

*Prediction of aircraft trajectories for air traffic control
using machine learning approaches*

A DISSERTATION PRESENTED

BY

Marko Hrastovec

TO

THE FACULTY OF COMPUTER AND INFORMATION SCIENCE

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

IN THE SUBJECT OF

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APPROVAL

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— Marko Hrastovec —

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- [3] M. Hrastovec, F. Solina. Machine Learning Model for Aircraft Performances. *6th International Conference on Research in Air Transportation*, Istanbul, May 2014.
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Tanji, Luku, Niki in Binetu

Vprašanja beročega delavca

Kdo je gradil Tebe s sedmerimi vrati?
V knjigah bereš imena kraljev.
Ali so kralji privlekli tja kamnite klade?
In tolikokrat porušeni Babilon,
kdo ga je zmeraj znova postavil? V katerih hišah
zlato bleščeče Lime so bivali graditelji?
Kam so šli na večer, ko je bil
dograjen kitajski zid,
njegovi zidarji? Veliki Rim
je poln slavolokov. Kdo jih je postavil? Nad kom
so triumfirali cesarji? Ali je imel toliko opevani Bizanc
za svoje prebivalce res le palače? Celó v pravljíčni Atlantidi
so v noči, ko jo je zalilo morje,
utapljaajoči se klicali svoje sužnje.

Mladi Aleksander je osvojil Indijo.
On sam?
Cezar je porazil Galce.
Ali ni imel s sabo vsaj kuharja?
Španski kralj Filip je jokál, ko je šlo njegovo brodovje
na dno. Ali ni jokál nad tem nihče drug?
Friedrich II. je zmagal v sedemletni vojni. Kdo
razen njega je še zmagal?

Na vsaki strani zmaga.
Kdo je pripravil zmagoslavni pir?
Vsakih deset let velik mož.
Kdo je poplačal stroške?

Toliko podatkov.
Toliko vprašanj.

Bertolt Brecht, 1898-1956, prevod Ervin Fritz

POVZETEK

Zračni promet se spopada z velikimi izzivi za prihodnost. Zaradi ekonomske krize so se povečali pritiski na znižanje stroškov, medtem ko se na drugi strani pojavljajo zahteve za vlaganja v raziskave in razvoj, ki bodo omogočile varno delovanje ob predvidenem povečanju prometa. Eno od področij, ki se pojavlja v skoraj vseh načrtih za prihodnost, je boljše računanje trajektorij letal, oziroma boljše vedenje o tem, kje se bo letalo nahajalo ob določenem času. Ko vemo, kje letala bodo, lahko načrtujemo in optimiziramo varne zračne poti dlje v prihodnost, kar je zelo pomembno za vedno gostejši promet. Letalski prevozniki minimizirajo stroške z načrtovanjem optimalnih poti. Pri tem upoštevajo mnogo dejavnikov, kot so vremenske napovedi in omejitve v zračnem prostoru. Ne morejo pa upoštevati ostalega prometa. Kontrola zračnega prometa s pregledom nad vsemi letali skrbi za varno uporabo zračnega prostora. Kontrolorji se odločajