviation routes, electrification goals, and long-term costs.

The FREAP is directed at government decision makers. Government decision makers are defined as government entities that, either directly or through requests to other parties, have the ability to control investments in charging stations, cost penalties for using fossil fuel, subsidies for electrical aviation, contracts for subsidized routes (PSO routes), and contracts for other pilot projects within electrical aviation.

To determine the optimal locations for charging stations, the FREAP considers possible EA routes around these locations and the reuse of older EA models even when new models are available. Therefore, the FREAP should make an estimate of the different candidates for EA routes and keep track of the number of airplanes bought of the different models. Charging stations can only be built among the existing airport network and there is no planning for the construction of new airports.

Time Periods and Technology Development

FREAP is a strategic problem with a time horizon of several years. The planning period is divided into time segments, each consisting of a fixed number of years. In each period, the decision maker chooses the best routes for EA and where to build new charging stations. In each new time period, new EA models are expected to become available, with range and/or capacity improved over previous models.

To incentivize early investments in electric aviation, decision makers set strategic goals for how much of the CA network should be replaced with EA in each period. Decision makers can enforce these investments by, i.e., setting up pilot contracts for EA routes, subsidizing EA routes, or enforcing that prechosen PSO routes must be flown with EA. These decisions can then affect both the development of EA and the investments of EA from aircraft operators.

Regarding EA airplane movements, the FREAP should not focus on operational day-to-day decisions and can consider an average day for each period. Each airplane has an average number of operating flight hours per day. An airplane can spend time flying, stopping to transfer crew and passengers, and charging. Passenger demand, number of airports, and distances are assumed to be constant.

Operational requirements

The FREAP assumes that EA can replace CA in an existing network with predefined routes. It is also assumed that EA can substitute CA on any flight leg, as range restrictions can prevent EA from substituting complete CA routes. EA can then either partially or fully substitute the CA coverage along a flight leg. To ensure repeatability, there must also be the same number of EA airplanes for each model at each airport at the beginning and end of a day.

For an electric airplane to be able to fly a route, the length of the route must not exceed the airplane's range. The airplane must also be able to charge at a charging station when starting the route and before exceeding its maximum range. A charging station must be built to allow charging. There is no additional time needed to build the charging stations, as the FREAP provides a forecast in which the stations can be built within the planning time. When a charging station is built, it has sufficient charging capacity to cover all charging requests. Both the built charging stations and the purchased electric airplanes can be used in the upcoming time periods.

Objective

The objective of the FREAP is to minimize long-term costs by replacing CA coverage with EA routes and investing in charging stations. In addition to the direct government costs of investing and maintaining charging stations, the costs related to implementing the actual aviation network should be taken into account. This involves the fixed cost of investing in electrical airplanes, as well as operational costs for EA and CA in the network. The following costs are used:

- Cost of building charging stations
- Cost of operating charging stations
- Cost of purchasing electric airplanes
- Cost of operating electric airplane routes
- Cost of operating conventional airplane routes

5 Base Mathematical Model

This chapter presents the mathematical model for the Fixed Route Electric Aviation Problem (FREAP). The mathematical model is based on the model presented in Voll [2023], so formulations from Voll [2023] are reused in sections 5.3 and 5.4. First, Section 5.1 presents the different assumptions for FREAP. Next, the network is introduced in Section 5.2. The definitions and formulation are presented in Sections 5.3 and 5.4. Section 5.5 explains the generation of big M parameters. FREAP has an issue with tracking airplane movement and investments, which is expected to impact key insights from the model. The issue and its consequences are elaborated in Section 5.6. Later, in Chapter 6, two solution methods are proposed to handle the issue of airplane investments. The FREAP include additional variables for increased explainability. An overview of the variables that can be substituted is in Appendix C.B.

5.1 Assumptions

Here, the assumptions for the FREAP are presented. The model assumes that the energy and duration of flight are directly proportional to the distance flown, implying that additional energy or time expended during take-off and landing is included in the average speed and energy consumption. However, additional time is spent during stops and charging.

Individual movements of CA airplanes are not modeled, as these are assumed to have little impact on optimal long-term investments in electric airplanes. The model also does not model unique EA airplane movements, but requires that the number of EA airplanes of a model exiting and entering an airport is the same.

The model does not take into account flight schedules during a standard day. Therefore, demand is covered if there is a sufficient combination of EA seats and CA flow along an arc. The model does not take into account the need for airplane maintenance and assumes that the cost of purchasing a specific airplane model is the same for all periods.

5.2 Description of the Network

Here, the network used in the FREAP is presented. Figure 2 shows an example network with 6 airports. The full view shows the direction of EA flights and the number of flights, while the simplified view only shows where there are flight arcs between nodes. In later sections, only the simplified view is used.

The network uses paths to handle the limited range of different airplane models. The network consists of nodes, arcs and paths. The nodes are the different airports, arcs are direct flights between two airports (A - B), and paths are a sequence of one or more arcs (A - B - C). A path is an ordered set of two or more airports. In the

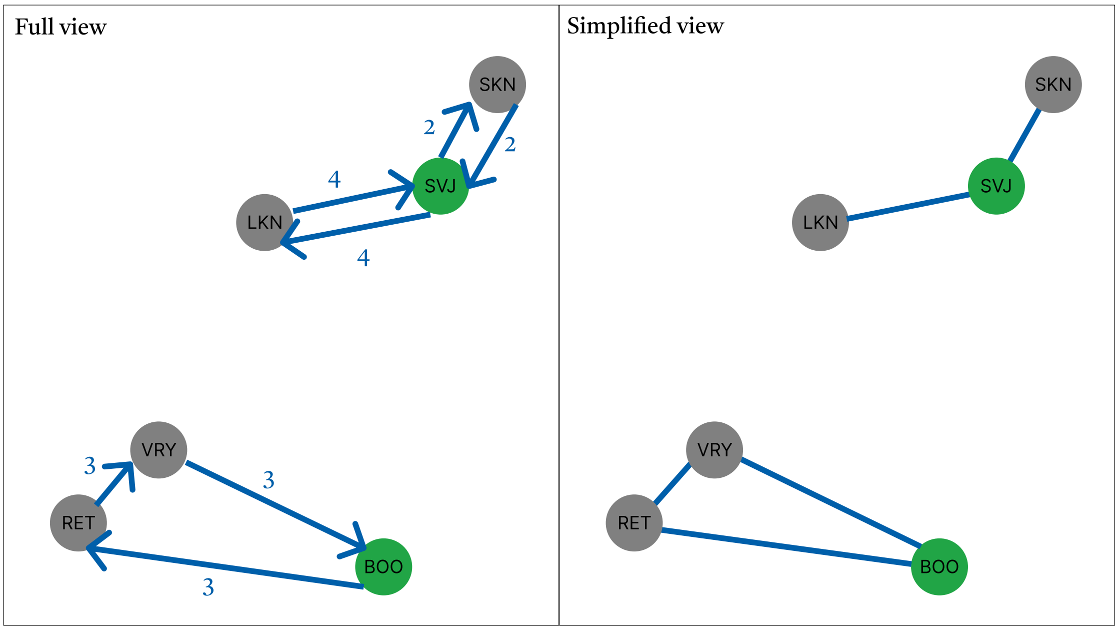

Figure 2: Illustration of full view and simplified view of an airplane network

example, the lower left airplanes travel arcs (BOO, RET), (RET, VRY) and (VRY, BOO), which is repeated 3 times. The path is then $p_1 \in \{\text{BOO, RET, VRY, BOO}\}$. In a path, the start node is called the origin, while the end node is the destination. BOO is both the origin and destination in path p_1.

To handle charging, we assume that an EA-airplane charges at the start and end of a path. By extension, an EA model cannot fly a path that is longer than the range of the model. In the full view example, a model will not be allowed to travel the path $p_2 \in \{\text{RET, VRY}\}$ since there is no charging station at both RET and VRY. If a model has a range lower than the length of path p_1, the model will also not have the option of flying path p_1.

Each path takes a certain time to travel. The time to travel is calculated from a combination of fixed time per stop, time per charging stop, time per kilometer traveled, and path length. Time is used to calculate how much an airplane can travel, and by extension the number of airplanes purchased. Depending on the airplane models available, tracking of airplane investments, and the number of operational flight hours, the flow in the lower left network may be covered by 1, 2 or 3 airplanes.

5.3 Definitions

Main Sets:

$\mathcal{N}$	Set of all airports i, $\mathcal{N} \in \{i_1, ..., i_N\}$
$\mathcal{A}$	Set of all direct arcs (i, j) between airports, $\mathcal{A} \in \{(i_1, i_2), ..., (i_{N-1}, i_N)\}$
$\mathcal{P}$	Set of all possible EA paths p between airports, $\mathcal{P} \in \{p_1, ..., p_P\}$
$\mathcal{T}$	Set of all time periods t, $\mathcal{T} \in \{t_1, ..., t_T\}$
$\mathcal{M}$	Set of possible airplane models m, $\mathcal{M} \in \{m_1, ..., m_M\}$

Case-Specific Sets:

$\mathcal{P}^m$	Set of all paths p that are shorter than or equal to the range R_m of model m
$\mathcal{P}^{ij}$	Set of all paths p that contain the arc (i, j) minimum once
$\mathcal{P}^{O(i)}$	Set of all paths p where i is the first airport/origin of the path
$\mathcal{P}^{D(i)}$	Set of all paths p where i is the last airport/destination of the path
$\mathcal{A}^p$	Set of all direct arcs (i, j) between airports that are part of path p
$\mathcal{A}^Q$	Set of all direct arcs (i, j) where the demand G_{ij} is greater than or equal to the lowest EA capacity Q_m
$\mathcal{M}^t$	Set of possible airplane models available in period t

Parameters:

A_{ij}	Arc distance between node i and j. Measured in kilometres
G_{ij}	Number of passengers along arc (i, j) in original CA network
Q_m	Passenger capacity of EA airplane model m
R_m	Range of EA airplane model m. Measured in kilometres
α_t	Required percentage of decrease in conventional aviation passenger-miles in period t. Set by decision makers
T^K_{mp}	Time to fly path p for an airplane of type m. Calculation is presented in Appendix C.A. Measured in minutes
T^D	Number of minutes in a standard day that an electric airplane is in operation. Measured in minutes
C^I_i	Cost of building a charging station on airport i in period t
C^S_i	Cost of operating a charging station on airport i in period t
C^B_m	Cost of buying an EA airplane of type m
C^E_m	Cost of flying an EA airplane of model m in period t, per km flown
C^G_t	Cost of flying fossil fuel airplanes in period t, per passenger-km flown
M^C_{mp}	Big M value for that a path p cannot be used by model m unless a charging station is built at the start and end of path p

Decision variables:

x_p^{tm}	Number of times an airplane of model m flies path p in period t
w_{ij}^{tm}	Number of times an airplane of model m flies arc (i,j) in period t
b^{tm}	Number of airplanes of model m that are owned in period t
y_i^t	1 if a charging station is built at airport i in period t
s_i^t	1 if a charging station is operational at airport i in period t
r_{ij}^t	Number of passengers that travel with CA on arc (i,j) in period t
o_{ij}^t	1 if CA is routed through arc (i,j) in period t. Only used if (i,j) has an initial demand greater than or equal to the lowest EA capacity

5.4 Formulation

5.4.1 Objective

$$\min z = \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} C_i^I y_i^t \tag{1}$$

$$+ \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} C_i^S s_i^t \tag{2}$$

$$+ \sum_{m \in \mathcal{M}} C_m^B b^{t_T m} \tag{3}$$

$$+ \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} \sum_{(i,j) \in \mathcal{A}} C_m^E A_{ij} w_{ij}^{tm} \tag{4}$$

$$+ \sum_{t \in \mathcal{T}} \sum_{(i,j) \in \mathcal{A}} C_t^G A_{ij} r_{ij}^t \tag{5}$$

The objective is to minimize the combination of operational costs and investment costs for electric aviation, and the remaining use of conventional aviation. Objective term (1) is the cost of building charging stations, whereas objective term (2) is the cost of operating charging stations. Objective term (3) is the cost of purchasing electric airplanes and is paid only once. The variable costs for the use of EA are in objective terms (4) and describe the costs per km traveled with electric aviation. The costs related to fossil aviation are in objective term (5) and relate to the operational cost of each passenger-km run with conventional aviation.

5.4.2 Network Constraints

$$\sum_{p' \in \mathcal{P}^{O(i)}} x_{p'}^{tm} - \sum_{p'' \in \mathcal{P}^{D(i)}} x_{p''}^{tm} = 0 \qquad t \in \mathcal{T}, m \in \mathcal{M}^t, i \in \mathcal{N} \tag{6}$$

$$\sum_{p \in \mathcal{P}^{ij}} x_p^{tm} = w_{ij}^{tm} \qquad t \in \mathcal{T}, m \in \mathcal{M}^t, (i,j) \in \mathcal{A} \tag{7}$$

$$x_p^{tm} \leq M_{mp}^C s_{O(p)}^t \qquad t \in \mathcal{T}, m \in \mathcal{M}^t, p \in \mathcal{P}^m \tag{8}$$

$$x_p^{tm} \leq M_{mp}^C s_{D(p)}^t \qquad t \in \mathcal{T}, m \in \mathcal{M}^t, p \in \mathcal{P}^m \tag{9}$$

Constraints (6) secure the allowed EA movement between nodes, so that the movement of electric airplanes in and out of an airport is always equal for each model. w is defined as the sum of EA seats along an arc in constraints (7). To ensure sufficient coverage of charging stations, constraints (8) and (9) require that, for a path to be used, it must have a charging station at the origin and destination node of the path.

5.4.3 Operational Requirements

$$\sum_{p \in \mathcal{P}^m} T^K_{mp} x^{tm}_p \leq T^D b^{tm} \qquad t \in \mathcal{T}, m \in \mathcal{M}^t \tag{10}$$

$$r^t_{ij} \geq Q_{min} o^t_{ij} \qquad t \in \mathcal{T}, (i,j) \in \mathcal{A}^Q \tag{11}$$

$$r^t_{ij} \leq G_{ij} o^t_{ij} \qquad t \in \mathcal{T}, (i,j) \in \mathcal{A}^Q \tag{12}$$

$$s^t_i = \sum_{t'=0}^{t} y^{t'}_i \qquad t \in \mathcal{T}, i \in \mathcal{N} \tag{13}$$

$$s^t_i \geq s^{(t-1)}_i \qquad t \in \mathcal{T} \tag{14}$$

$$b^{tm} \geq b^{(t-1)m} \qquad t \in \mathcal{T}, m \in \mathcal{M}^t \tag{15}$$

Constraints (10) count the number of planes needed to fly the total number of routes for each airplane model in a day. This implementation can affect the solution, where the problem is elaborated in Section 5.6 and different solutions are proposed in Chapter 6. The two constraints (11) and (12) target the problem of small remainders of CA when routes are covered in EA, and state that if a route has original demand G_{ij} greater than or equal to the lowest EA capacity Q_{min}, the CA coverage r^t_{ij} should be either 0 or higher than or equal to Q_{min}. Constraints (13) establish that $y^t_i = 1$ for the period t that a station is first operated. Preservation of charging stations is handled in constraints (14). Constraints (15) address that if an airplane is bought in one period, it can be used in the following periods.

5.4.4 Strategic Progress

The FREAP measures strategic progress by requiring a percentage decrease from the initial number of passenger kilometers covered by conventional aviation. This is chosen as it captures a combination of decreasing CA emissions through the length traveled and the number of passengers traveling, while not incentivizing unnecessary long routes [Voll, 2023].

$$\sum_{m \in \mathcal{M}^t} Q_m w^{tm}_{ij} + r^t_{ij} \geq G_{ij} \qquad t \in \mathcal{T}, (i,j) \in \mathcal{A} \tag{16}$$

$$r^{t-1}_{ij} \geq r^t_{ij} \qquad t \in \mathcal{T}^{t \neq t_0}, (i,j) \in \mathcal{A} \tag{17}$$

$$\sum_{(i,j) \in \mathcal{A}} A_{ij} r^t_{ij} \leq (1 - \alpha_t) \sum_{(i,j) \in \mathcal{A}} A_{ij} G_{ij} \qquad t \in \mathcal{T} \tag{18}$$

Constraints (16) require that the existing aviation demand is covered by a combination of CA and EA. Furthermore, constraints (17) state that the amount of CA along an arc cannot increase over time, so that the arcs covered by EA cannot be discontinued. Strategic progress is measured by constraints (18), which require that there is a decrease in original CA passenger-miles flown $\sum_{i,j \in \mathcal{A}} A_{ij} G_{ij}$ by α_t% in period t

5.4.5 Non-Negativity and Binary Constraints

$$
\begin{aligned}
y_i^t &\in \{0,1\} && t \in \mathcal{T}, i \in \mathcal{N} && (19)\\
s_i^t &\in \{0,1\} && t \in \mathcal{T}, i \in \mathcal{N} && (20)\\
o_{ij}^t &\in \{0,1\} && t \in \mathcal{T}, (i,j) \in \mathcal{A} && (21)\\
x_p^{tm} &\in \{0,1,...,M_{mp}^C\} && t \in \mathcal{T}, m \in \mathcal{M}^t, p \in \mathcal{P}^m && (22)\\
b^{tm} &\in \{0,1,...\} && t \in \mathcal{T}, m \in \mathcal{M}^t && (23)\\
w_{ij}^{tm} &\geq 0 && t \in \mathcal{T}, m \in \mathcal{M}^t, (i,j) \in \mathcal{A} && (24)\\
r_{ij}^t &\geq 0 && t \in \mathcal{T}, (i,j) \in \mathcal{A} && (25)
\end{aligned}
$$

Constraints (19)-(21) enforce binary restrictions on y_i^t, s_i^t and o_{ij}^t. Constraints (22) and (23) enforce non-negative integer restrictions on variables x_p^{tm} and b^{tm}. x_p^{tm} has an upper bound of M_{mp}^C from constraint (8) and (9), while b^{tm} has no upper bound. Furthermore, constraints (24) and (25) enforce non-negativity on variables w_i^{tm} and r_{ij}^t. w_{ij}^{tm} will always be an integer, as it is defined as a sum of integers x_p^{tm}.

5.5 Big M Parameters

$\boldsymbol{M_{mp}^C}$ is used in constraints (8) and (9), where it is an upper bound to the number of airplanes x_p^{tm} of model m that traverse path p in period t. M_{mp}^C is set to the maximum number of airplanes of a model m to travel along arc (i,j) in period t, where (i,j) is in path p. This number can be estimated by calculating how many airplanes of model m with sufficient range for arc (i,j), are needed to fully cover demand G_{ij}. Finally, +1 is added to enable a model having to fly a trip that does not cover demand along a path to make the sum of movements in and out of a node equal. The calculation is presented in Appendix C.C.

5.6 Counting Airplanes Bought

The FREAP counts the number of EA airplanes purchased, in constraints (10), by using the total number of airplane hours needed. This implementation does not ensure that purchased airplanes b^{tm} move in a connected route and use a feasible number of airplane hours. As mentioned in Section 2.3.1, the airplanes bought b^{tm} are not a high-priority insight, but rather used to simulate how airlines can use and reuse the airplanes purchased in the proposed routes. However, in its current state,

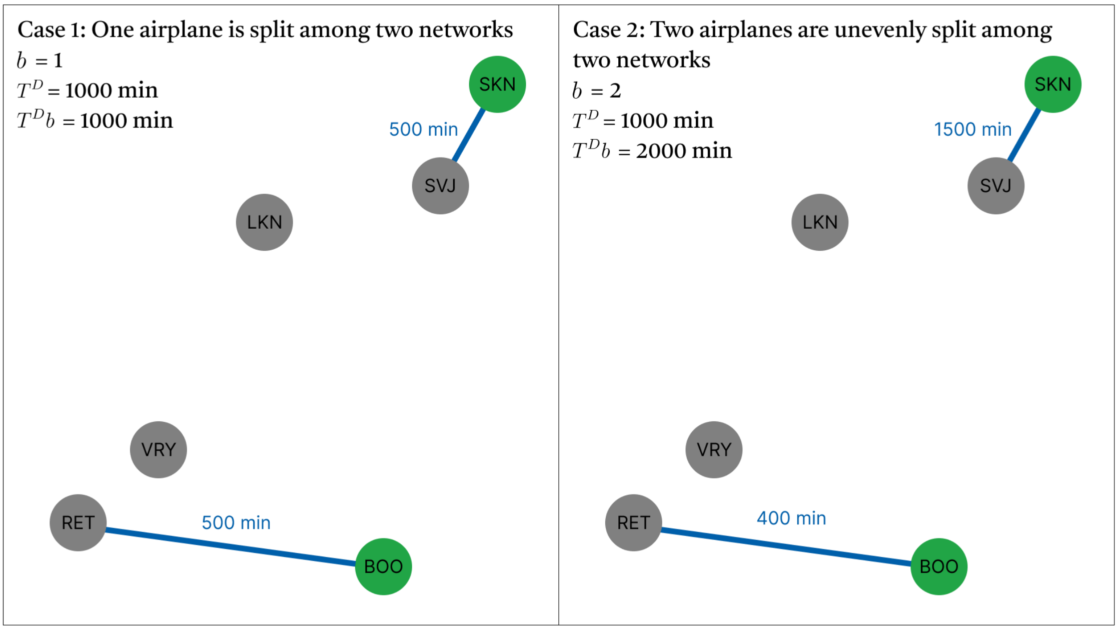

Figure 3: Example of problem cases with 1) an illegally split airplane model route and 2) uneven distribution of flight hours

the model can buy one model of an airplane and distribute it unevenly across several routes.

Two examples of infeasible routes are presented in Figure 3. The blue text represents the number of minutes used along each arc. An example is that if the SKN-SVJ-SKN path takes 100 minutes and is repeated 5 times, that corresponds to 500 minutes in Figure 3. T^D refers to the number of minutes in a day, and $T^D b$ refers to the number of airplane model hours that are available when b airplanes are purchased.

In Case 1, one airplane is divided into two disconnected networks. In this case, both networks are feasible under constraints (6) and (10), since the airplane can travel back and forth to form a closed loop, and the sum of hours of both loops satisfies $\sum_{p \in \mathcal{P}} T_p^K x_p \leq T^D b$. In Case 2, two airplanes are purchased, but the flight hours are distributed in an infeasible way. This allows us to purchase a number of aircraft, with some flying extensively in certain regions, while others only make a single round trip to meet demand.

If the model allows airplanes to cover demand by only traveling short trips in disconnected regions, the model can recommend building charging stations in regions where the capacity of the airplane is not close to covering demand. As an edge case: If a high-range and high-capacity model travels to several disconnected regions to cover demand by one round trip, this possibility should not indicate that a charging station should be built in these regions. Instead, charging stations should be built in regions where there is enough demand for a full day of electric aviation. Possible solutions to the problems in Figure 3 are presented in Section 6.1.3.

6 Model Extensions

This chapter presents two model extensions for tracking aircraft investments and movements. To deal with the problem presented in Section 5.6, two methods are proposed: One heuristic and one exact. The heuristic Regional Division Method (RDM) is presented in Section 6.1 and involves the generation of regions for each separate subnetwork of electric aviation. The exact Individual Routing Method (IRM) is based on Voll [2023] and uses the routing of each individual airplane to count the number of airplanes used. The IRM is presented in Section 6.2.

6.1 Regionally Divided Method

The RDM (Regionally Divided Method) provides a better estimate of feasible airplane movements by requiring that there is a sufficient number of airplanes allocated to each disconnected subnetwork of EA flights. This is implemented by first solving the FREAP and then requiring that the number of airplanes within each model's subnetwork (regions) is sufficient to cover the flight hours flown within that subnetwork.

Regional division addresses the main problems with constraint (10), which are the fractional distributions of airplanes along several routes and the possibility of single and short routes that are not connected to other plane movements. The RDM requires that for each subnetwork of EA, that the number of airplanes purchased of each model is sufficient to cover flight hours used. From this, EA should be used in areas that are both connected to charging stations and where the airplane model's capacity is fit for the area demand. A consequence is that the RDM can eliminate infeasible EA flights that cover low demand through a few flights, as it becomes more profitable to fly near existing charging stations and in areas that have a demand better adapted to the airplane capacity.

First, the concept of regions is explained in Section 6.1.1. Next, the formulation of the RDM is introduced in Section 6.1.2. Section 6.1.3 presents how regions can be used to solve the problems in Figure 3, and how this can affect charging station locations. In addition to the formulation, several choices have been made regarding the forming of regions, allocating paths to regions, and defining when a satisfying solution is achieved. These technical decisions are presented and discussed in Section 6.1.4. Finally, the algorithm and termination condition for the RDM are presented in Section 6.1.5.

6.1.1 Description of Regions

A region is a subset of airports. Regions have two formats: Regions (electric) R^E are airports that are directly connected through EA subnetworks. If an airport has no EA traffic, it is not part of an R^E region. Regions (all) R^A are when all airports are allocated to a region. Airports that are not part of R^E are then added to the region with their closest R^E airport.

The concept of regions is best illustrated by an example. R^E and R^A are presented in Figure 4, where R^E is on the left and R^A is on the right side. EA movements are shown through the blue lines. R^E are the different subnetworks that are directly connected via EA. In R^E in Figure 4 VRY and LKN do not belong to a region, since they do not have any EA traffic. R^A are the regions where the non-EA-connected airports have been added to their closest R^E region. This is marked on the right hand side, where VRY has been added to region r_1, and LKN has been added to region r_0.

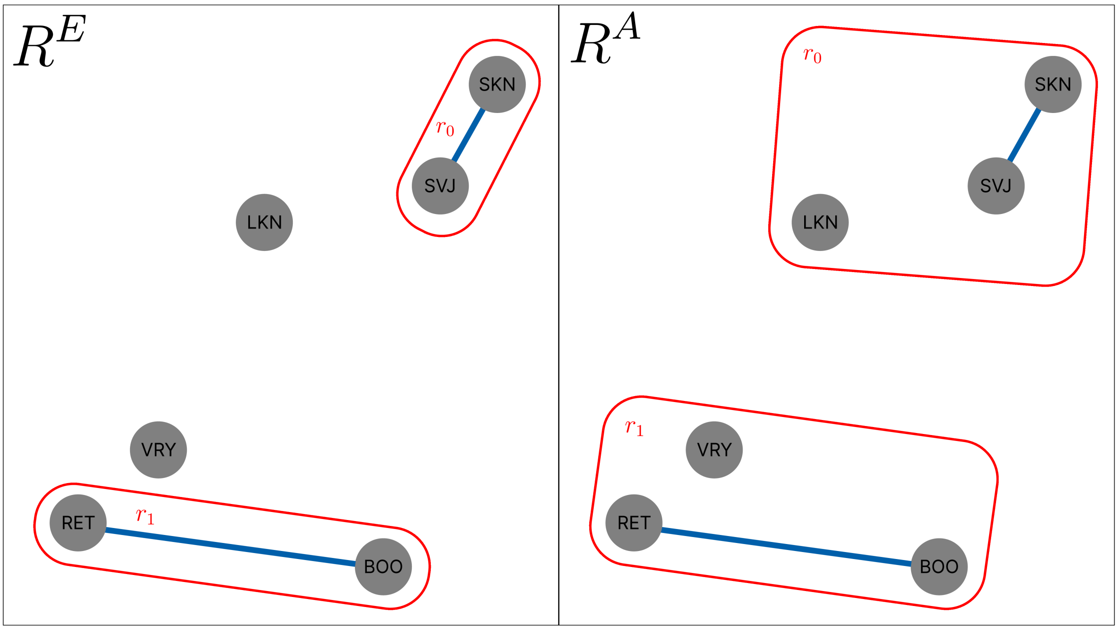

Figure 4: Example of region division, with the region groups R^E on the left side and R^A on the right side

In the RDM, a restriction is added that states that the number of airplanes assigned to each region r, must cover the number of flying hours used in the regions from R^A. R^A is used instead of R^E because the RDM solution may suggest new routes that involve new airports. Using R^A then includes more possible solutions in the next steps. Furthermore, the RDM must verify that the new solution is feasible, which is further elaborated in Section 6.1.5.

6.1.2 Formulation

RD Sets

$\mathcal{R}_{tm}$	Set of all region indexes r for model m in period t
$\mathcal{N}^E_{tmr}$	Set of all airports i that are part of region r for model m in period t, through EA-traffic
$\mathcal{N}^A_{tmr}$	Set of all airports i that are part of region r for model m in period t, including airports that were not initially part of an EA subnetwork. $\mathcal{N}^E_{tmr} \subseteq \mathcal{N}^A_{tmr}$
$\mathcal{P}_{tmr}$	Set of all paths p that contain an airport in region r for model m in period t, from the set $\mathcal{N}^A_{tmr}$

RD Variables

u^{tmr}	Number of airplanes bought of model m that are assigned to region r in period t

RD Additional Constraints

$$\sum_{r \in \mathcal{R}_{tm}} u^{tmr} = b^{tm} \qquad t \in \mathcal{T}, m \in \mathcal{M}^t \tag{26}$$

$$\sum_{p \in \mathcal{P}_{tmr}} T^K_{mp} x^{tm}_p \leq T^D u^{tmr} \qquad t \in \mathcal{T}, m \in \mathcal{M}, r \in \mathcal{R}_{tm} \tag{27}$$

Constraints (26) state that the planes assigned to the different regions r sums up to a total of planes bought b^{tm}. Since b^{tm} is preserved over time from constraints (15), the total number of planes are preserved over time, but they can be assigned to different regions in each period. Constaints (27) state that the planes bought in each region must be able to cover the required travel hours for each model.

6.1.3 Solution to Example Problems

The RDM is capable of addressing the problem in Figure 5, as it requires the allocation of an integer number of aircraft to each region. Possible solutions can be to buy more airplanes and increase EA travel along both arcs, or to close one of the arcs and reroute, where Figure 5 shows the latter. In this case, the rerouting has led to a new arc (LKN,SVJ) and the need for an additional charging station. The result is that all charging station locations have been changed.

The RDM solves the problem in Figure 6 by providing each region with a separate number of flight hours used, which corresponds to the number of airplanes assigned to the region. In the example solution, the airplanes are redistributed in a feasible way, where the airplane in region r_0 travels less and new routes are created in region r_1. However, a solution may also be to discontinue EA in a region as in Figure 5.

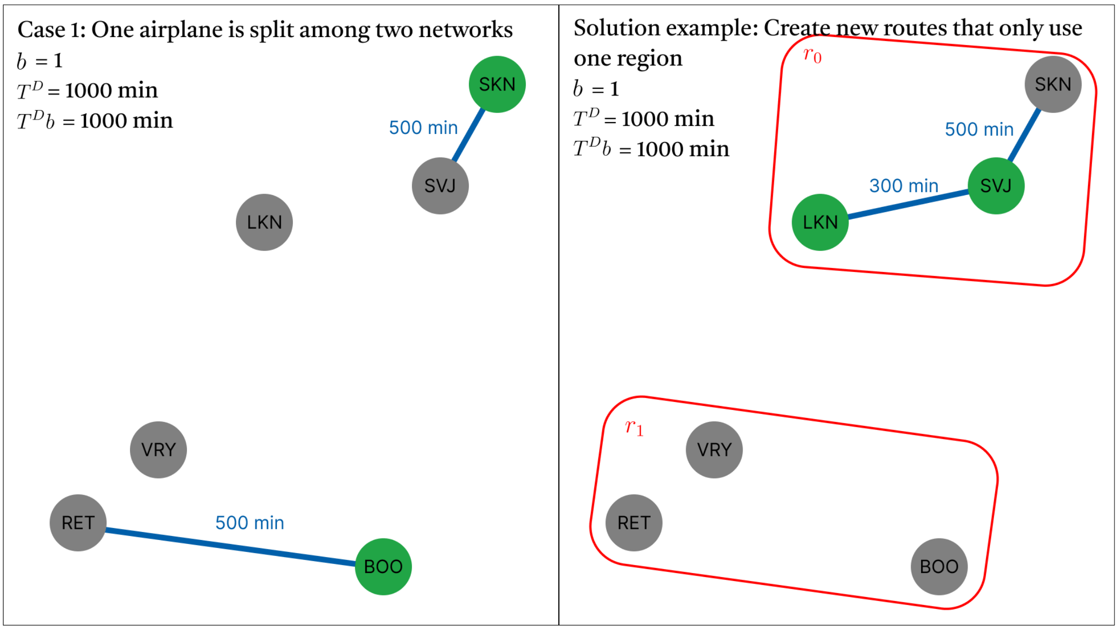

Figure 5: Solution example 1) where one airplane is distributed over two disconnected networks

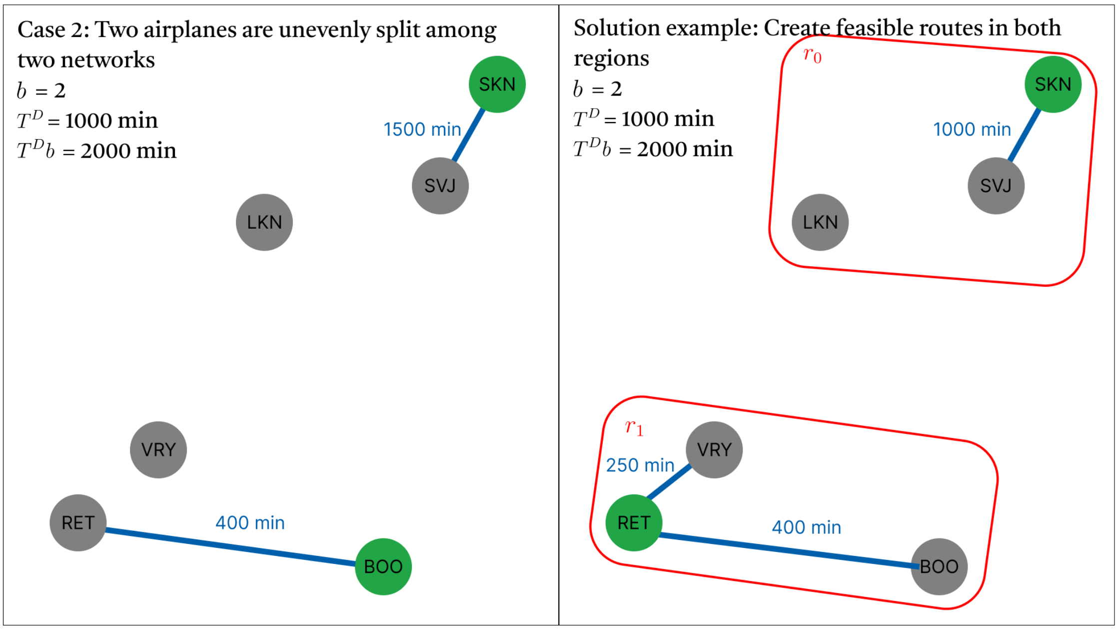

Figure 6: Solution example 2) where two airplanes are bought and one covers low-fraction demand in one network, while the other travels for longer than what is allowed

6.1.4 Decisions on Regions and Path Allocation

Forming Regions

Regions are formed in the following way:

1. Identify separate EA regions $\mathcal{N}^E_{tmr}$: Identify all separate subnets containing EA travel, using nonzero w^{tm}_{ij} for each (t, m) from the previous solution. Create a region for all airports connected by EA travel of model m in period t. This is defined as set $\mathcal{N}^E_{tmr}$ with regions $\mathcal{R}_{tm}$

2. Create regions with all airports $\mathcal{N}^A_{tmr}$: First set $\mathcal{N}^A_{tmr} = \mathcal{N}^E_{tmr}$. Then, for each airport $i \in \mathcal{N}$ that has not been added to a region in $\mathcal{N}^E_{tmr}$, identify the closest airport in $\mathcal{N}^E_{tmr}$ and add it to the region of that airport in $\mathcal{N}^A_{tmr}$

Allocating Paths to Regions

In the RDM, paths are allocated to a region if the path involves an airport within that region. As paths contain several airports, this means that one path can be part of many regions. There are several options for allocating paths to regions. One option is to see if their start or end airport is part of the region. Using only the start or end airport can lead to a more accurate estimation of the necessary number of airplanes within a region, since each path is only allocated to the region of one airport. A disadvantage of this approach is that regions can be counterintuitive, since paths can involve movements to other regions. If airplanes do not start or end at the same airports, it can also occur that airplane paths are intertwined or crossing, but their paths are linked to different regions. Instead, using all airports that are part of a path leads to an overshoot of the number of airplanes needed to satisfy demand. The model may then not prefer to use paths that are part of many regions due to the increased investment cost. It has been preferred to use all airports that are part of a path, as the airplanes purchased are not the highest priority insight to consider and it is preferable to have an overshooting rather than an undershooting on required airplane capacity.

6.1.5 Defining Termination Condition

The RDM defines when it is done by checking if the remaining network is feasible with respect to the regional constraints. This means that for each connected EA region R^E_{tm}, there is an integer number of airplanes allocated to that region that is sufficient to cover EA travels within that region.

The termination criterion for a single iteration is simpler than for the full implementation. Assuming that we solve the FREAP or a previous RDM, generate all-including regions R^A_1 and restrictions for these regions. We then add these restrictions from R^A_1 and reoptimize. This gives the set of directly connected EA regions R^E_2. The solution is then valid if each $r_e \in R^E_2$ is a subset of a region $r_a \in R^A_1$, and no other r_e is a subset of r_a. If this is the case, we know that the new subnetworks r_e are subsets of the regions r_a from the previous case, and there is no case where 1) two or more r_e subnetworks have been split up within an r_a or 2) new r_e subnetworks have been formed that do not fit within the restrictions of R^A. For a single run, the termination criteria can look like this:

> For each r_e in the direct EA subnetworks R_2^E there exists one and only one r_a in previously solved regions R_1^A so that $r_e \subseteq r_a$

However, the solution will not always be valid in a single iteration. In the case of several iterations, it is possible to keep or discard the old regions for the next iteration. If we discard older regions, and keep creating a new model and new regions each time the model is not valid, there is a chance of getting stuck in an infinite loop. The solution could then produce regions that are the same as a prior solution. To avoid infinite loops, the RDM keeps the old constraints r_a and adds new r_a constrains whenever a new r_a region is part of a solution.

The idea is similar to the single iteration example, but because the r_a regions can overlap between solutions, it becomes more complicated. First, we must remove that each region r_e can only be a subset of one r_a, since many R^A regions will overlap. Next, for a region r_a to represent a valid constraint for r_e, it cannot contain more than one r_e. If r_a contains more than one r_e, the restriction for r_a does not guarantee the validity of both r_e subnets. When an r_a contains only one r_e, we know that r_e is covered by the r_a restriction that is part of the run. The final termination condition is in Algorithm 1 and can be summarized like this:

> For every $r_e \in R^E$, there exists an $r_a \in R^A$ such that $r_e \subseteq r_a$ and all remaining $r'_e \in \{R^E | r'_e \neq r_e\}$ are not a subset of r_a

6.1.6 RDM Algorithm

To avoid infinite loops, each new model iteration must be unique. This is achieved by using regional constraints from both the previous and the most recent solution, as explained in Section 6.1.5. In the implementation, a maximum iteration counter is added to prevent long runs. The first $isValidStart$ on line 4 is also not implemented, as in Gurobi Optimizer, the solution is reused in line 10 if the initial solution is still valid with the restrictions from line 9.

Algorithm 1 RDM Termination Criteria

```
procedure isValid(R^E, R^A_tot)
    map^AE ← {}
    done ← True
    for r_a ∈ R^A_tot do
        for r_e ∈ R^E do
            if r_e ⊆ r_a then                          ▷ Check if r_e is a subset of r_a
                if map^AE[r_a].exists() then ▷ Remove r_a if min two r_e are subsets
                    delete(map^AE[r_a])
                    break 2                  ▷ Exit loop and continue to next r_a
                end if
                map^AE[r_a] ← r_e                        ▷ Map r_e to r_a if r_e ⊆ r_a
            end if
        end for
    end for
    maplist^AE = map^AE.values()         ▷ List of all r_e mapped at least once
    for r_e ∈ R^E do
        if r_e not in maplist^AE then              ▷ Only valid if all r_e mapped
            done ← False
            break
        end if
    end for
    return done                                    ▷ Return termination status
end procedure
```

Algorithm 2 Regionally Divided FREAP

```
procedure RegionallyDividedFREAP
    MOD ← InitializeFREAPModel()                      ▷ Initialize FREAP model
    solution ← Solve(MOD)
    done ← IsValidStart(solution)
    R^A_tot ← {}          ▷ Initialize dictionary containing all previous regions
    while not done do
        R^A_new ← GetNewRA(solution)                         ▷ Get new R^A regions
        R^A_tot.updateRegions(R^A_new)                  ▷ Add new regions to R^A_tot
        MOD.addRegionConstraints(R^A_new)          ▷ Add new region constraints
        solution ← Solve(MOD)                      ▷ Solve with new restrictions
        R^E ← GetRE(solution)                                      ▷ Generate R^E
        done ← IsValid(R^E, R^A_tot)                  ▷ Check termination criteria
    end while
    return solution
end procedure
```

6.2 Individual Routing Method

The IRM models each individual airplane movement to ensure that routes are possible to follow. The method tracks individual airplanes in a similar way as Voll [2023], but uses pregenerated paths to ensure sufficient charging capacity. This is implemented by requiring that the combination of EA flows x_p^{tm} can be distributed into allowed EA routes d_{pl}^{tmk} for each unique airplane (m, k). Since all EA flows x_p^{tm} can be distributed into specific airplane movements, the method guarantees that airplane movements and purchases are feasible, based on the assumptions provided.

First, the network and tracking of individual airplanes are introduced in Section 6.2.1. Next, the formulation is presented in Section 6.2.2. The tracking of individual airplanes involves a significant increase in complexity. To minimize the negative effect on runtime, Section 6.2.3 introduces different options to fix variables from the FREAP solution and then to solve combinations of the IRM. To wrap up, the algorithm for IRM is presented in Section 6.2.5. The IRM is based on the main model in Voll [2023], so formulations and definitions are reused in Section 6.2.2 and Section 6.2.1.

6.2.1 Description of the Network

Individual electric airplanes travel in an aviation network, where flight leg l increases by one in each path traveled. Node 0 is a sink node, with a distance of 0 from all other nodes. Each airplane ends its trip in node 0. To handle the possibility that an airplane visits the same airport several times, the model keeps track of the number of flight legs flown. A network to represent the allowed flights is shown in Figure 7. The network consists of sink node 0 and two airports KKN and VDS, where there is a charging station in KKN.

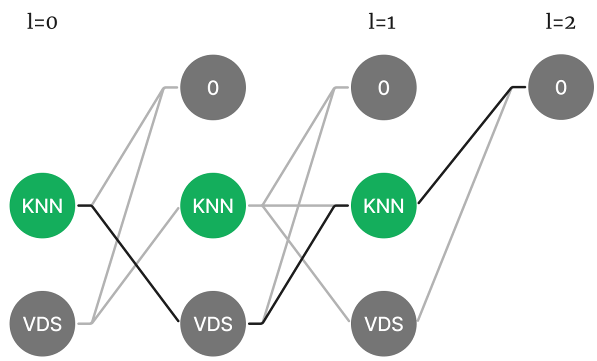

Figure 7: Example of EA movement in the IRM

In addition to the FREAP paths, the network has added direct paths from all nodes to node 0. There is no requirement for a charging station at node 0. The airplane shown follows the route (KKN, VDS, KKN, 0), where l increases by one whenever a new path is initiated. As all non-0 paths must start and end at a charging station, the paths in the example are (KKN, VDS, KKN) and (KKN, 0).

6.2.2 Formulation

IR Sets

$\mathcal{N}^0$	Set of all airports i, including node 0
$\mathcal{P}^0$	Set of all possible EA paths between airports i, including paths to node 0
$\mathcal{P}^{D(i)^0}$	Set of all paths p where i is the last airport/destination of the path, including paths to node 0. Node 0 can be a destination from all airports
$\mathcal{K}^m$	Set of all model indexes k for model m. A unique airplane is identified by the combined index (m, k)
$\mathcal{MK}$	Set of all unique airplanes (m, k), $\mathcal{MK} \in \{(m_1, k_1), ..., (m_M, k_K)\}$
$\mathcal{L}^m$	Set of all potential flight legs l traveled by a unique airplane of model m
$\mathcal{L}^{m0}$	Set of all potential flight legs l traveled by a unique airplane, including flight leg 0

IR Variables

d_{pl}^{tmk}	1 if the unique airplane (m, k) travels path p in flight leg l in period t

IR Replaced Constraints

$$T_{mp}^{K} d_{pl}^{tmk} \leq T^D \qquad t \in \mathcal{T}, (m, k) \in \mathcal{MK} \tag{28}$$

$$\sum_{k \in \mathcal{K}} d_{p0}^{tmk} \leq b^{tm} \qquad t \in \mathcal{T}, (m, k) \in \mathcal{MK}, p \in \mathcal{P}^m \tag{29}$$

Constraints (28) ensure that each individual airplane do not travel for longer than the available time T^D in one full day. To ensure that the right number of airplanes are purchased, constraints (29) require that an airplane is purchased for it to be allowed to fly in a day. Constraints (28) and (29) can substitute constraints (10) from FREAP, as they present stricter requirements.

IR Additional Constraints

$$\sum_{k\in\mathcal{K}}\sum_{l\in\mathcal{L}} d_{pl}^{tmk} = x_p^{tm} \qquad t\in\mathcal{T}, m\in\mathcal{M}^t, p\in\mathcal{P}^m \tag{30}$$

$$\sum_{p'\in\mathcal{P}^{O^0(i)}} d_{p'l}^{tmk} = \sum_{p''\in\mathcal{P}^{D^0(i)}} d_{p''(l-1)}^{tmk} \qquad t\in\mathcal{T}, mk\in\mathcal{MK}, i\in\mathcal{N}, l\in\mathcal{L}^0 \tag{31}$$

$$\sum_{p\in\mathcal{P}^0} d_{pl}^{tmk} \leq 1 \qquad t\in\mathcal{T}, mk\in\mathcal{MK}, l\in\mathcal{L}^0 \tag{32}$$

$$d_{pl}^{tmk} \in \{0,1\} \qquad t\in\mathcal{T}, mk\in\mathcal{MK}, p\in\mathcal{P}^0, l\in\mathcal{L}^0 \tag{33}$$

Constraints (30) define x_p^{tm} as the sum of individual airplane movement coverage d_{pl}^{tmk} excluding node 0. Constraints (31) secures allowed movements d_{pl}^{tmk} of unique airplanes (m,k). Whenever an airplane reaches a path destination $D(i)$, the next path must have that airport as the origin $O(i)$. To track movements, the departing flight increases flight legs l with 1. Note that constraints (31) is repeated for $i \in \mathcal{N} \neq \mathcal{N}^0$, so all airplanes are able to end their route by exiting to node 0. Furthermore, constraints (32) specify that an airplane cannot be in more than one place at a time, utilizing maximum one path p per flight leg l. d_{pl}^{tmk} is defined as binary in constraints (33). In the preliminary report Voll [2023], a constraint required that the same number of airplanes of each model are starting and ending the day at each airport, to ensure repeatability. This is ensured by variable x_p^{tm} via constraints (30) and (6), where the total flow of airplanes from and to an airport is always the same.

6.2.3 Fixing Variables

To solve IRM, the proposed solution method is to first solve FREAP, fix some variables of the FREAP result, and then solve IRM. Three variables have been identified for fixing: The number of airplanes purchased, the CA routes served and the building of charging stations. The recommendation is to only fix the number of airplanes purchased. If it is desired with an implmentation that does not fix any variables, an alternate implementation is presented in Appendix D. However, no fixing of variables leads to an even more dramatic increase in runtime, which is why this implementation is not the main recommendation.

Fixed Number of Airplanes Bought

$$b^{tm} = \backslash \geq FREAP(b^{tm}) \qquad t\in\mathcal{T}, m\in\mathcal{M}^t \tag{34}$$

Constraints (34) require that the same number of airplanes is used in the FREAP solution as in the IRM solution. Fixing b^{tm} may remove potential solutions or lead to infeasibility. For a stricter bound, equality should be used, but $\geq$ can be used to prevent infeasibility.

As mentioned in Section 2.3, the number of airplanes bought is a low priority insight from the model. However, they help the model to showcase how airlines can act and present an option that satisfies strategic requirements. Fixing the airplanes bought then functions primarily as a simulation of a possible scenario, where the IRM is tasked with providing the scenario with a feasible selection of routes.

Fixed CA lines served

$$r_{ij}^t \leq FREAP(o_{ij}^t)G_{ij} \qquad t \in \mathcal{T}, (i,j) \in \mathcal{A} \tag{35}$$

Constraints (35) refer to that we cannot create new CA routes in places where there were no CA routes in the FREAP solution. In any solution, there will be many routes that are not in use, which this quickly eliminates.

The selection of which routes should have CA is also not a key insight of the model. However, routes that do not have CA indirectly influence routes with EA, as non-CA routes must be covered by EA. A consequence may be that a solution incentivizes even more EA due to the need to cover non-CA-routes and cover the best additional routes. An advantage of setting an upper bound to CA routes is that it removes a lot of the complexity, but it also significantly restricts which areas where CA can be flown instead of EA. Restricting where to place the EA routes also affects the optimal location of charging stations.

Fixed location of charging stations

$$s_i^t = FREAP(s_i^t) \qquad t \in \mathcal{T}, i \in \mathcal{N} \tag{36}$$

Constraints (36) involve fixing the building and maintenance of charging stations for each period.

Fixing the location of charging stations involves fixing one of the less complex aspects of the model, while not gaining more information on the FREAP's key insights. Assuming that the goal of the model is to find when and where to invest in charging stations, this is not recommended. However, if the objective is first to find the optimal placement and then identify new routes, or to ensure that the FREAP solution is feasible, constraints (36) can be useful. An option with both individual routing and redirecting demand between endpoints, can be found in Voll [2023].

6.2.4 Limiting Sets and Symmetry-Breaking Constraints

$\mathcal{L}^m$ has the upper bound of the maximum possible number of flight legs to take in a day. This is the same as using the maximum M_{mp}^C for each model from Appendix C.C and add 1. +1 is added to include the final travel to node 0.

$\mathcal{K}^m$ has the upper bound of b^{tm} when the number of airplanes is fixed from a previous solution. In the case of not using the equality ($b^{tm} \geq FREAP(b^{tm})$) L^m can be expanded with 1 for each model m, to keep $\mathcal{K}^m$ as small as possible. This solution may exclude potential combinations with other b values, but b values will always be restricted when using constraints (34). If not fixing b^{tm}, $\mathcal{K}^m$ can be set to the maximum number of airplanes to buy of each model to cover the strategic demand [Voll, 2023]. However, the size has a major impact on runtime and should therefore be minimized as much as possible. As the maximum value from Voll [2023] is based on an extreme case assuming that airplanes only cover the longest routes possible, the real maximum k-value is in most cases significantly lower. The recommendation is therefore to explore different values and find a suitable range from the results recieved.

As the recommendation for limiting sets is to fix the number of airplanes provided, testing indicated that there was no gain in introducing symmetry-breaking constraints. The only symmetry left in the model, is then which model k travels the different combinations of routes, which primarily leads to an increase in complexity rather than efficiency. However, if the model does not have a strict upper bound for $\mathcal{K}_m$, symmetry-breaking constraints from Voll [2023] can be implemented. An option for expanding the range of b^{tm} values and implementing the symmetry-breaking constraints from Voll [2023] is provided in Appendix D.

6.2.5 IRM Algorithm

The IRM uses Algorithm 3.

Algorithm 3 Individual Routing FREAP

procedure IndividualRoutingFREAP
  SOL ← solveFREAP()
  MOD ← createNewIRM(SOL) ▷ Initialize IRM model
  MOD.AddConstraint(b^{tm} = SOL(b^{tm})) ▷ Fix b from FREAP solution
  solution ← Solve(MOD)
  if *solution* = Infeasible **then**
    MOD.ExpandSet(L^m)
    MOD.RemoveConstraint(b^{tm} = SOL(b^{tm}))
    MOD.AddConstraint($b^{tm} \geq$ SOL(b^{tm}))
    solution ← Solve(MOD)
    Terminate
  else
    Terminate
  end if
  return *solution*
end procedure

7 Test instances

This chapter describes the different test instances for the FREAP. Section 7.1 introduces the different airport networks used. Next, the generation of costs is discussed in Section 7.2. Section 7.3 presents the time parameters used. Finally, the different test instances for technological developments and strategic goals are presented in Sections 7.4 and 7.5. Section 7.3 is largely reused from Voll [2023].

7.1 Airport Networks

The airport networks used are based on the Norwegian aviation network. Data have been obtained from Statistics Norway's Table 08511 [Statistics Norway, 2023], which shows the number of seats on inland flights in airports in Norway. The model uses data from month 9 2022 to month 8 in 2023 to calculate the average demand in one day. The number of seats in each direction can be far from the number of passengers in the air. In most airline networks, there is a load factor, which is the percentage of seats available that are used. Since we do not know the desired load factor for the different flights, using seat data ensures that the solution is minimum as good as the existing aviation network. However, it may lead to overshooting on the necessary number of flights. When comparing the seat data for m9 2022-m8 2023 [Statistics Norway, 2023] with the passenger data for Q1 2022 [Statistics Norway, 2022], the average total load factor is 47% passengers per seat.

The latitude and longitude values were found using Google Maps [Google, 2023]. Next, distances between airports were calculated using geopy.distance.geodesic. This calculates the Vincenty distance between two coordinates. The Vincenty formula uses an accurate ellipsoidal model of the Earth, which provides accurate results for distances of up to 0.5 mm on the ellipsoid used [Panigrahi, 2014]. Vincenty is slower, but provides more accurate values than the commonly used Haversine formula, which assumes the earth to be a perfectly round sphere [Mahmoud and Akkari, 2016].

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Table 4: Airport networks used in test instances

Name	Airports	Total α_t [%]	Contents*
A9	9	2, 10, 50	ALF,HFT,HVG,MEH,BVG,BJF,VAW,VDS,KKN
A21	21	2, 10, 50	Airports north of BOO, including BOO
A24	24	0.05, 1.5, 6	Airports south of BOO
A45	45	0.1, 2, 6	Active airports in Norway

*All networks have excluded airports VDB, NVK, RYG, NTB, SKE, VRY and LYR

The four main networks that are used are presented in Table 4. Of the networks, the 9 airport network was used in Voll [2023] and represents the subsidized short-distance KKN-ALF network in northern Norway. Demand has now been corrected to match Statistics Norway [2023]. The division between A21 and A24 is carried out at Bodø Airport (BOO), which is the city with the highest population in northern Norway, where TOS is close behind [Store Norske Leksikon, 2023]. As a general rule, the population in Norway is significantly higher in the southern regions. Consequently, the A21 network is characterized by low demand and few hubs, while the A24 network has a higher demand and more hubs. From the full network and corresponding subnetworks, airports Fagernes Leirin, Narvik lufthavn, Verøy Lufthavn, and Moss lufthavn have been removed, as they currently do not operate CA. Notodden Lufthavn and Skien lufthavn have been removed as they have fewer than 10 passengers a year. Svalbard Longyear has been removed as it is separated from the mainland, has low demand, and is considered highly unlikely to be substituted with EA. The strategic goals used for 3-period runs with the different networks are presented in Appendix E.A.

7.2 Costs

There is a high uncertainty regarding the costs of EA [Ydersbond et al., 2020]. Because of this, the costs have been evaluated based on how they relate to each other and how cost relationships will affect the outcome of the model. First, the logic behind the cost relationships is discussed, along with a set of cost cases. Next, the equations for generating the costs are introduced. Finally, an overview of the numerical cost values is displayed in Table 5.

Cost Relationships

Costs and units in FREAP are presented in Table 5. The investment costs are C^I_{ti}, C^S_{ti} and C^B_m, and the variable costs are C^E_{tm} and C^G_t. Investment costs will increase if EA usage increases, as it requires more investments in airplanes and charging stations.

Name	Cost type	Unit
C^I_{ti}	Charging station inv	Per charging station built
C^S_{ti}	Charging station oper	Per charging station operated per period
C^B_m	Airplane inv	Per EA airplane bought
C^E_{tm}	Operational EA cost	Per EA airplane km
C^G_t	Operational CA cost	Per CA airplane passenger-km

Table 5: Overview of costs, where EA costs have been highligted

First, the cost hierarchy within the EA costs should be addressed. The largest single investment in the model is charging stations, as it requires the most planning and potential power grid investments. The investment cost C^I_{ti} can be combined with the maintenance cost C^S_{ti}, as presented in Appendix C.B. The purpose of C^S_{ti} is primarily to involve an additional cost penalty for investing in early periods. Since the most important cost is investment and operation is given if an investment is made, C^S_{ti} is lower than C^I_{ti}. We still desire for this to have an effect, so the cost is set at approximately one-tenth of the investment cost, which is usually comparable to the cost of buying an EA aircraft. As this thesis uses up to 6 periods, the operating cost of a single airport, will also not exceed the investment cost of an airport.

Next, the question is which routes are used, which is dependent on 1) which airplanes are available and 2) the cost of flying the routes. Although the cost C^E_{tm} is directly related to the routes chosen, the operational EA cost mainly influences to what extent the model punishes the routes for being long, and how it prioritizes flying with EA rather than CA. On the contrary, the airplanes bought C^B_m influence the range and capacity of the airplanes, and subsequently the routes that can be flown. When choosing routes, it is therefore a higher priority to consider the different models that are available and bought, since available models add restrictions to routes flown and the ability to cover demand. The suggested cost hierarchy is in equation (37).

$$C^I_{ti}y^t_i + C^S_{ti}s^t_i > C^B_m b^{tm} > C^E_{tm}A_{ij}w^{tm}_{ij} \tag{37}$$

A reasonable assumption to make about costs is that the total costs in EA are higher than the total costs of CA, shown in equation (38). If this were not the case, the network would immediately replace all possible routes with EA and there would be no need for government incentives to invest in EA.

$$C^I_{ti}y^t_i + C^S_{ti}s^t_i + C^B_m b^{tm} + C^E_{tm}A_{ij}w^{tm}_{ij} > C^G_t A_{ij}r^t_{ij} \tag{38}$$

Next, different cases are presented on whether or at what point in the costs it should become cheaper to use EA than CA. Three options are being considered, where option 2 is the Base Case:

1. **After a charging station is built, it should be cheaper with EA than CA routes**: $C^B_m b^{tm} + C^E_{tm}x^{tm}_p < C^G_t r^t_{ij}$. In this case, the combination of buying and operating EA is cheaper than CA. Here, the model would first minimize the number of charging stations that can be built, and then fill up all EA routes that are possible with the chosen charging stations. An issue with this approach is that it does not consider the high price of investing in airplanes. The model can then recommend routes that do not consider the reuse of older airplane models, as the investment cost in airplane models is so low. If the goal is to use a cost model like this, it should be considered to remove tracking of purchased airplanes b^{tm}.

2. **After a charging station is built and an airplane is bought, it should be cheaper to use all EA airplanes to their full potential**: $C^E_{tm}x^{tm}_p < C^G_t r^t_{ij}$. In this case, there is a significant cost to investing in airplanes, which incentivizes the reuse of older aircraft on new routes. Once an EA airplane is purchased, this airplane should fly at its full capacity, as long as there are feasible routes with remaining demand. The assumption also matches the insights of Section 2.1.3, in which we expect that the variable costs of EA may be lower than CA for short-distance flights.

3. **It is always more expensive to use EA than CA:** $C^E_{tm}x^{tm}_p > C^G_t r^t_{ij}$. This is the case where the model will try to minimize all investments to get as close as possible to the strategic goal α_t in constraint (18). In this case, situations can occur when an airplane only travels for a few hours a day and has surplus travel hours, since the target α_t is reached and the model prefers to cover the remaining demand with CA. This can be preferred if the goal is truly cost minimization if EA is more expensive, but it can beat the purpose of using EA investments to reduce emissions, as it can lead to surplus EA capacity.

Equations for Calculating Costs

Cost of Investing in Charging Stations C^I_i

No analysis of the cost of investing in charging stations has been done, so the base cost is assumed to be around the same for all charging stations. However, this leads to a lot of symmetry in the results. An example is if a route moves A-B-A or B-A-B and is repeated, it does not matter whether the charging station is built in A or B. To remove symmetry, each charging station investment cost gets the latitude of the airport added. In practice, the airports become slightly more expensive the further north the airport is located. The latitude coordinates of the full Norway network are in the range of 58-71. The formulas for C^I_i and C^S_i are presented in Equation (39)-(40).

$$C^I_i = C^{I0} + latitude(i) \tag{39}$$

$$C^S_i = \frac{C^{I0}}{10} \tag{40}$$

Cost of Operating EA C^E_{tm}

The cost of operating EA C^E_{tm} should be multiplied by a factor close to the capacity of the model Q_m. This is because r^t_{ij} is per passenger kilometer, while x^{tm}_p is per airplane kilometer, resulting in $r^t_{ij} \gg x^{tm}_p$. To make the operational cost of EA equal to CA in the objective function, the following formula can be used:

$$C^E_{tm}Q_m = C^G_t$$

However, a reasonable assumption is that there is a nonlinear relationship between the capacity of an EA airplane per trip, and the cost per trip. This is because the cost per trip also includes costs such as crew, airport fees, and power consumption. In these costs, an increase in aircraft size is expected to reduce the cost per passenger. Therefore, the proposition is to add a logarithmic function where part of the cost is fixed and part of it follows the function $\frac{x}{ln(x)}$. The calculation is presented in Equation (41), where $\beta = 0.25$ in the implementation.

$$C^E_{tm} = C^{E0}((1-\beta)Q_m + \frac{\beta Q_m}{ln(\beta Q_m)}) \tag{41}$$

Cost of Purchasing EA models C^B_{tm}

In the case of EA models, the cost should also scale according to the capacity of the model. An analysis has not been performed regarding different EA model costs; therefore, to counteract the effect of cheaper models per passenger, we assume that the cost per capacity increases with increased total capacity. This is implemented by multiplying the cost by a factor $\zeta > 1$. The calculation is presented in Equation (42), where $\zeta = 1.1$ in the implementation.

$$C^B_m = C^{B0} Q_m \zeta \tag{42}$$

Cost of Conventional Aviation Passenger-miles C^G_t

The cost of conventional aviation is expected to increase over time due to increased emission penalties. As mentioned before, if CA becomes more expensive than EA in total, the model invests as much as possible in EA. To not impact the cost hierarchy from equation (37), the growth in CA costs has been set to increase by a small constant in each time period. The calculation is presented in equation (43), where $\eta = 0.1$ in the implementation.

$$C^G_t = C^{G0} + \eta t \tag{43}$$

Numerical Cost Values

For all scenarios, the range of resulting variables varies based on a combination of time variables, strategic goals α and the airport network used. To fit the data presented in this thesis, the ranges have been grouped into multiplies of 10, where an additional multiplication with 10 makes it more expensive than the other decisions and the opposite with a division. To maintain the cost hierarchy in (37), there is an additional level of multiplication whenever there is a higher value than the one before or a division when something is cheaper. I.e. in Case 3, where all EA costs are higher than CA costs, the equal weights C^{E0} are multiplied by 10^1, C^{B0} by 10^2 and C^{I0} by 10^3.

Table 6: Overview of cost propositions for different cases

Name	Scale for equal weight	Value	Case 1	Case 2	Case 3
$C^{I0}_i(C^I_i)$	*1000*100	10^5	10^6	10^7	10^8
$C^{B0}_m(C^B_m)$	*100*100	10^4	10^3	10^5	10^6
$C^{E0}_m(C^E_m)$	*1	1	10^{-2}	10^{-1}	10
$C^{G0}_t(C^G_t)$	*1	1	1	1	1

7.3 Time Parameters

The time parameters used are the same as in Voll [2023], and consist of the operational time per day T^D and the time per path T^k_{mp}. First, the operational time per day is presented. Then, the time per path is broken down into time per stop T^S, time per kilometer traveled T^F_m and additional time per charging stop T^C, as presented in Appendix C.A.

Operational Time in a Day T^D

Operational time per day has been estimated from a network in Northern Norway. Using the knowledge of Avinor [2023a], flights to Kirkenes Airport started departing at 04:45, while the last flight landed at 01:00. The maximum operational time is then limited to 18 hours per day = 1080 minutes.

Time per path

Time per path consists of time per stop, time per km traveled and additional time per charging stop. The calculation of time per path is in Appendix C.A.

Time per Stop T^S

T^S is the fixed time per stop. Using data on the KKN-ALF network, the WF977 flight was followed by a route on Avinor [2023a]. The planned time per stop was identified as 15 minutes, as presented in Appendix B.A. Using airplanes with larger passenger capacity, the time per stop is expected to increase as it takes more time to board a larger number of passengers. Although, since large uncertainties are involved in the time parameters, most EA airplanes tested have a low passenger capacity, and time per stop only impacts the maximum possible number of flights, the time per stop is assumed to be constant.

Time per Kilometre Travelled T^F_m

T^F_m is the number of minutes spent per km traveled by model m. Since the model assumes a linear relationship between time and distance, T^F_m is a rough estimate of the speed at which an airplane travels. Using data from B.A, the shortest travel (KKN, VDS) has an average speed of 15 min / 38 km = 0.39, while the longest travel (HFT, TOS) has an average speed of 45 min / 212 km = 0.21. EA speeds should not be far from the range (0.2, 0.4) to be comparable with CA. For Eviation's 9-seater Alice, the maximum speed is 260 KTAS [Eviation, 2023], which corresponds to 0.125 and is unreastically high. For simplicity, we assume the average speed is the half of maximum speed, resulting in 0.25 for Alice. The T^F_m per model is presented in Table 8 and the data collection for each model is elaborated in Appendix E.B.

Additional Time per Charging Stop T^C

Additional time per charging stop is expected to vary a lot based on the technology chosen. To observe how the model reacts to different charging times, the charging times $T^C = 0$, 15, 30 and 60 are tested, which are presented in Table 7. For battery swap technologies, it should be possible to do so within the stop time T^S, so $T^C = 0$. The Base Case of 15 minutes is a rough estimate based on the fastest time Tesla provides to charge up to 200 miles [Tesla, 2023]. Similarly, Heart Aerospace's ES-30 claims a 30-minute charging time [Aerospace, 2023]. A 30 minute charging time corresponds to 15 minutes additional time per stop, since 15 minutes have already been added per stop T^S.

Table 7: Test instances for charging times

Charging time [min]
15
0
30
60

7.4 Technological Developments

This section describes the different test instances for technological developments. The different airplane models lay the foundation of which models are available. Then, scenarios are introduced on how the models can show up in different situations.

Different Airplane Models

The airplane models used in test instances have been estimated using a combination of inspiration from existing and retired EA projects and the attempt to provide a wide range of possible models, capacities, and ranges. As EA is new technology, it is impossible to accurately predict technological developments, so the model instead assumes that whenever a new time period is reached, a new plane model is available. This is because, in cases where technology developments do not go as expected, a more realistic outcome is that the strategic implementation is postponed or accelerated, rather than the model becoming infeasible and stopping the entire implementation. Flying speed T^f_m is the least accurate value and is elaborated in Section 7.3. An overview is presented in Table 8, while the table is further elaborated in Appendix E.B.

Technological Progress Scenarios

For technological progress scenarios, we consider different options of progress from the base case. The base case has been shortened to 3 periods, where we keep period t_0, t_3 and t_4 and their corresponding strategic goals in Table 7.5. The reason why

Table 8: Overview of airplane models used in test instances

Model	R^m	Q^m	T_m^f	Inspiration
m_0	100	9	0.25	Eviation-9 (Alice)
m_1	150	12	0.24	eCaravan-12
m_2	200	19	0.23	ES-19
m_3	250	30	0.22	ES-30
m_4	300	38	0.21	Hypothetical-38

this test only has 3 periods in contrast to 5, is that the strategic goals are set based on the technology available. So if the maximum model range in a period is unable to cover the strategic requirements in Table 11, the model becomes infeasible. However, in a real-world scenario, the only consequence of infeasibility is that an investment would have to be postponed, not that the entire project is impossible. To provide insights, the scenarios generated are generated to be feasible. In addition, a new model is created for the optimistic case in Table 9.

Table 9: Additional airplane model for optimistic test case

Model	R^m	Q^m	T_m^f	Inspiration
m_5	400	50	0.19	Hypothetical-50

Table 10: Airplane models available in technology development scenarios

Case	t_0	t_3	t_4
Base case	$[m_0]$	$[m_1, m_2, m_3]$	$[m_4]$
Optimistic case	$[m_0, m_1]$	$[m_2, m_3, m_4]$	$[m_5]$
Pessimistic case	$[m_0]$	$[m_2]$	$[m_4]$
Strategic goal	1%	30%	60%

7.5 Strategic Goals

This section describes the different test scenarios for strategic goals. First, it is elaborated on how the strategic goals used always depends on the network used. Next, the issue of different ambition levels and paths to the same end goal is introduced. Finally, the test instances for a different number of known periods are presented.

Network Dependency

As a general rule, the level of strategic goals must be adapted to the network used. This is because the impact of the strategic goal will vary based on the distribution of airports. A hub structure leads to larger long-range airplanes transporting the majority of passengers between hubs, while smaller short-range airplanes primarily transport passengers from smaller airports to hubs. The consequence is that most of the demand is along longer ranges and between different hubs. Since EA aircraft are expected to have shorter range and lower capacities, it is impossible for EA to

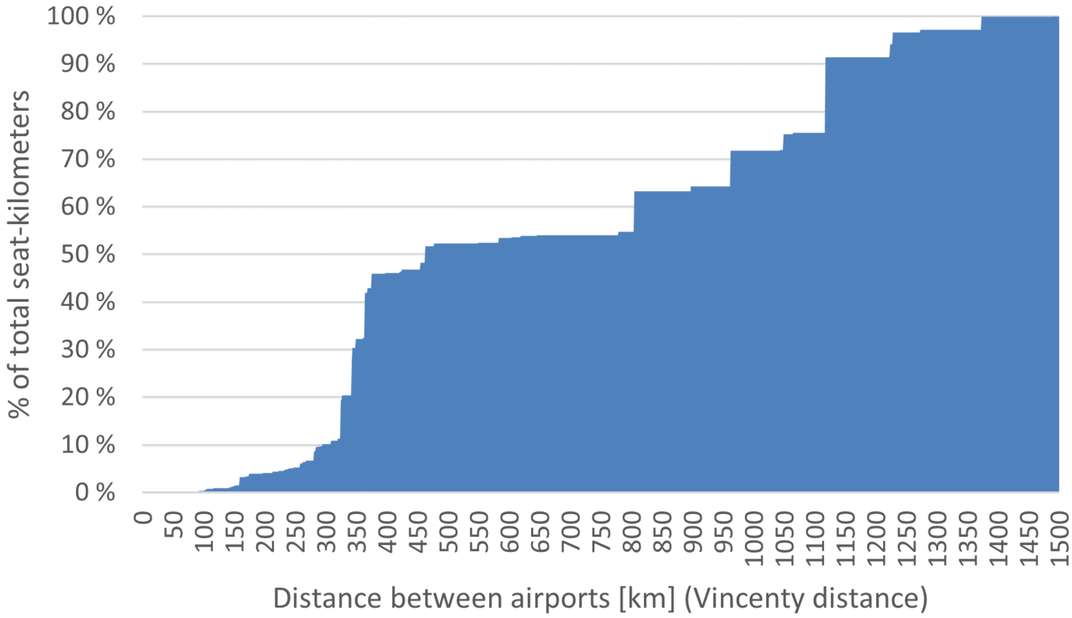

Figure 8: Distribution of seat-km in domestic flights in Norway m9 2022 - m8 2023

substitute all long-range aircraft and cover much demand using existing routes. This has several implications on how we plan on using electric aviation in general, but for the model, it means that the more hubs that are involved in a network, the lower the strategic goals have to be for the model to be feasible. This is especially visible in the larger A45 network, where about 66% of plane seats are routed through Oslo Airport [Statistics Norway, 2023], which results in especially low strategic goals. The total distribution of passenger demand is shown in Figure 8.

Table 11: Overview of maximum strategic coverage for different airplane ranges in Norway, where the Base Case is highlighted

Range	G_{ij}	G_{ij}/All	$G_{ij}/r \leq 300$	$A_{ij}G_{ij}$	$A_{ij}G_{ij}$/All	$A_{ij}G_{ij}/r \leq 300$
100	6070	2,37%	9,81%	426574	0,36%	3,60%
150	16050	6,26%	25,95%	1637275	1,39%	13,81%
200	34976	13,65%	56,54%	4725730	4,03%	39,85%
250	40859	15,94%	66,06%	6068069	5,17%	51,17%
300	61856	24,14%	100,00%	11859271	10,10%	100,00%
All	256286	100,00%	414,33%	117386881	100,00%	989,83%

*Values are calculated from G_{ij} and A_{ij} in the A45 network, as described in Section 7.1

Table 11 presents the relative and maximum possible strategic coverage with the different available flight ranges. This also depends on how strategic progress is measured. As it is unrealistic to achieve 100% coverage when assuming fixed routes, the implementation only considers routes with ranges below 300 km, as the available models have ranges up to 300 km. Therefore, only ranges below 300 km are used in constraint (18) to calculate the maximum total CA coverage. The highlighted section of Table 11 is then the maximum possible coverage to provide a feasible solution.

Different Ambition Levels

Using the A45 network as the base case, different ambition levels are proposed in Table 12.

Table 12: Ambition levels out of $r \leq 300$, where the maximum possible value is highlighted

Case	t_0	t_1	t_2	t_3	t_4
Low Ambitions	0.5%	3%	10%	20%	40%
Base Case	1%	8%	20%	30%	60%
High Ambitions	2%	10%	30%	40%	80%
Maximum possible	3.6%	13.8%	40.0%	51.2%	100%

Different Paths to End Goal

Different paths to an end goal refer to having the same final strategic goal, but different goals for previous periods. This explores how different subgoals for decision makers can affect the optimal solution. The different periods tested are in Table 13.

Table 13: Test cases of different paths to the same end goal

Case	t_0	t_1	t_2	t_3	t_4
Slow Progress	0.40%	4%	12%	20%	60%
Base Case	1%	8%	20%	30%	60%
Fast Progress	2.50%	12%	35%	45%	60%

Number of Known Periods

To explore how multiple period planning affects the final solution, we test how the model is impacted by solving for all periods simultaneously or only solving for one period at a time. This is implemented by first solving the problem for data from period t_0, fixing the solution for t_0, solving with data from both periods t_0 and t_1, and so on. This is repeated until period t_4 is reached.

8 Computational Study

This chapter presents a computational analysis of the fixed route electric aviation problem. First, the testing environment is presented in Section 8.1 and the format of tables and figures is introduced in Section 8.2. Next, a technical analysis of the model is done in Section 8.3. Here, the performance of FREAP, IRM and RDM is discussed. RDM is then considered the preffered model for future insights. Then, an economic analysis is done in Section 8.4, which explores how RDM responds to changes in costs, strategic goals, and technological developments.

8.1 Testing Environment

The model and model expansions introduced in Chapter 5 and Chapter 6 were implemented using Gurobi Optimizer. Testing has been carried out on the test instances presented in Chapter 7. The model was run in Gurobi Optimizer on a computer with the specifications shown in Table 14. All tests were carried out with a maximum optimality gap of 0.5% and for a maximum of 24 hours.

Table 14: Computer hardware and software used for solving the model

Processor	AMD Ryzen 5 5600X 6-Core Processor 3.70 GHz
Operating system	Windows 11 Home
RAM	16.0 GB
Gurobi Optimizer version	10.0.1 build v10.0.1rc0 (win64)
Python version	Python 3.11.2

8.2 Result Format

This section presents tables and figures that illustrate the aviation network. Network figures such as Figure 11 show the network in the last planning period, with each dot representing an airport. If the airport is not gray, it indicates that a charging station has been built there. Gray airports can be used for EA transport, but each EA trip must begin and end at a charging station before its range is exceeded. The color of the dot states the period in which the charging station was constructed, and the color coding for different periods is shown in the upper left corner of the figure. The color codes for the construction of a charging station are also shown in Figure 9. The blue lines represent the movement of EA traffic, and the thickness of the line indicates the amount of EA demand routed along the arc. The thickness of each line is determined by a logarithmic scale, where the maximum thickness is set relative to the maximum strategic coverage.

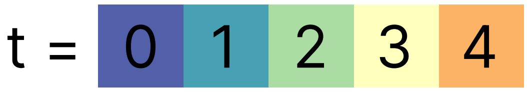

Figure 9: Color coding of which period a charging station is built

An Insight table such as Table 17 has the name of the test cases in the columns and the following rows:

- **Strategic goals** [%]: The strategic goals α_t as described in Section 5.4.4, which are set by decision makers. α_t is the desired percentage decrease in CA passenger-miles. Each spot in the vector increases t by one, like this: $[\alpha_0, \alpha_1, ...]$
- **Strategic coverage** [%]: Model output of strategic goals. Shows the percentage that CA passenger-miles have decreased in the solution. Calculated by $\sum_{ij} r_{ij}^t A_{ij} / \sum_{ij} G_{ij} A_{ij}$
- **# Airplanes bought** t_4: The number of airplanes bought of airplane model m in period t_4. In all periods except for the single period planning case, FREAP will only invest in the newest available airplane models. Therefore, the numbers correspond to the number of airplanes purchased in the first period when the model was available. Each spot in the vector increases m by one, like this: $[b_0, b_1, ...]$
- **# Stations built**: The number of new charging stations built in each period. Calculated by $\sum_i y_i^t$
- **# EA arcs manned**: The number of arcs (i, j) that has minimum one EA airplane flying along the arc in period t
- **RDM iterations**: The number of iterations required for the RDM algorithm after solving the initial FREAP. Iterations are 0 if the FREAP solution is valid according to the RDM criteria
- **Objective**: Objective value of solving the model. Refers to the final RDM objective value if no other method is specified

8.3 Technical Analysis

This section presents a technical analysis of the FREAP model and the two solution methods RDM and IRM. First, a discussion follows of how the methods relate to each other in Section 8.3.2. Next, Section 8.3.1 explores the performance of the models on different aviation networks. Subsequently, the results of the A9 runs are explored, where solutions for FREAP, RDM and IRM are very similar. Then, the results of the slow progress case from Table 13 are explored, as a situation where the RDM and FREAP solution differ.

8.3.1 Performance on Different Networks

FREAP, RDM and IRM have been tested on the networks A9, A21, A24 and A45 from Section 7.1. The different runtimes are presented in Table 15. From the tables, FREAP and RDM are significantly faster than IRM. IRM scales exponentially and cannot solve larger instances than A24 with 3 periods to optimality within 24 hours. RDM scales around the same scale as FREAP, but is multiplied by a constant around the number of iterations needed plus one. Furthermore, all models perform better on A24 than on A21, where IRM cannot solve A21 within the given time frame. This may be because the A9 and A21 networks have many low-demand routes, while the A24 has more high-demand. This shows that the demand distribution in a network also impacts the runtime.

In the tests carried out in this thesis, the RDM iterations have not exceeded 13 and the average number of iterations is 2-3. RDM scales around the same as FREAP because additional regional constraints have a low impact on complexity. As a consequence, RDM provides solutions very similar to FREAP but with the same scaleability as FREAP. However, the RDM escapes the problem of distributing fractional airplanes to different regions, which is expected to give more accurate charging station location recommendations.

Of all the tests performed in this thesis, only one has yielded 0 RDM iterations, which means that most FREAP runs involve some form of fractional distribution of the purchased aircraft. An infeasible distribution of airplanes does not have to impact optimal charging station locations, but this is still a risk, as explained in Section 5.6. As RDM on average performs on the FREAP runtime multiplied by 3-4, it represents a good trade-off for more accurate results, but not too large a solution time. In comparison, the IRM provides accurate results but is too slow to be used in any real-life scenarios.

Table 15: Solution times for FREAP, RDM and IRM on different networks

Solution time [s]	FREAP	RDM	IRM
A9	2.59	5.56	279.48
A21	51.32	131.74	-
A24	0.47	2.35	2995.39
A45	89.06	252.79	-

8.3.2 Relationships Between Methods

The three solutions each provide different bounds for the optimal solution. The initial FREAP model provides a version of the problem with a simplified tracking of airplane investments, as mentioned in Section 5.6. To handle this solution, IRM provides an accurate solution where we are certain to get feasible airplane movements, while RDM uses a heuristic to approximate feasible airplane movements.

Since the practical difference between FREAP and IRM is that IRM and RDM have an added set of restrictions, FREAP provides a lower bound to the IRM and RDM solution. In most cases, FREAP becomes a lower bound, IRM an upper bound, and RDM is somewhere in between. However, it is theoretically possible for RDM to have a higher objective than IRM. This can happen in a case where the FREAP and IRM solution are similar, but where more than 1 RDM iteration is required, resulting in overlapping regions. Since overlapping regions add a constraint on the number of aircraft required, it can lead to regional aircraft requirements more strict than the IRM.

8.3.3 Example Result: The A9 Network

This section explores further how FREAP, RDM, and IRM respond to the smallest network A9. The network for period t_2 is presented in Figure 10 and additional insight in Table 16.

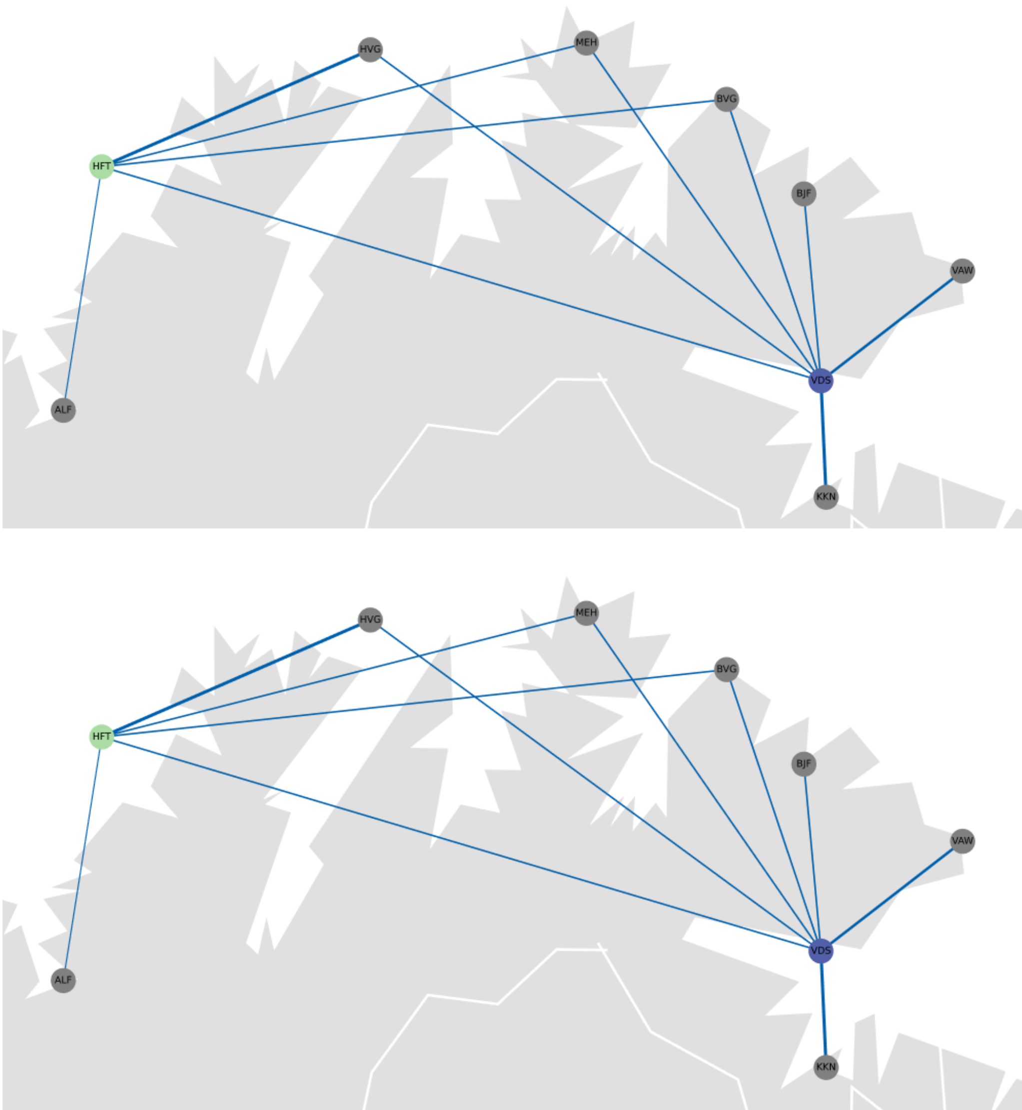

Figure 10: The A9 network in t_2 with FREAP on the top and RDM and IRM results below

Table 16: Insights on A9

	FREAP	RDM	IRM
Solution time [s]	2.59	5.56	279.48
# Airplanes bought	[1,1,1]	[1,1,1]	[1,1,1]
# Stations built	[1,0,1]	[1,0,1]	[1,0,1]
Objective	3.15881e+07	3.15881e+07	3.15881e+07
Note		1 iteration	

RDM and IRM provide the exact same solution, while FREAP is slightly different, which can be observed by the one iteration of RDM. To find out why, we can explore the FREAP and RDM data, where FREAP breaks the RDM criteria in (t_2, m_1). In FREAP for (t_2, m_1), model m_0 is not used, and model m_1 is assigned to the routes (HFT-ALF-HFT), (HFT-HVG-HFT) and (VDS-KKN-VDS). Observing Figure 10, the network containing (VDS,KKN) is separate from the network (HFT,HVG,ALF), making the split of model m_1 infeasible. RDM solves this issue by redirecting m_1 to only (HFT, HVG, ALF) and using m_0 to cover the remaining demand on (VDS,KKN). There can be many reasons why m_0 was not used in period t_2, but is most likely because the optimal solution involves m_2 flying (VDS,KKN), which covers most of the demand along (VDS,KKN) and the combination of m_1 and m_2 is then a slightly better fit to cover the demand. Since much of the demand in the northern regions is very low, there may also be no other relevant options for the m_0 model except (VDS,KKN). The RDM and FREAP solutions are both approximately equal in terms of their objective value. In this case there were no changes in charging station locations, but RDM instead provided a more feasible solution where no airplanes were split along a route. We also observe that IRM and RDM provides the same solution, but where RDM is significantly faster.

8.3.4 Example Result: The Slow Progress Case

In most of the results of the test instances in Chapter 7, there are no differences between the charging station locations in the FREAP and RDM solution. However, there are often some differences in the allocation of flight routes and the number of aircraft purchased, as in Section 8.3.3. Of the results presented in Section 8.4, this occurs in the Base Case of airplane models available in Table 10 and the slow progress case in Table 13. The slow progress network is shown in Figure 11.

In the slow progress case, we observe a situation where FREAP builds split subnetworks and RDM instead uses connected routes, as in Problems 1 and 2 in Section 5.6. In this example, FREAP builds in the network (EVE,ANX,TOS), while RDM only expands in the south. The first obvious fractional distribution is in period t_3, where FREAP only has one airplane of m_0, and this single airplane is assigned to both (ANX,EVE) and (HOV,FRO) in the same time period. However, throughout the planning periods, model m_0, m_1 and m_3 are distributed along both the northern (EVE,ANX,TOS) network and southern networks. As FREAP purchases the model distribution of [1,5,9,2,9], we can also expect there to be illegal distributions

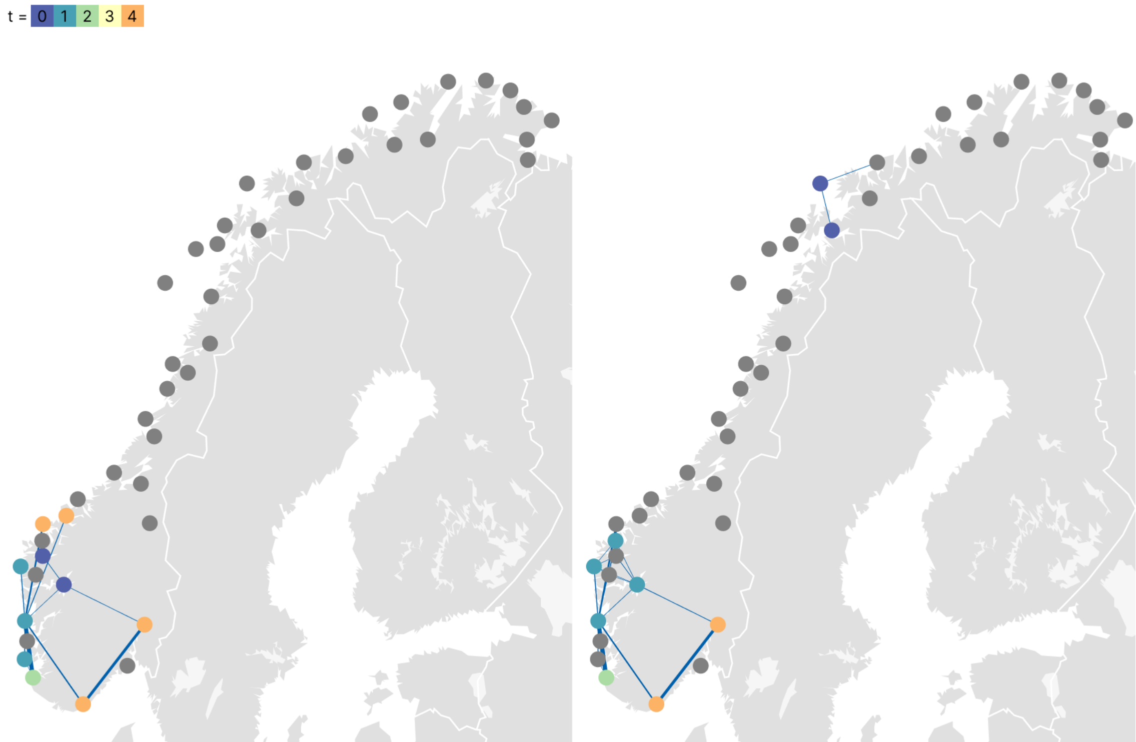

Figure 11: Example of RDM and FREAP charging station differences from the slow progress case, where RDM is to the left

of capacity with the other models, such as in problem 2 of Section 5.6, but these are harder to detect when more models are present. Since it is no longer allowed to distribute fractional EA capacity in the (EVE,ANX,TOS) network, the RDM chooses to not invest in EVE and ANX, and instead focuses on the southern network. As EVE and ANX are the first two charging stations built, the change affects most of the future development of the network.

8.3.5 Concluding Method Recommendation

To conclude, RDM and FREAP often provide similar key insights, where RDM has an average runtime of 3-4 multiplied with the FREAP runtime. However, FREAP will in most cases provide solutions that involve an illegal fractional distribution of EA routes, in which an illegal distribution can impact optimal charging station locations. By using RDM, it is guaranteed that routes are planned in a way where there is sufficient demand in a connected network to be covered by the models, and that the chosen locations are well adapted to a connected EA-network. In comparison, the IRM ensures the same, but is too slow to solve real-world instances of the problem. Therefore, the RDM is recommended, as it is sufficiently fast for real-world problems and the recommended routes are sufficiently accurate to provide good charging station recommendations. Therefore, RDM is the recommended model to use and is used in the upcoming sections.

8.4 Economic Analysis

This section describes results related to managerial insights and how the model reacts to different possible outcomes. The effects of different cost scenarios are presented in Section 8.4.1. Next, Section 8.4.2 presents how different strategic goals affect the outcome of the model. Finally, Section 8.4.3 explores how technology development scenarios impact the optimal solution. The information format for tables and figures in this section are explained in Section 8.2.

8.4.1 Cost Scenarios and Solutions

This section explores how the different cost scenarios of Table 6 affect the optimal solution. The networks of the last period are presented in Figure 12 and additional insights are provided in Table 17.

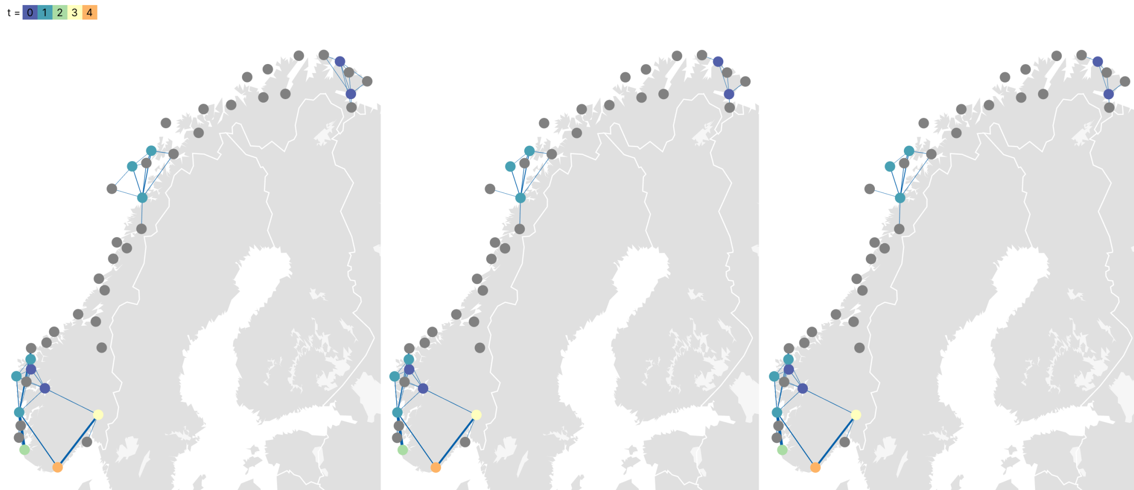

Figure 12: Period 4 networks in Cost Cases 1, 2 and 3 beginning from the left

Table 17: Insights on cost cases

	Case 1	Case 2 (BC)	Case 3
Strategic goals [%]	[1,8,20,30,60]	[1,8,20,30,60]	[1,8,20,30,60]
Strategic coverage [%]	[1,8,25,30,64]	[1,8,21,30,60]	[1,8,20,30,60]
# Airplanes bought t_4	[3,11,11,3,9]	[3,11,8,4,7]	[3,11,8,4,7]
# Stations built	[4,6,1,1,1]	[4,6,1,1,1]	[4,6,1,1,1]
# EA arcs manned	[12,52,68,79,88]	[12,43,45,62,69]	[12,43,45,63,69]
RDM iterations	4	2	2
Objective	1.88108e+08	4.26584e+08	2.77132e+09

All cases invest in the same charging infrastructure, suggesting that cost variations do not significantly affect the optimal charging station locations. The primary distinction between the cases is that the lower-cost cases have a lower objective value, invest more in EA airplane models, and thus have a greater strategic coverage.

The main difference between the runs is to what extent the cost cases maximize the value of their charging stations and airplane models purchased. As cost relationships are similar in all cases except variable EA costs, Cases 2 and 3 also have the same number of airplane models bought, but Case 3 has an even tighter bound towards strategic goals. As discussed in Section 7.2, this is because Case 3 has a higher variable cost of EA and does not reward reuse of EA models once the strategic goal has been achieved. In Case 2, EA models will continue to fly after the strategic goal has been met, whereas in Case 3, they will be prevented from flying even if there is still EA capacity.

Case 3 involves one more EA arc than Case 2 in period t_3, yet it has a lower strategic coverage. This shows that there is no direct relationship between the number of EA arcs and the electric coverage, as it is the way that EA covers demand along the arcs that is significant. Case 2 can fly more times back and forth along an arc and cover more demand, while Case 3 may fly along more distinct arcs to get as close to the strategic goals as possible.

In Case 1, it should be noted that the EA coverage is not as high as expected, as the cost of obtaining a new EA aircraft is expected to be lower than that of CA. As seen in Appendix B.B, there exist other routes that can be electrified with the charging station investments, such as HOV-MOL-HOV. This implies that the cost case is still at a point where the cost of EA per passenger mile is higher than that of CA. The reason for this could be due to the extra demands placed on aircrafts for flying back and forth with models, as well as the fact that EA may not be able to adjust to the demand, as each plane has a fixed capacity and can end up with unused seats. However, Case 1 has invested more in EA than Cases 2 and 3 by buying more airplane models, resulting in a higher strategic coverage. In addition, there are large differences in the objective values, which is expected, since there are major differences between costs, making Case 1 fundamentally cheaper than Case 2 and Case 3.

The results of the charging station locations indicate that the model is robust to changes in costs, even when the cost scenarios vary significantly. As discussed in Section 7.2, there is a great deal of uncertainty surrounding costs, which is why the test cases included large ranges of values. The minor differences in the charging station locations suggest that the model is resilient to cost variations. It may also imply that other factors, such as restrictions on EA range and strategic goals, are more influential in determining charging station investments.

8.4.2 Strategic Goals

Different Ambition Levels

RDM was tested using different Ambition Levels from Table 12. Insights are presented in Table 18 and the last period EA networks are shown in Figure 13.

An initial observation is that the strategic coverage is consistently close to the strategic goal. The cost hierarchy in Section 7.2 guarantees that investing in EA models

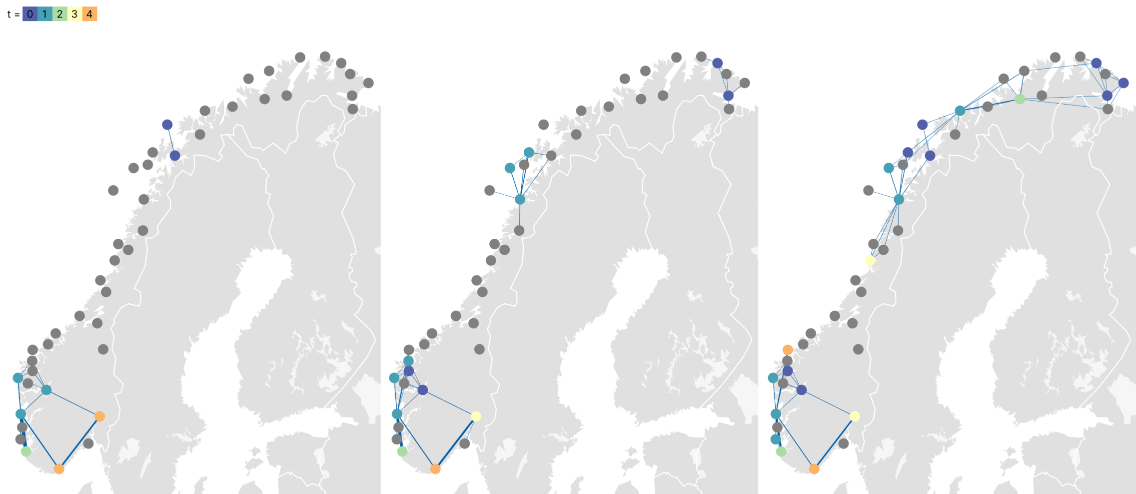

Figure 13: Period 4 networks in High Ambitions, Base Case and Low Ambitions beginning from the left

Table 18: Insights on different ambition levels

	Low Ambitions	Base Case	High Ambitions
Strategic goals [%]	[0.5,3,10,20,40]	[1,8,20,30,60]	[2,10,30,40,80]
Strategic coverage [%]	[0.7,3,12,21,40]	[1,8,21,30,60]	[2,10,31,40,80]
# Airplanes bought t_4	[1,3,5,4,4]	[3,11,8,4,7]	[7,11,13,4,10]
# Stations built	[2,3,1,0,2]	[4,6,1,1,1]	[8,6,2,2,2]
# EA arcs manned	[2,7,11,16,25]	[12,43,45,62,69]	[20,42,52,84,110]
RDM iterations	2	2	5
Objective	3.23731e+08	4.26584e+08	5.48019e+08

and charging stations is never more cost-effective than investing in CA. Therefore, all solutions will be close to the strategic goals. The consequence is that decision makers must have a conscious approach to setting strategic goals.

The different ambition levels have had a major impact on the placement of charging stations. Base Case (BC) begins by investing in the KKN-ALF-network and SDN-SOG, while Low Ambitions invest in ANX-EVE. The High Ambitions case invests in the period t_0 investments of both Low Ambitions and BC. BC then invests in the airports around BOO. Low Ambitions do not invest in BOO, as the demand covered in southern Norway is sufficient. Next, we observe that both BC and Low Ambitions invest only in the southern network, while High Ambitions also continue to expand in the northern regions. Since High Ambitions is pushed to invest in the northern regions at an early point, it is also incentivized to build out these networks in later periods.

We observe that range restrictions have a greater impact on earlier periods, resulting in the need for more investments in charging stations. High Ambitions and BC require many investments in EA at an early point, but they flatten out over time. This is because the model must invest in several low-range routes at an early stage to meet strategic coverage requirements, which require extensive investments in charging stations. Later periods, however, can cover more demand with fewer stations. The later periods are then less restricted by range due to the more advanced aircraft models.

The large investments in the south suggest that any implementation has a greater effect per investment in areas with higher demand. High-demand routes ensure that EA can be fully used while the remaining demand is taken care of by CA. Therefore, in the short term, the best option is to replace high-demand routes with EA to reduce emissions and minimize costs. However, in the long run, high-demand routes can be replaced with zero emission alternatives such as trains or green hydrogen aviation. Consequently, low-demand PSO routes might be the only routes that are guaranteed to be electrified in the long term. This is because short-distance routes often have fewer zero emission options, since the infrastructure required is more expensive than substituting CA routes with EA.

FREAP assumes a fixed cost for investments in charging stations, regardless of the demand for and number of EA flights to and from the station. This means that the cost of a charging station per flight in and out is lower when more demand is routed to and from it. On the other hand, areas with high-demand are likely to have better access to crew and infrastructure, which can reduce the cost of charging stations and maintenance. As this report has not focused on exact cost estimates or scaling of charging infrastructure, this is considered beyond the scope of the thesis. However, a fixed cost per charging station will also contribute to prefering high-demand routes.

Model preference for high-demand routes should be taken into account when planning EA routes. If ambition levels are set high in the early stages, the RDM will invest in the north, as in the High Ambition case. However, this requires a large number of charging stations to be built in initial periods, which could lead to higher long-term costs as technology may improve over time. Therefore, if the aim is to electrify certain routes long-term, such as the KKN-ALF network, we can consider adding requirements that "these routes must be electrified in the end", which forces the model to invest in these routes at some point in the strategy.

Same End Goal with Different Subgoals

RDM was tested using data from Table 13 on different subgoals to the same end goal. Insights are presented in Table 19 and the networks of the last period are shown in Figure 14.

From these results, we see a trend that higher goals in earlier periods lead to more investments in charging stations and airplanes, and that these early investments continue to impact the upcoming periods. The Fast Case consistently has higher values in airplane investments, except in the last period, where it is able to reuse the previous models to reach the strategic goal. The opposite effect is observed in the Slow Case, where m_4 is the highest with $m_4 = 9$. In the Slow Case, there is also a situation where RDM rather purchases more of an airplane in an earlier period than what is needed. In period t_2, the Slow Case buys several airplanes and has a

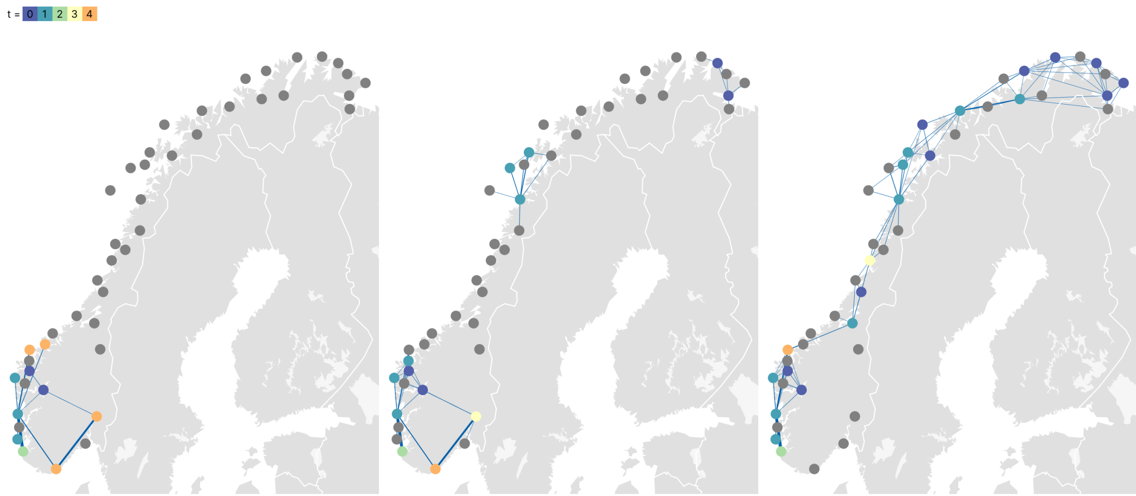

Figure 14: Period 4 networks in Slow Progress, Base Case and Fast Progress from the left

Table 19: Insights on test instances with the same end goal and different subgoals

	Slow Progress	Base Case	Fast Progress
Strategic goals [%]	[0.4,4,12,20,60]	[1,8,20,30,60]	[2.5,12,35,45,60]
Strategic coverage [%]	[0.6,4,20,20,60]	[1.1,8,21,30,60]	[2.6,12,35,45,60]
# Airplanes bought t_4	[1,4,10,0,9]	[3,11,8,4,7]	[8,16,16,4,5]
# Stations built	[2,3,1,0,4]	[4,6,1,1,1]	[10,9,1,1,1]
# EA arcs manned	[2,10,12,12,22]	[12,43,45,62,69]	[23,66,83,115,162]
RDM iterations	3	2	13
Objective	3.64179e+08	4.26584e+08	5.77388e+08

strategic coverage of 20% despite only needing 12%. Due to this investment, one does not have to buy any airplanes in period t_3. Since the m_2 airplane is available from period 2, it is more cost-effective to buy more airplanes earlier and reuse them in the upcoming periods. This is possible due to multiple period planning, where the model can see a more cost-effective solution by investing early. In a real-life situation, early investments are also advantageous since they contribute to faster technology developments.

The Fast Case is affected by a similar trend as the High Ambition Case, which is that high goals in early periods lead to many stations being built and subsequently a higher strategic coverage in the northern regions. In contrast, the Slow Case exploits that it only has to invest in SOG and SDN in the first period and continues to expand in the south. As a consequence, the Fast Case consistently has more than 6 times as many EA-arcs manned as the Slow Case in each period. The Fast Case has to invest in many low-demand routes, while the Slow Case covers demand by using few high-capacity airplane models along few high-demand routes. This is also an example of the model preferring high-demand routes when possible, since it is easier to cover all demand along these routes.

Despite having the same end goal, there are major differences in the objective value between the cases. The newer models are more cost-effective per passenger and kilometer than the older ones, giving the Slow Case a major advantage by delaying investments in aircraft and charging stations. This highlights a common problem with new technologies, which is that early adopters are likely to lose money. However, if no one invests in the early stages, then technology development will progress at a slower rate. This is why it is essential to set strategic objectives, understanding that initial investments will yield a lower return per investment. We must create a network where the initial investments do not yield immediate returns, but where the initial investments can be utilized in the best way possible. This involves planning for the long-term reuse of older stations and aircraft models.

It should also be mentioned that these are some of the most different networks from all the test instances, despite having the same end goal. It shows that the optimal strategy is greatly impacted by the pace with which we want to implement electric aviation. Ambitious early goals favors more remote regions, while slower progress leads to more focus on high-demand routes.

8.4.2.1 Different Number of Known Periods

To explore the impact of knowing multiple periods, RDM was tested with the Base Case using multiple period planning (MPP) and the Single Period Case (SP) that solves for one period at a time. Insights are presented in Table 20 and the airplane networks are shown in Figure 15.

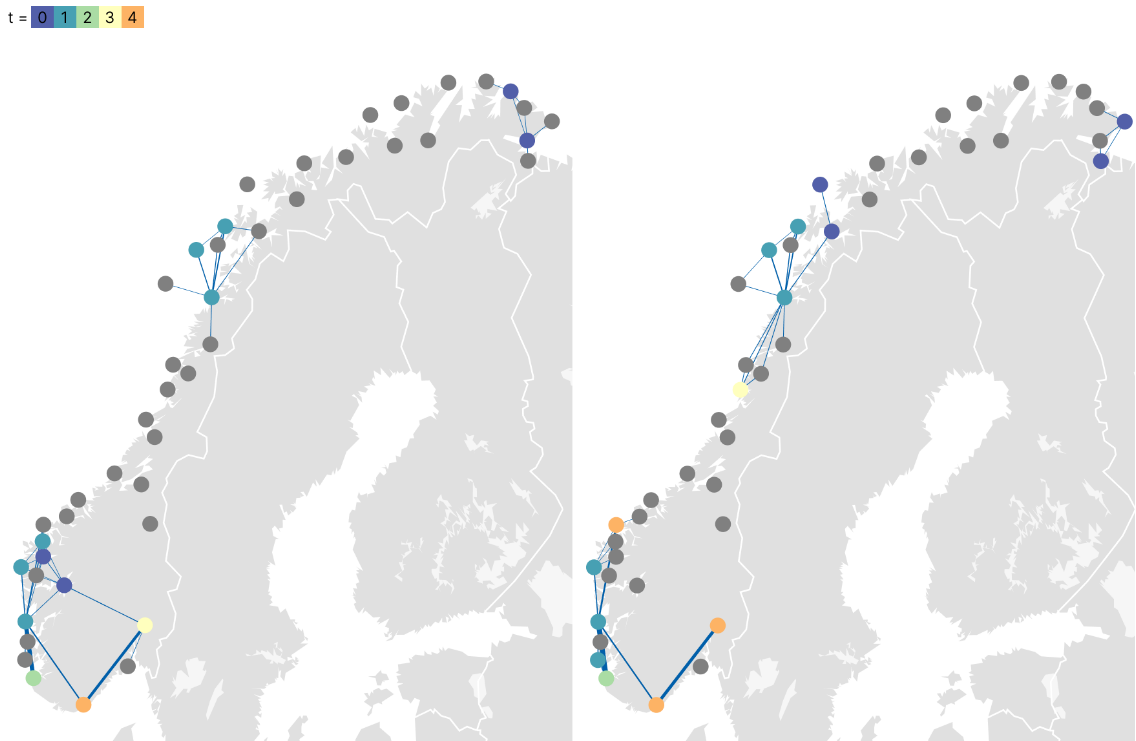

Figure 15: Period 4 networks in different planning horizons, with the MPP Base Case and Single Period Case from the left

Table 20: Insights on multiple periods versus planning for one period at a time

	Base case (MPP)	Single period (SP)
Strategic goals [%]	[1,8,20,30,60]	[1,8,20,30,60]
Strategic coverage [%]	[1,8,21,30,60]	[1,8,20,30,60]
# Airplanes bought t_4*	[3,11,8,4,7]	[2,10,11,2,7]
# Stations built	[4,6,1,1,1]	[4,6,1,1,3]
# EA arcs manned	[12,43,45,62,69]	[8,23,27,48,60]
RDM iterations	2	1
Objective	4.26584e+08	4.45929e+08

*SP did not always invest in the newest model as in previous runs. Out of the total, it purchased 1 of m_1 in t_2 and 4 of m_3 in t_4

SP yields an objective value that is 4.5% greater than the Base Case. When taking a closer look at the data, the cost of investing in charging stations is 33.6% of the objective value of SP. Dividing this by the built stations $4 + 6 + 1 + 1 + 3 = 15$, each new investment in a charging station leads to an increase in the objective value of 2.24%. The result is that the additional cost of two charging stations is expected to be the main driving force for the increased objective value.

SP invests in older airplane models at a later stage and can therefore not use them in the earlier periods. Investing in older airplane models can be beneficial if the models are better suited to the demand in the area. A smaller plane may be preferred over a newer one, as the cost per EA flight and EA-airplane remains the same even if not all seats are filled. Also, older airplanes have a lower total cost than newer ones. SP has not been able to benefit from the ability to reuse models earlier, resulting in a negative effect on the objective value.

When contrasting the networks, they both invest in the same general areas, yet there are notable contrasts in the timing of investments and development in those areas. For example, SP does not invest as much in the southern regions as the MPP, except for periods t_1 and t_4. A clear distinction here is in the first period, where both invest in the northern KKN-ALF network, but MPP invests in the southern SDN-SOG while SP invests in ANX-EVE. ANX-EVE may be the best short-term option, but MPP instead invests in the south, as it will expand in the south in the long run. The result of the accumulated investment in the north is that SP needs to invest in additional charging stations in the last period, leading to an overall increase of 4.5% in the objective value.

The MPP is able to plan for all periods simultaneously, allowing for more cost-effective investments in EA routes, charging stations, and models. SP, on the other hand, invests more in the northern regions due to a shorter planning horizon. In the long run, earlier SP investments are not enough to achieve the strategic goals, so the model has to invest in more charging stations in the south. This reinforces the notion that the northern regions are suitable for the initial stages of adoption of electric aviation, but the return on investment is higher in the southern regions.

8.4.3 Technology Developments

Charging Time

This section explores how different charging times influence the model result. The charging times used are presented in Table 7. The last period network is in Figure 16 and different insights are in Table 21.

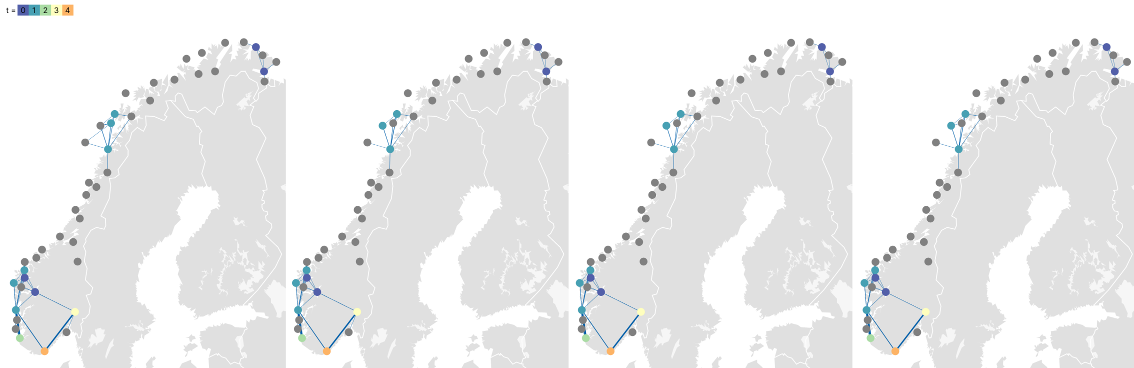

Figure 16: Period 4 networks in cases with charging time t=0, t=15, t=30 and t=60 from the left

Table 21: Impact of Different Charging Times

	0 min	15 min (BC)	30 min	60 min
Strategic goals [%]	[1,8,20,30,60]	[1,8,20,30,60]	[1,8,20,30,60]	[1,8,20,30,60]
Strategic coverage [%]	[1,8,22,30,60]	[1,8,21,30,60]	[1,8,21,30,61]	[1,8,20,30,60]
# Airplanes bought t_4	[3,9,7,3,6]	[3,11,8,4,7]	[4,13,10,5,9]	[5,17,12,7,11]
# Stations built	[4,6,1,1,1]	[4,6,1,1,1]	[4,6,1,1,1]	[4,6,1,1,1]
# EA arcs manned	[12,45,49,63,73]	[12,43,45,62,69]	[12,43,45,61,67]	[12,43,45,67,74]
RDM iterations	2	2	3	2
Objective	4.14298e+08	4.26584e+08	4.45953e+08	4.71487e+08

The test instances show an expected outcome that increasing charging times leads to an increased objective function, an increased need to purchase EA airplanes, and more unique routes, but with no impact on charging station locations. The reason there are no differences in charging station locations is most likely that a charging station enables us to cover the demand of surrounding routes. So, the demand and routes available are independent of the aircraft models' hours in a day and subsequent ability to cover demand.

No differences in charging station locations, but large differences in purchased airplanes, are an indication that the number of airplanes purchased does not have a large impact on optimal charging station locations. As mentioned in Section 7.3, the charging time of airplanes only affects the number of trips that an airplane can carry out in a day, again affecting the number of airplanes needed to meet strategic demand. This supports the hypothesis that the number of airplanes purchased is not a high-priority insight and should not have a major impact on optimal charging station investments.

8.4.3.1 Airplane Models Available

This section explores how various airplane models that are available affect the outcomes of RDM. RDM has been tested with values from Table 9 and Table 10, where this run contains only 3 periods. Insights are presented in Table 22 and the network is shown in Figure 17.

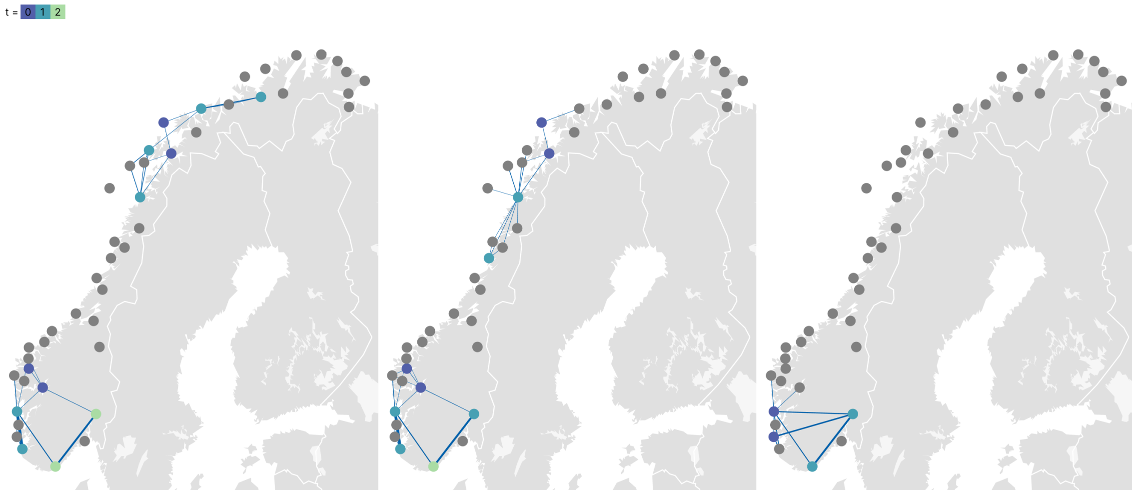

Figure 17: Period 2 networks in Pessimistic Case, Base Case and Optimistic Case from the left

Table 22: Impact of different model availability

	Pessimistic	Base Case	Optimistic
Strategic goals [%]	[1,30,60]	[1,30,60]	[1,30,60]
Strategic coverage [%]	[1,30,60]	[1,30,60]	[1,33,60]
# Airplanes bought t_4*	[2,-,20,-,7,-]	[2,0,4,9,8,-]	[0,2,0,0,8,4]
# Stations built	[4,6,2]	[4,5,1]	[2,2,0]
# EA arcs manned	[4,38,48]	[4,44,56]	[4,14,18]
RDM iterations	1	2	0
Objective	3.23065e+08	3.00539e+08	2.11966e+08

*If a model is not available in the test instance, this is marked with '-'

The initial observation is that the model only ever invests in the newest model, despite older models being available. This is in line with the previous sections, where all periods are known. No investments are made in older models, as the newer models offer a higher range and lower cost per passenger mile. Additionally, the Pessimistic Case is required to invest in a large number of airplanes to reach the strategic goal, which leads to a worse objective than the Base Case.

When analyzing the location of the charging stations, the type of airplane models available has a major effect on the growth of the EA network and the charging station locations. The Optimistic Case only invests in the southern area, while the Pessimistic and Base Case both invest in the northern and southern regions. As in previous examples, it indicates that, whenever possible, the model prefers to invest in the southern high-demand networks. However, if the model has to invest in low-demand networks in the early stages, it may also expand the charging station networks in the low-demand networks.

Since this implementation also has only three periods, corresponding to t_0, t_3, and t_4 in 5-period runs, the Base Case also looks different from in the other test cases. In particular, it invests in (ANX, EVE) instead of (BVG, VDS) in the first period, expands further down south of BOO, and no longer invests in (FRO, HOV). Since the period and range restrictions of the original period t_1 and t_2 are no longer there, the model chooses to skip some investments from these periods. This is another example of how different strategic goals and range restrictions, as a combination, have an impact on optimal charging station locations.

It should also be noted that the Optimistic Case is the only test case where the RDM iterations are 0. As observed in Table 22, this case invests in significantly fewer EA arcs than the Pessimistic Case and Base Case. When investing in fewer arcs, it is easier to satisfy the RDM termination criteria, as it is less likely that a single airplane capacity is split between disconnected subnetworks. However, it shows that there exist cases where FREAP does not provide a solution with an illegal distribution of EA models. Although the rarity of a 0-iteration result also highlights the purpose of RDM to identify feasible distributions of EA models.

9 An Implementation in Norway

This section focuses on an implementation in Norway and further adapts the RDM to provide insights that can be used in a Norwegian context. First, the findings of the managerial insights are summarized in Section 9.1. The relevant findings of Chapter 2 are summarized in 9.2. Then, a discussion follows in Section 9.3 on what the differences are between the current strategy and the findings of the RDM, and how to adapt the RDM to better suit the existing strategy. Section 9.4 presents expansions to the RDM, before the RDM is run again, and the updated results are presented in Section 9.5. Finally, a discussion of the final results follows in Section 9.6.

9.1 Summarized Managerial Insights

To summarize, the combination of strategic goals and range restrictions of available airplane models have a large impact on optimal charging station investments. When possible, the RDM prefers high-demand routes, as it is easier to cover all demand with EA without having surplus EA seat coverage. This is observed both in cases where the available airplane models and the strategic goals are modified. Furthermore, different cost structures have not been found to have a major impact on the optimal solution, assuming that they maintain the cost hierarchy of Equation (37).

Regarding optimal charging station investments, which locations are optimal varies. With long-range models or lower strategic requirements, the RDM always invests in the southernmost network if possible (t_1 and t_2: BGO and SVG. t_3 and t_4: KRS and OSL), while investments in HAU, FRO and HOV varies. When range restrictions have a greater impact and northern investments are necessary to achieve strategic goals, the RDM often recommends forming a network around BOO and the surrounding islands and expanding in the northernmost region around KKN.

The results of the managerial insights are that the RDM prefers high-demand routes whenever available and therefore prefers to expand the aviation network in the south if this is possible. A consequence is that the RDM is unlikely to invest in the northern regions unless this is specified or range restrictions make the northern regions more attractive. Investments in high-demand regions make sense to have the highest environmental impact per investment, but this can also come in conflict with the Norwegian long-term goal of covering low-demand PSO routes with EA.

9.2 Current Situation in Norway

Norway has an ambitious approach to electric aviation. The previous goal of the airport owner, Avinor, was to electrify all domestic air travel by 2040. As mentioned in Section 2.2, the expectation is that the first commercial EA route will be Stavanger-Bergen, but Samferdselsdepartementet is also open to PSO routes for EA if relevant technology becomes available before 2028. There is a long-term goal of reducing greenhouse gases by 80-95% compared to 1990 by 2050, which involves zero emission domestic travel. For many of the publicly subsidized routes, it is too expensive to invest in other zero emission travel alternatives than aviation, making electric aviation a long-term goal for PSO routes. The expectation is that the first EA route will be Stavanger-Bergen but that long-term, all or most of the PSO routes should be electrified.

The available range of EA models compared to the Norwegian geography also impacts the feasibility of a fast EA transformation. The Heart ES-30 currently expects to reach a range of 300 km electric by the mid 2030s and 400 km electric by the late 2030s [Aerospace, 2023], but there are large uncertainties regarding technology and battery development. The Stavanger-Bergen route is around 160 kilometers long, and, using the Vincenty distance, the distances between the largest hubs are 325 km (Oslo-Bergen), 462 km (Bergen-Trondheim), and 363 km (Trondheim-Oslo). Some are more than 400 km, and the distances between Trondheim and the northern hubs Bodø and Tromsø are even longer. Recently, many EA projects have been postponed or transferred to hybrid electric aviation, as hybrid aviation can significantly decrease emissions, but have less penalties in terms of range and capacity. To achieve full electrification by 2040 would then require speeding up the process of electrification, either by starting to invest in hybrid aviation or electric aviation. However, the Norwegian government has limited influence on the development of range and capacity due to the fact that battery technology is mainly driven by other markets, such as electric cars.

9.3 Adapting the FREAP to the strategy in Norway

The first difference between the RDM results and the Norwegian strategy is the input data on available airplane models and strategic goals, especially with respect to the starting point of electric aviation. In the Norwegian strategy, Stavanger-Bergen (SVG-BGO) is proposed as the first commercial EA route. Regarding the input data, the data in Section 7 assume that the first commercial EA airplane has a range of 100 km and investments start at this point, while SVG-BGO is 161 km. This means that the Norwegian implementation starts at a later technological stage than the analysis in Section 8.4. Additionally, if there is a long-term goal of electrifying most air travel, there must exist electric airplanes that can travel between the largest hubs. Assuming there is no rerouting of existing demand, the first range must then be greater than 160 km to cover SVG-BGO, and the last range must be greater than 462 km to travel between the three largest hubs. As there are large uncertainties regarding technology developments, we still expect the capacity, charging speed, and flying speed to be around the same level. The revised airplane models are shown in Table 23 and involve the available periods and airplane models.

As changes in maximum range also affect how high the strategic coverage can be set, the strategic goals have been revised. The new goals have a low starting ambition level to allow slow initial testing and scaling, and then increase to 25% of the total passenger-miles in the network and 48% of maximum available passenger-miles with a 500 km range. Strategic goals are not set close to maximum, so there is room to prioritize better-suited routes and charging station locations. The modified strategic goals are in Table 24. Differences in available demand on a network level can be seen in Appendix B.B.

Table 23: Revised airplane models

Model	R^m	Q^m	T_m^f
q_0	200	9	0.25
q_1	250	12	0.24
q_2	300	19	0.23
q_3	350	30	0.22
q_4	400	38	0.21
q_5	500	50	0.20

Table 24: Revised strategic coverage goals and their maximum possible values, where the α values used are highlighted and maximum α values are to the right

Range	α,All	$\alpha, r \leq 500$	$A_{ij}G_{ij}$/All	$A_{ij}G_{ij}/r \leq 500$
200	0.00105	0.002	0.04028	0.07708
250	0.02091	0.04	0.05186	0.09924
300	0.03137	0.06	0.10120	0.19364
350	0.07842	0.15	0.32246	0.61701
400	0.18298	0.35	0.46147	0.88301
500	0.25094	0.48	0.52261	1

From Section 8.4.2, we observe that the RDM proposes the KNN-ALF network only in earlier stages of an implementation and more long-range high-demand routes at later points. This is in contrast to the Norwegian strategy of starting with a larger city and moving on to low-demand routes over time. However, if long-range planes are available at an early point, the RDM starts on the routes with the highest demand, as in the optimistic development case in Section 8.4.3. We know that in the long term the KNN-ALF network has to be electrified as there are no real zero emission alternatives for transport. However, the RDM is right in that there is a greater impact and lower costs when electrifying routes with higher demand. The question then is whether we wish to have the largest possible impact per investment or invest in projects that are certain to be electrified long-term. These issues have been broken down into two points that the RDM does not capture at the moment.

1. **Additional regional political incentives surrounding electric aviation investments**, such as enthusiasm or reluctance for electric aviation, existing competence in a region or power grid capacity. Policies and incentives can be quantified by altering the costs of charging station investments and maintenance, or adding restrictions that some routes should be electrified or not.

2. **Long-term requirement of electrification of low-demand routes**. Long-term, high-demand long-range routes will most likely be replaced by hydrogen aviation or alternative travel options, such as trains, as these options are better suited for high-demand routes. However, for short-range low-demand routes,

EA is expected to be the cheapest zero emission option. And since there is a long-term requirement for zero emission aviation, we know that in the end, the low-demand PSO routes also have to be electrified. This becomes a contrast to the RDM, which prefers high-demand routes whenever available.

The additional regional incentives can be handled by 1) modifying investment or maintenance costs, or 2) requiring that some regions are invested in. In the case of Norway, we can assume that investment costs will be lower in the larger cities, as they are likely to have a more advanced power grid and greater access to infrastructure and competence requirements. In the first implementations, we might want EA in areas with extensive infrastructure and resources to identify possible pitfalls and challenges, before implementing EA in places with less robust infrastructure and economies. There is also great value with added enthusiasm to the project, which is present in Stavanger and is not captured by the FREAP.

Since the RDM already prefers the southern high-demand regions, it is uncertain whether modifying costs leads to larger differences in results. Therefore, we instead choose to fix certain strategic decisions, such as the installation of a charging station in Bergen and Stavanger in the first period.

Requiring that low-demand routes are covered long-term can be implemented with some requirement that these routes must be electrified in the last period. the RDM can then decide which period is the optimal time to make the investment. It should also be mentioned that some routes have an average number of flight seats lower than 9 passengers a day, such as KKN-MEH [Statistics Norway, 2023], making an EA 9 passenger aircraft able to cover the existing CA coverage. So, many low-demand routes are also better adapted to the long-term reuse of older models.

There are several ways to force the optimization model to implement low-demand routes, but two examples are: 1) requiring that specific stations are built, or 2) requiring that there is no remaining CA coverage along specific arcs. Method 1) was tested, but the result was that some stations were built without any EA routed from the station, which is most likely due to the more effective use of EA models along other routes. Therefore, option 2) was preferred, which requires that a number of routes are fully electrified. The variable o_{ij}^t is used, which is 0 if there is no CA routed along the arc. Since o_{ij}^t is only used in the FREAP if (i, j) has an initial demand greater than or equal to the lowest EA capacity, the RDM must be expanded so that there exists an o_{ij}^t for all arcs in the region that have existing demand.

9.4 Model Additions

To adapt FREAP to the findings of Section 9.3, investments in the first stage in SVG and BGO are fixed, and it is required that four arcs are fully electrified in two northern networks. The two special case networks are formed: $\mathcal{S}_1$ (KKN-ALF) and $\mathcal{S}_2$ (Airports surrounding BOO). Both networks have been referred to as especially relevant for the implementation of electric aviation in government reports [Avinor, 2018].

Sets

$\mathcal{S}_1$	['ALF', 'BVG','BJF','HFT','HVG','KKN','MEH','VDS','VAW']
$\mathcal{S}_2$	['BOO','RET','VRY','LKN','SVJ','SKN']
$\mathcal{S}$	Set of special case airport networks $\mathcal{S} \in \{\mathcal{S}_1, \mathcal{S}_2\}$
$\mathcal{A}^s$	Set of arcs (i, j) of the airport network s where $G_{ij} \geq 1$

Additional Constraints

$$y_i^{t_0} = 1 \qquad i \in \{SVG, BGO\} \tag{44}$$

$$r_{ij}^{t_T} \geq o_{ij}^{t_T} \qquad (i, j) \in \mathcal{A}^s, s \in \mathcal{S} \tag{45}$$

$$r_{ij}^{t_T} \leq M^A o_{ij}^{t_T} \qquad (i, j) \in \mathcal{A}^s, s \in \mathcal{S} \tag{46}$$

$$\sum_{(i,j)\in\mathcal{A}^s} o_{ij}^{t_T} \leq |\mathcal{A}^s| - 4 \qquad s \in \mathcal{S} \tag{47}$$

Constraints (44) state that charging stations are built in SVG and BGO in the first period. Next, constraints (45) and (46) set $o_{ij}^{t_T} = 1$ if CA demand is routed along arc (i, j) in the last period t_T. Finally, constraints (47) require that at least 4 arcs are fully electrified in the last period for sets s.

9.5 Results from New Runs

The result of the modified model using airplanes from Table 23 and strategic goals from Table 24 are shown to the left in Figure 18, with insights in Table 25. Results for the remaining periods are found in Appendix F. In addition, a run was carried out without constraints (45)-(47), where the network is shown to the right in Figure 18. The RDM was also run without constraints (44), but this only reached optimality gaps between 4.2% and 5.5% within the time limit and resulted in the same network and insight table as the run with constraints (44)-(47). The RDM was run with an optimality gap of 2% and a maximum time of 8 hours per RDM iteration. The optimality gap is greater than the previous 0.5% because the run is significantly more complex than those tested in Section 8, as it has one additional time period and increased airplane ranges. As mentioned in Section 3.3.1, an increase in the range leads to an exponential increase in the number of possible paths. The airplane model with a range of 300 km leads to 2300 paths and 5197 combinations of (m, p). In contrast, the revised model with 500 km range leads to 7396 paths for model m_5 and 19905 combinations of (m, p), making the new run significantly more time consuming.

The result is very different from the runs in Section 8.4, because the implementation begins at a more advanced stage of range development. As hub travels are available to a greater extent, they are more invested in. We observe that both in the case with and without constraints (45)-(47), the northern investments are also centered on the hubs Tromsø and Bodø. This highlights that hubs are good starting points for EA investments and a natural place to build initial charging stations.

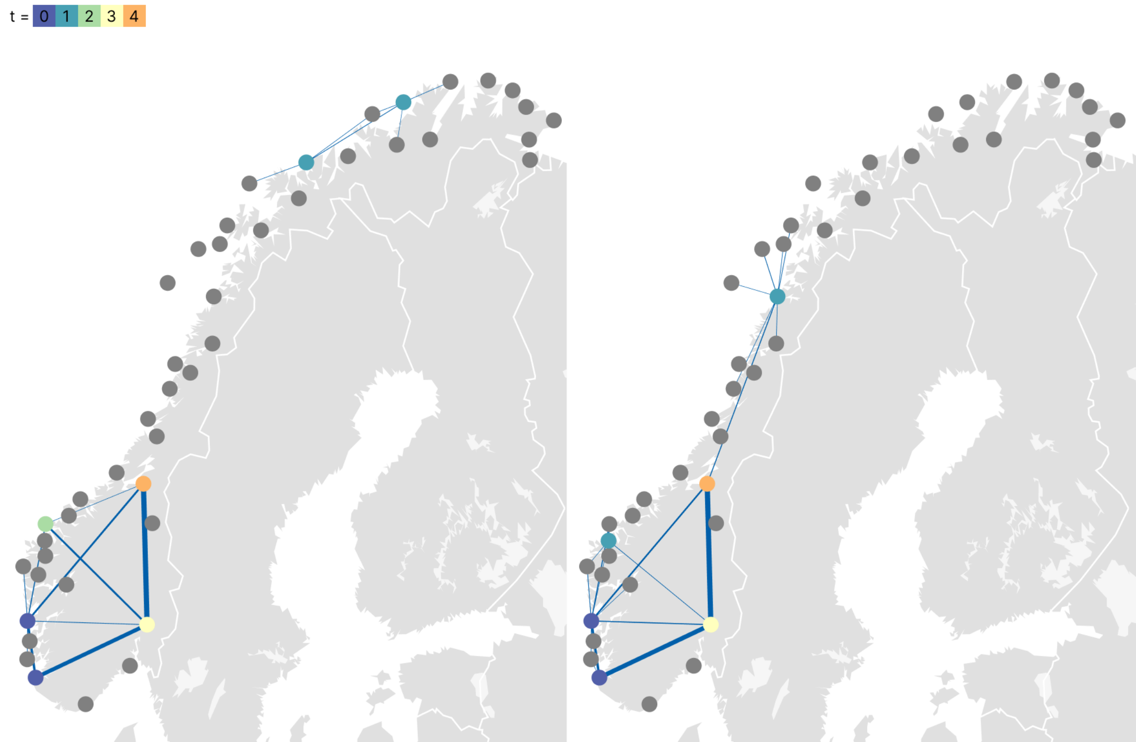

Figure 18: Period t_5 run for revised model on Norway and results without constraints (45)-(47) to the right

Table 25: Insights on the modified Norway runs

	Full run Norway	W/o (45)-(47)
Strategic goals [%]	[0.2,4,6,15,35,48]	[0.2,4,6,15,35,48]
Strategic coverage [%]	[3,4,6,16,39,48]	[1.6,4,6,15,40,48]
# Airplanes bought t_4	[20,6,5,14,25,7]	[11,13,7,13,27,6]
# Stations built	[2,2,1,1,1,0]	[2,2,0,1,1,0]
# EA arcs manned	[2,16,20,24,28,31]	[2,19,27,33,35,41]
RDM iterations	2	4
Objective	5.23119e+08	5.1323e+08

Another observation is that many airplanes are bought in the first period but fewer charging stations. As mentioned in Chapter 2 there are large uncertainties regarding technology developments, so the number of airplanes provided becomes more of an indication of the recommended amount of EA capacity than exact science on what should be bought within a certain range. Since the capacity is 9 passengers for t_0 and m_0, many airplanes are needed to meet this demand. However, it is interesting that the initial strategic coverage 3% is so much higher than the goal 0.2%. This has indirectly created a situation with a scaleable initial EA coverage. In this situation, SVG and BGO can start with 2-4 airplanes to reach 0.2% coverage, and expand the fleet to 20 airplanes as they learn from the project and build competence.

The number of built charging stations is also not as high as in previous sections, and more charging stations are needed at airports with many electric aircraft operating simultaneously. This increases the cost of charging equipment. In contrast to most results of Section 8.4, there is no need for large investments in charging stations in the early periods, as strategic goals are less restricted by range. Therefore, it is possible for government entities to build extensive charging infrastructure in some hubs, rather than having to focus on many hubs.

As there is a high degree of uncertainty in the results, these results should be used as decision support rather than final recommendations. However, the trend is clear: the RDM recommends investing in hubs and forming high-demand routes surrounding and between hubs.

9.6 Discussion on Results

When considering the differences between the RDM solution and the current Norwegian plan, the main difference is the willingness to invest in low-demand networks. The modified RDM still strongly prefers high-demand routes and placing charging stations in hubs, whereas many strategic reports in Norway prefer long-term implementation in the PSO network. The advantages of the PSO network are the low demand along routes combined with low capacity in EA airplanes, and few zero emission options. On the other hand, investing in low-demand PSO routes in the early stages has many disadvantages. If we start by investing in only low-demand routes in areas with fewer resources, it becomes harder to:

1) do proper research on the implementation, as resources to test technology concepts will be scarce and knowledge will be fragmented across several airports. Poor knowledge sharing makes it harder to learn from initial investments and make better decisions in the next implementations. When building in only a few airports at a time, with higher demand, it is possible to test different charging infrastructure systems, handling of airplane models, and route planning. The knowledge that accumulates will be centralized in a few key locations, making it easier to reuse that knowledge for future implementations.

2) scale as quickly and intelligently as desired, as there is less access to resources and competence, and there is less CA demand available to substitute. Development may be slower in smaller regions. Due to greater access to resources and infrastructure, hub airports are expected to be able to scale and learn from pilot projects at a faster rate than smaller airports. As much of the purpose of a step-wise implementation of EA is to boost technology developments, it is a goal in itself that expansions and development happen as quickly as possible. As new investments build on older experiences, slow implementations of initial projects can risk delaying long-term expansions of EA.

3) reduce as much of the emissions as possible. Slower scaling and less demand to cover lead to lower reduction of emissions. Covering a lot of demand using low-demand routes requires extensive coverage of charging stations across several airports, which again leads to more expensive infrastructure.

The advantages of high-demand routes are highlighted in the first planned commercial EA route, Stavanger-Bergen. This route stands out for several reasons. First, there is political enthusiasm within the region and the financial capacity to realize this kind of project. Projects like Elnett can exist to test different infrastructure options. Moreover, the large population and access to educational institutions makes it easier to build up competence within EA. Finally, it is easier to make the route commercially viable due to high demand and short distances.

Then, there is the question of to which extent infrastructure can be re-used with different investment options. As mentioned in Chapter 2, an implementation of zero emission EA requires access to renewable power, and the consumption of renewable power is relevant both to green hydrogen aviation and electric aviation. If EA is long-term replaced with hydrogen aviation in high-demand regions, the zero emission power infrastructure can be reused for green hydrogen generation, and EA planes can be transferred to the different PSO routes. This may lead to the construction of EA charging stations that will have to be replaced in some of the larger cities, but as technology progresses, many charger investments will have to be replaced over time anyway. The information gained from conducting initial research in larger cities may be preferable, so the infrastructure built later along the PSO routes is better suited to stand the test of time. Having several EA travels to one location will require a lot of area to charge, affecting both larger and smaller airports. If charging area becomes redundant over time, it can then be used for renewable energy production, further enhancing the possibility of airports as power hubs.

In the long term, some high-demand EA routes can also be maintained, or high-demand EA capacity can be moved to adjacent lower-demand routes as high-demand routes are replaced with hydrogen aviation. Hydrogen aviation, conventional aviation, and electrical aviation can exist in an airport at the same time, as different air travels target different market segments. EA with a longer stop time, but lower cost per trip, may be more suitable for the transport of goods or be easier to sell to consumers for travel. Similarly to how several different airlines operate the same route, different types of aircraft should be able to traverse the same airspace. There is also no reason why the hub EA infrastructure could not be reused for surrounding lower-demand routes. The OSL charging capacity could be used for round-trip OSL-TRF or OSL-KRS, where the same applies to BVG and its surrounding lower-demand airports, and TRD to stations like KRS, MOL, RRS, OLA, OSY and RVK. The charging capacity at an airport must not only be used for that airport or between hubs. In order to make the most progress in the early stages, it is therefore better to invest in high-demand routes and build charging stations in hubs. Then, when more zero emission options for high-demand routes become available, such as bullet trains or green hydrogen aviation, EA traffic can be redirected to lower-demand routes.

10 Concluding Remarks

The purpose of this thesis is to provide an unbiased tool for investments in charging station locations and which routes should be electrified long-term, and contrast the results with Norway's existing EA strategy to identify areas for improvement. The existing literature concerning EA and Norway's current strategy was examined, and then a model was developed for the Fixed Route Electric Aviation Problem (FREAP). To ensure a more feasible estimation of routes, two solution methods were proposed: The exact Individual Routing Method (IRM) and the heuristic Regional Division Method (RDM).

Through a technical analysis, it was shown that IRM is too slow to solve real-world instances of the problem, but that RDM provides a fast solution that sufficiently handles the issue of disconnected infeasible EA-travels. In the economic analysis, it was explored how different cost, strategic, and technological scenarios impact the RDM output. Changes in costs and charging time had little impact on charging station locations. In contrast, available aircraft models and strategic goals had a large impact.

The Norwegian strategy focuses on the implementation of EA along the SVG-BGO route in the first period and, over time, on the replacement of the PSO network with EA. The RDM was modified to better account for Norwegian requirements and the results were presented. When taking into account the updated results, the RDM recommends building several high-demand routes and building charging stations on hubs.

This thesis concludes that it is recommended to prioritize high-demand routes over the PSO network until there are other zero emission options available for the high-demand routes. A long-term implementation of EA requires the building of competence, rapid scaling of infrastructure, and the goal of reducing as much as possible emissions with the technology in which it is invested. The construction of charging stations in hubs and routing EA along high-demand routes are expected to yield higher rewards, a greater reduction in emissions, and faster technological developments.

When other zero emission options, such as bullet trains or green hydrogen aviation, can substitute demand along high-demand routes, the charging infrastructure on hubs can still be used to maintain some high-demand EA travels. Additionally, other EA capacities can be rerouted to lower-demand routes surrounding the hubs. Over time, EA airplanes can be employed to lower demand routes surrounding the hubs, and EA and other zero emission options may fly simultaneously, operating different market segments. In more remote regions that currently have PSO routes, charging stations can be built after EA projects have been tested, so that the built-up experience can be used to create more durable charging infrastructures that require less maintenance. Finally, when hub routes are zero emission, older low-capacity airplane models can upgrade battery capacities and move to operate remote PSO routes.

11 Future Research

For future research, many different aspects can be explored. The first proposition is to involve the scaling of charging infrastructure. There is much existing literature on how to scale charging infrastructure for electric aviation [Salucci et al., 2019] [Trainelli et al., 2021]. Another option is to further investigate the costs of infrastructure in different airports or to provide airports with maximum charging and area capacities. Researching infrastructure scaling can help ensure that the recommended number of EA fligths between airports are feasible on an airport level.

As in the case of Heart Aerospace's ES-30, EA models are expected to get an increasing range as battery technology progresses, making it an option to swap out batteries in older models to increase the range of bought airplanes. RDM can be expanded upon in a way where the range of airplanes bought increases over time, or where there is an option to invest in range upgrades in the airplanes purchased. This affects where airplanes should be allocated. For example, if we initially purchase a large number of 9-19-passenger aircraft to service the SVG-BGO route in Norway, we may eventually upgrade to larger planes along the SVG-BGO and use the 9-19-passenger planes in northern areas to cover routes with lower demand.

A future research point is to explore creating new routes and redirecting demand between endpoints using electric aviation. This can involve either revising the routes of the entire network or choosing specific routes for changes. To form new routes, demand can be considered between endpoints rather than per arc, as described in Section 3.2.1. As mentioned in Section 7.5, national strategic goals are forced to be small due to the inability to replace high-demand long-range routes with electric aviation. Currently, most aviation networks use a hub structure because it is cost-effective and time-efficient. However, if much traffic must be replaced by zero emission aviation, it is necessary to form new routes to adapt to range limitations. An attempt was made to construct new routes in Voll [2023], but this implementation proved too time consuming to solve in real-world situations. Future research can therefore explore how new routes can be created in a way that allows for more substitution from CA to EA, and detect new optimal routes in a more time-efficient model.

The last proposition is to use the RDM on hydrogen aviation or other alternative fuel infrastructure. In Chapter 3, we researched the literature on electric vehicles and, more generally, green vehicles. When considering the possibilities of zero emission aviation, electric and hydrogen aviation are the main contenders, where hydrogen aviation is expected to take a longer time to develop. However, since FREAP focuses primarily on investments in infrastructure, routes, and model restrictions, many of the principles are the same as for other alternative fuel problems. Therefore, it can be explored how the RDM can be expanded to involve hydrogen aviation. When the existing model is expanded, the charging stations become hydrogen production plants and the charging time and charging frequency may be reduced. However, investing in hydrogen plants is expected to be more expensive than charging infrastructure, so cost evaluations should be more extensive.

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A Word list

BC: Base Case. Test case used when nothing else is specified
CA: Conventional aviation (gasoline/fossil aviation)
CV: Conventional vehicle (gasoline/fossil vehicle)
EA: Electric aviation
EV: Electric vehicle
FREAP: Fixed Route Electric Aviation Problem. Main model of the thesis, which is later expanded upon using extensions IRM and RDM
IRM: Individual Routing Method. One of two model extensions in the thesis
RDM: Regional Division Method. One of two model extensions in the thesis
SoC: State of Charge

B Data

B.A Flight Movements

Table 26: Notes on movements of flights, following WF977 on January 23rd 2023

From	To	Departure	Arrival	Stop time
Kirkenes	Vadsø	21:20	21:35	15 min
Vadsø	Vardø	21:50	22:10	15 min
Vardø	Båtsfjord	22:25	22:45	15 min
Båtsfjord	Berlevåg	23:00	23:20	15 min
Berlevåg	Hammerfest	23:35	00:20	15 min
Hammerfest	Tromsø	00:35	01:20	15 min

Source: [Avinor, 2023a]

B.B Available Routes With Different Ranges

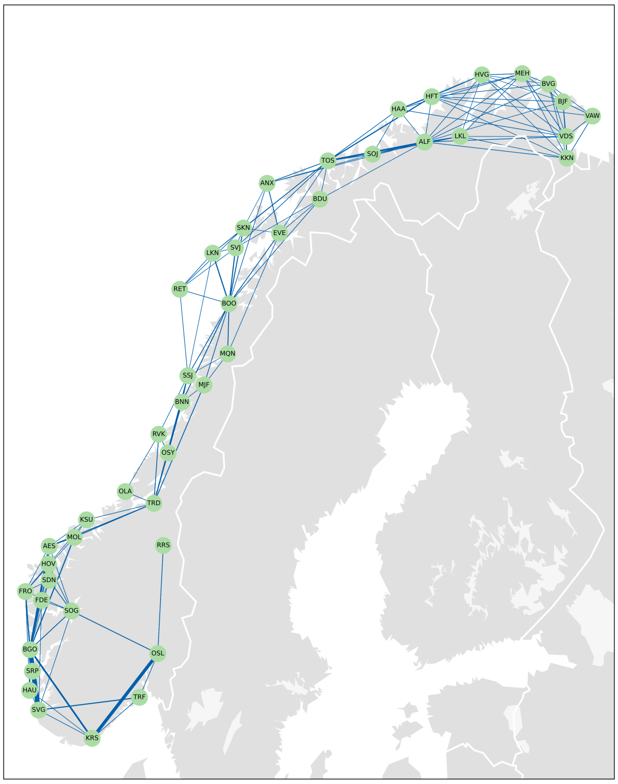

Figure 19: Available demand in the A45 network with range below 300 km

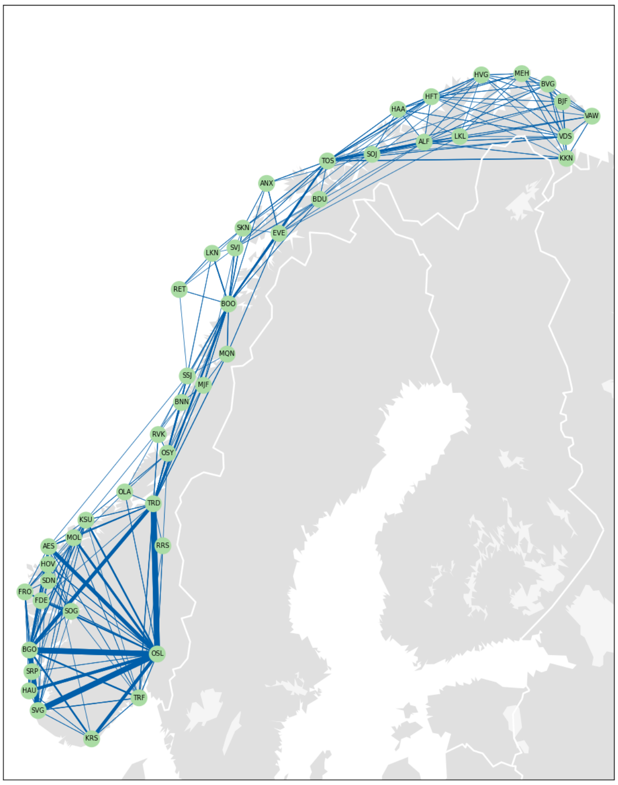

Figure 20: Available demand in the A45 network with range below 500 km

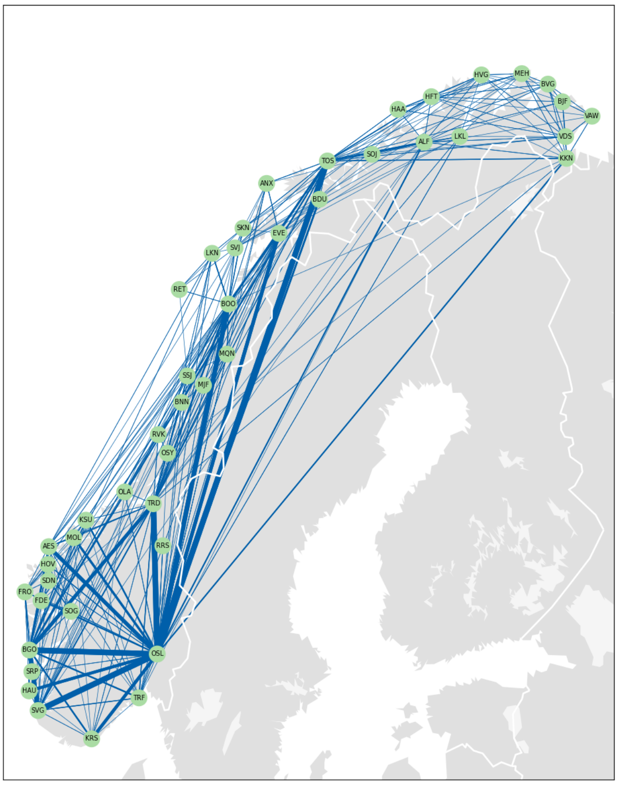

Figure 21: All available demand in the A45 network

C Mathematical Model Elaborations

C.A Time per Path Traveled of Model m

Time per path travelled is calculated as a combination of the following parameters:

T^S	Fixed time spent per stop made at an airport, to transfer passengers and crew. Measured in minutes
T^C_m	Additional time per charge needed to fully fast-charge an airplane of type m. Measured in minutes
T^F_m	Time spent per km traveled of type m. Measured in minutes per kilometer

$$T^K_{mp} = T^C_m + \sum_{(i,j)\in\mathcal{W}^p} (A_{ij}T^F_m + T^S)$$

C.B Variables that can be Substituted by Equality

FREAP: s^t_i can be substituted with the sum of y^t_i over all previous periods t. Another option is to bake the maintenance cost C^S_i into the fixed cost C^I_i and fully remove s_i^t. w_{ij}^{tm} can also be substituted by the sum of x over paths p that involve the direct arcs (i,j).

$$\begin{aligned} s_i^t &= \sum_{t'=0}^{t} y_i^{t'} && t \in \mathcal{T}, i \in \mathcal{N} \\ C_i^t &= C_i^S(|\mathcal{T}|-t) + fixed(C_i^t) && t \in \mathcal{T}, i \in \mathcal{N} \\ w_{ij}^{tm} &= \sum_{p \in \mathcal{P}^{ij}} x_p^{tm} && t \in \mathcal{T}, m \in \mathcal{M}^t, (i,j) \in \mathcal{A} \end{aligned}$$

RD FREAP: b^{tm} can be substituted with the sum of u^{tmr} over r.

$$b^{tm} = \sum_{r \in \mathcal{R}_A^{tm}} u^{tmr} \qquad t \in \mathcal{T}, m \in \mathcal{M}$$

IR FREAP: x_p^{tm} can be substituted with the sum of d_{pl}^{tmk} over l and k.

$$x_p^{tm} = \sum_{k \in \mathcal{K}} \sum_{l \in \mathcal{L}} d_{pl}^{tmk} \qquad t \in \mathcal{T}, m \in \mathcal{M}^t, p \in \mathcal{P}^m$$

C.C Calculation of Maximum Travels MC

Algorithm 4 Calculating M_{mp}^C

procedure $GetMC$
  for $m \in \mathcal{M}$ **do**
    for $p \in \mathcal{P}^m$ **do**
      $demand \leftarrow \max G_{ij}$ for $(i,j) \in \mathcal{A}^p$
      $M_{mp}^C \leftarrow \lceil \frac{demand}{Q_m} \rceil + 1$
    end for
  end for
  return M_{mp}^C
end procedure

D IRM Without Fixing b

For a less restricted result with higher accuracy and further increase in runtime, an alternative IRM is presented that does not fix the b^{tm} values to the FREAP solution. This implementation proposes using the FREAP solution to provide an upper and lower bound to the b^{tm} values.

New Bounds

The new bounds involve the use of the FREAP solution to generate an upper and lower bound to b^{tm}. k is generated from the FREAP solution and estimates a range of how much the solution is expected to vary. The possible range is dependent on variances in optimal airplane investments, which again is dependent on the network used, strategic goals and costs. For the data used in this assignment, a sufficient range is estimated to be $k = \lceil \frac{|\mathcal{N}|}{9} \rceil$.

$$b^{tm} \leq FREAP(b^{tm}) + k \qquad t \in \mathcal{T}, m \in \mathcal{M}^t \tag{48}$$

$$b^{tm} \geq FREAP(b^{tm}) - k \qquad t \in \mathcal{T}, m \in \mathcal{M}^t \tag{49}$$

Constraints (48) and (49) present a lower and upper bound to the b^{tm} variables.

Limiting Sets and Symmetry-Breaking Constraints

$\mathcal{K}^m$ gets a new upper bound of $FREAP(b^{tm}) + k$. In addition, we create the set $\mathcal{K}^{m\prime} \in \{k_1, ..., k_{K-1}\}$, which is all k-indexes except the highest available.

Since it is no longer given that all available airplanes will be used, some of the symmetry-breaking constraints from Voll [2023] are proposed. The two best performing constraints (35) and (36) of Voll [2023] are adapted to the modified IRM. These target the symmetry between different k-values.

$$\sum_{p \in \mathcal{P}^0} d_{p0}^{tmk} \geq \sum_{p \in \mathcal{P}^0} d_{p0}^{tm(k+1)} \qquad t \in \mathcal{T}, m \in \mathcal{M}^t, k \in \mathcal{K}^{m\prime} \tag{50}$$

$$\sum_{p \in \mathcal{P}^0} d_{p0}^{tmk} p \geq \sum_{p \in \mathcal{P}^0} d_{p0}^{tm(k+1)} p \qquad t \in \mathcal{T}, m \in \mathcal{M}^t, k \in \mathcal{K}^{m\prime} \tag{51}$$

Constraints (50) specify that if an airplane of model m is used in a period, the lower k values start to fly first. Furthermore, constraints (51) require that airplanes with the lowest k values begin to fly at the highest path indexes p.

Modified IRM Algorithm

With a higher upper bound for b, it is highly unlikely that the upper and lower bounds result in an infeasible solution. Therefore, the updated algorithm is less complex and is shown in Algorithm 5.

Algorithm 5 Modified Individual Routing FREAP

procedure MODIFIEDIRM
  SOL ← solveFREAP()
  MOD ← createModifiedIRM(SOL)
  solution ← Solve(MOD)
  return *solution*
end procedure

E Test Instances Elaborations

E.A Total Strategic Goals for 3-period Aviation Networks

The strategic goals used for 3-period runs for aviation networks in Section 7.1. The total strategic coverage is calculated from the "All" sum of passenger miles in the network and is not relative to the maximum EA range available. Using Table 11 as a reference, these represent the column $\frac{A_{ij}G_{ij}}{All}$ rather than $\frac{A_{ij}G_{ij}}{r \leq 300}$. All runs have the available models corresponding to $[m_0, m_2, m_4]$

Table 27: Strategic goals for total CA decrease in different aviation networks for a 3-period run

Network	t_0	t_1	t_2
A9	0.02	0.1	0.5
A21	0.02	0.1	0.5
A24	0.0005	0.015	0.0594
A45	0.001	0.0198	0.0594

E.B Airplane Models Used

The airplane models used have been made using inspiration from different existing and retired projects on electric aviation and trying to get a wide range of possible models. In this Section it is presented how the data relates to existing projects and the missing data has been generated.

Table 28: Overview of airplane models used in test instances

Model	R^m	Q^m	$T^{f}_{m}*$	Inspiration
m_0	100	9	0.25	Eviation-9 (Alice)
m_1	150	12	0.24	eCaravan-12
m_2	200	19	0.23	ES-19
m_3	250	30	0.22	ES-30
m_4	300	38	0.21	Hyp-38

Model m_0 is based on the model Alice from Eviation [Eviation, 2023]. The maximum range is not specified on their promotional site. However, the maximum speed is

260 KTAS and the maximum battery is 30 minutes [Eviation, 2023]. Assuming the average speed is half of max speed: 260 KTAS*30 min / 2 = 120 km, which is rounded down to 100 km.

Model m_1 is based on the now retired eCaravan, which again is based on a grand caravan [Hemmerdinger, 2020]. The model is stated to be able to fly 100 miles $\approx$ 160 km, which is rounded down to 150 km. It should also have a capacity on 4 passengers, but 12 is chosen as a baseline from a CA Grand Caravan which has a basis of 10-14 seats [Hemmerdinger, 2020].

Model m_2 is based on the now retired ES-19 [GreenAir News, 2023b]. It is likely that there will be minimum one 19-seat model available, since regulations for 19-seat airplanes are less strict [Ydersbond et al., 2020].

Model m_3 is based on the new project ES-30 [Aerospace, 2023]. The model is stated to have an expected fully-electric range around 200 km in the late 2020, up to 300 km in the mid 2030s [Aerospace, 2023]. The range is therefore set to 250 km.

Model m_4 is based on a hypothetical of an airplane with 38 seats and a range of 300 km.

The speeds of the models are composed. In the case of Eviation, the assumption is that average speed is half of the maximum speed, which corresponds to 240 km/h. This corresponds to covering 4 kilometers per minute, which is not significantly slower than CA aviation over short distances. To separate the airplanes, the speed has been increased by removing 0.01 for each next model in T_m^f, based on the assumption that newer models are faster than old ones.

F Results from the Modified Norwegian Network

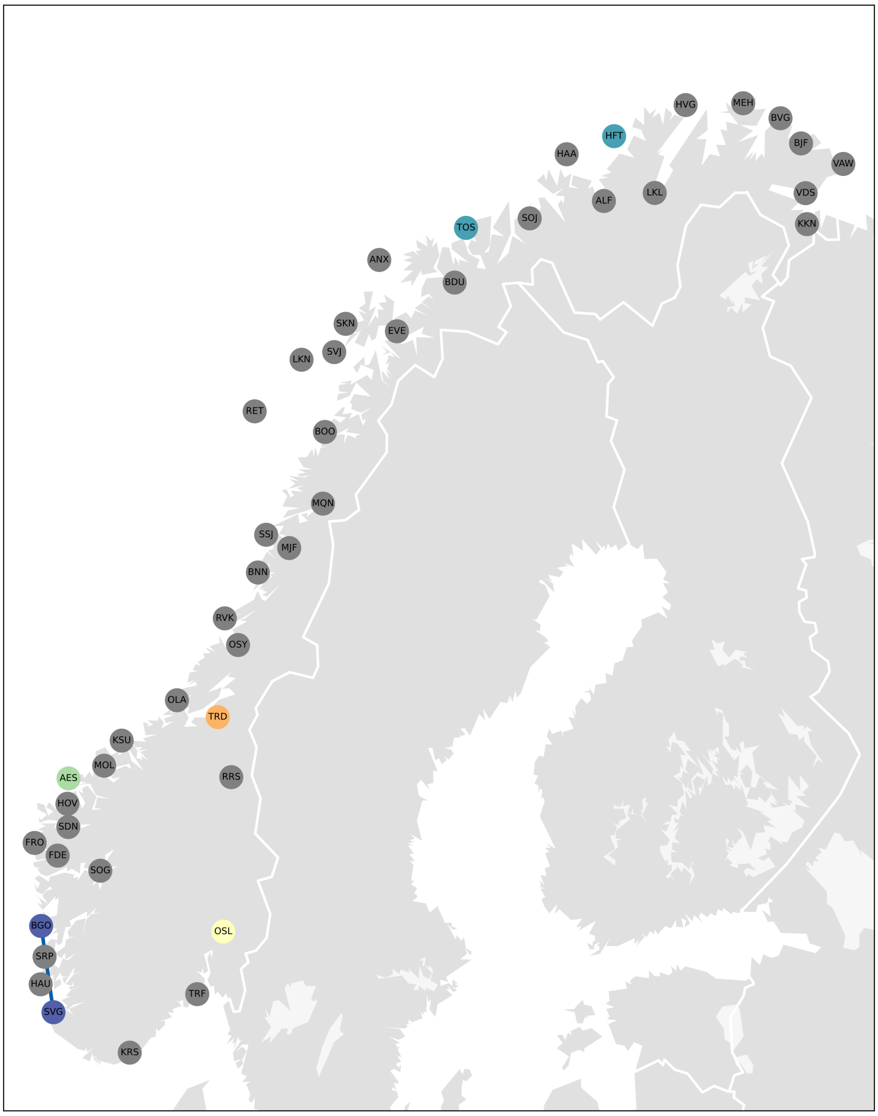

Figure 22: Modified Norwegian network results for period t_0

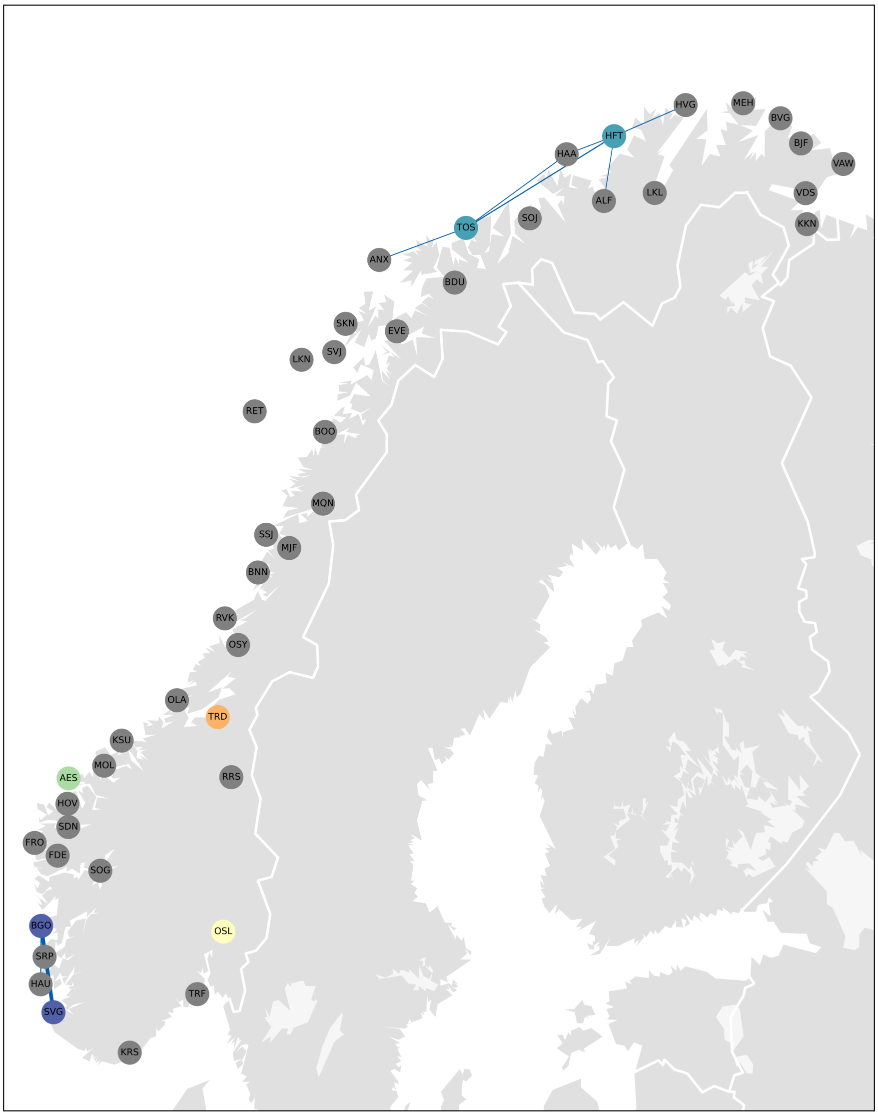

Figure 23: Modified Norwegian network results for period t_1

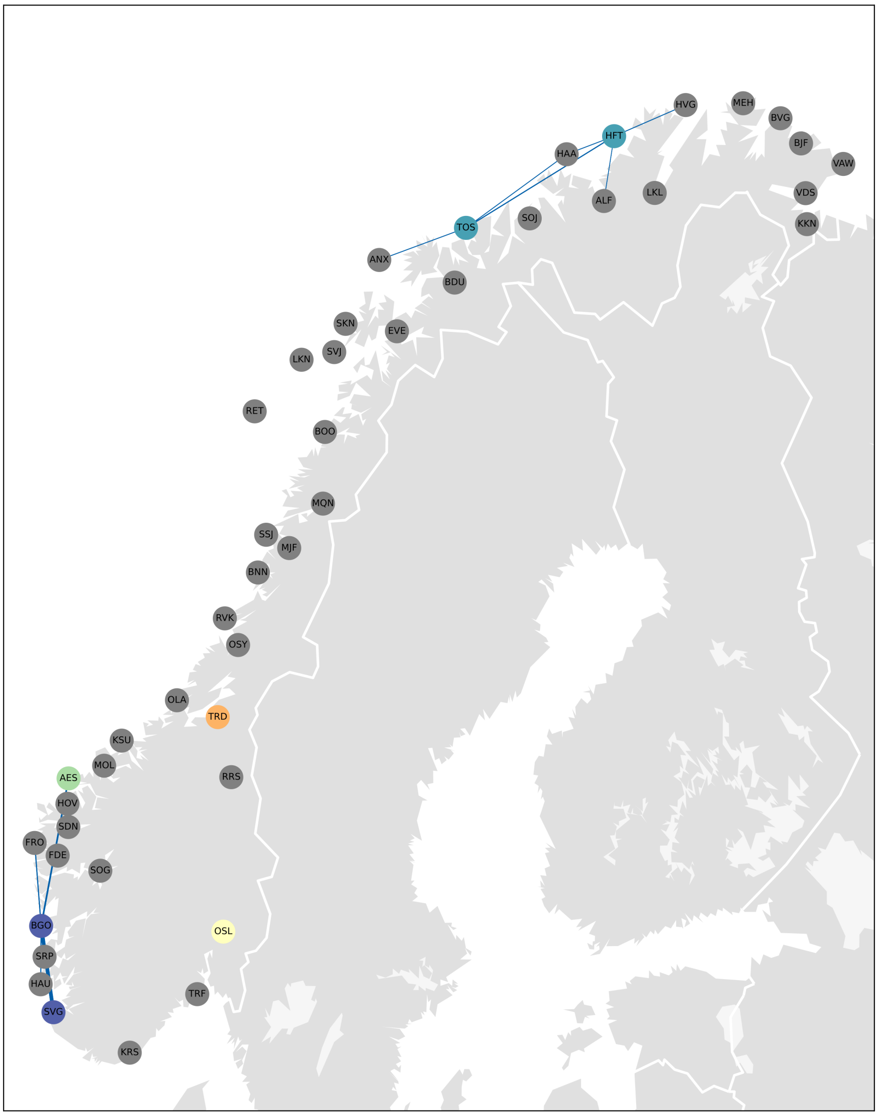

Figure 24: Modified Norwegian network results for period t_2

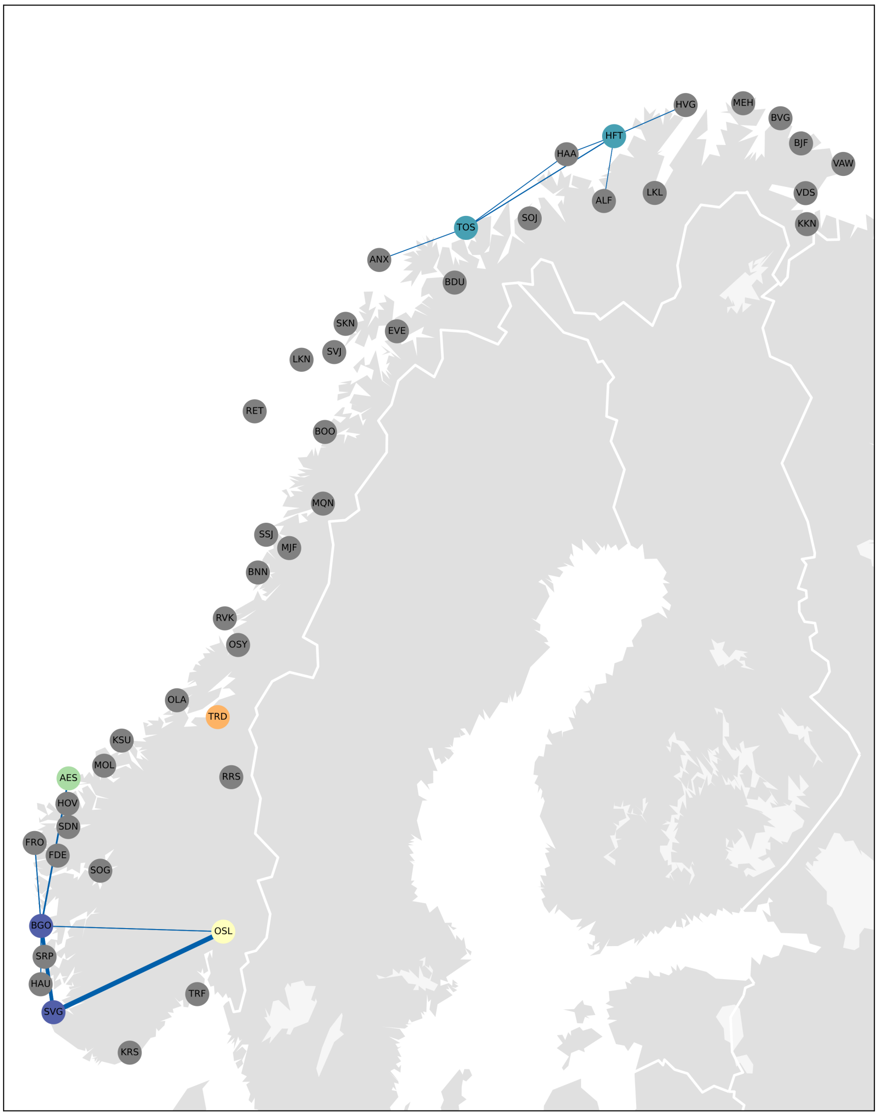

Figure 25: Modified Norwegian network results for period t_3

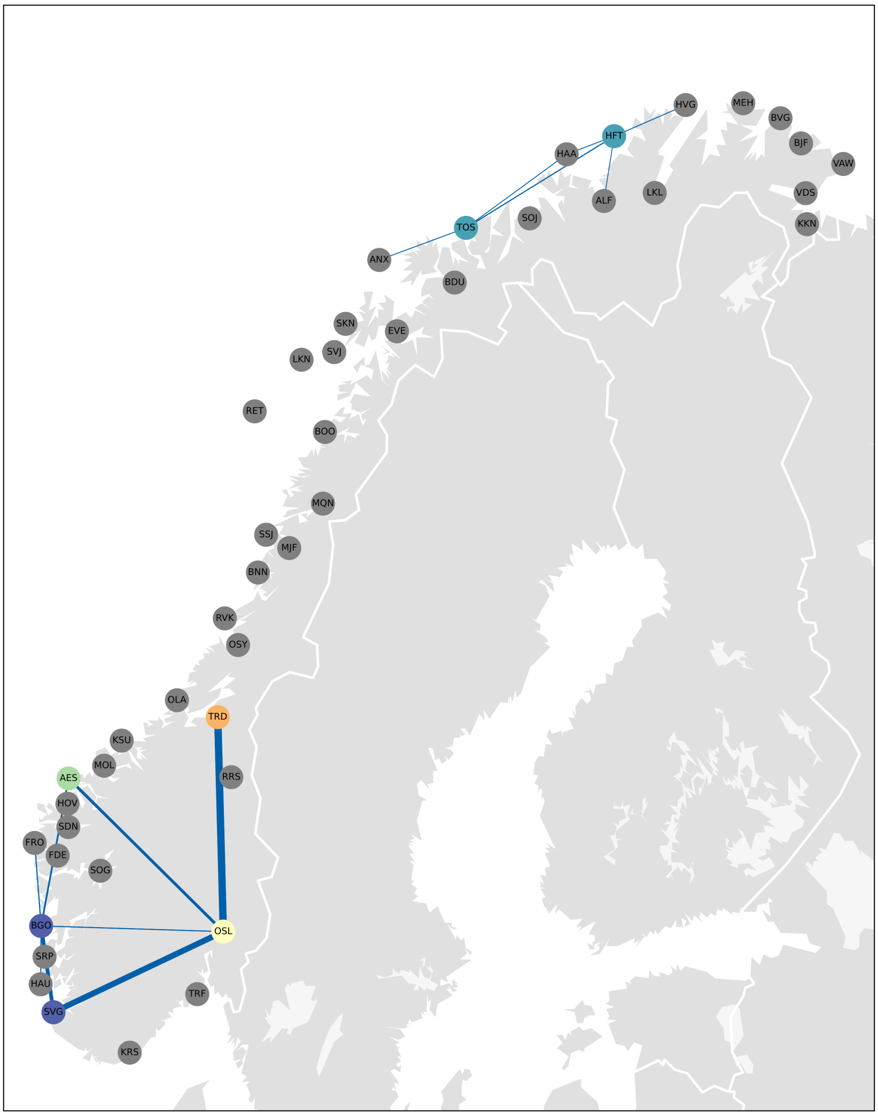

Figure 26: Modified Norwegian network results for period t_4

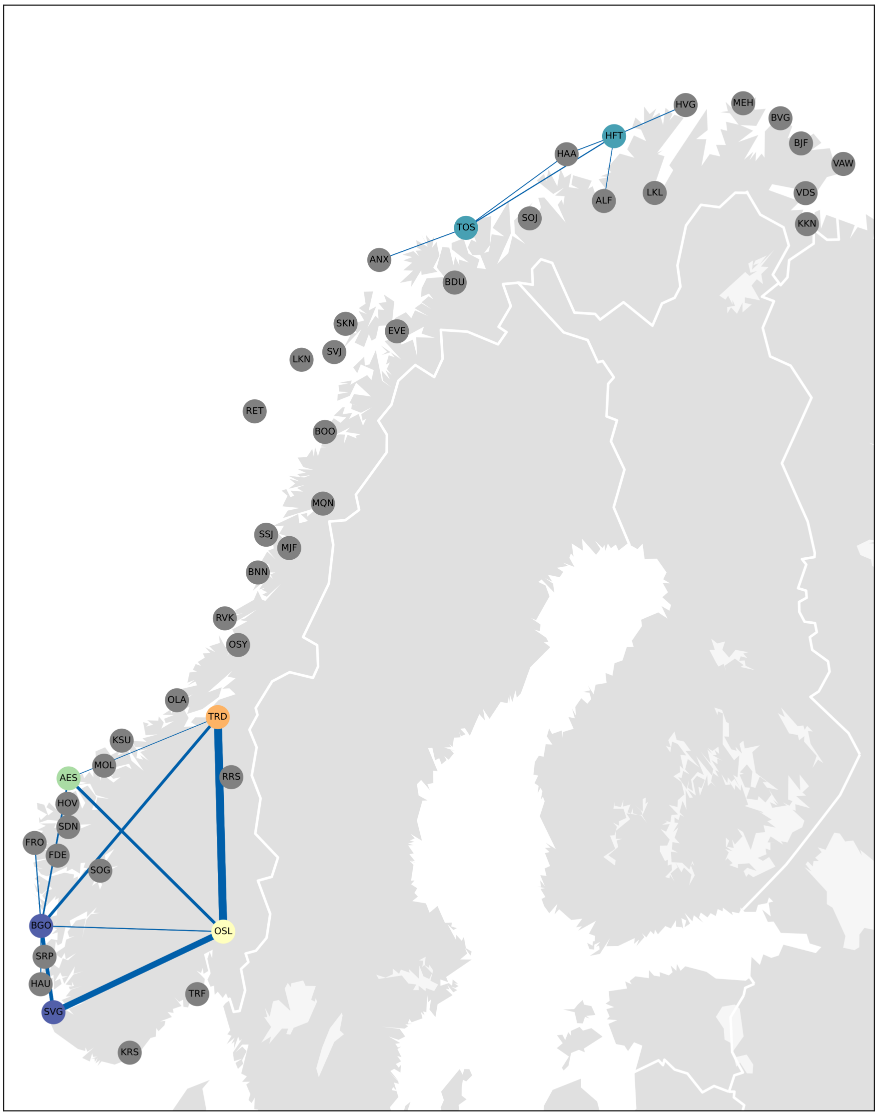

Figure 27: Modified Norwegian network results for period t_5

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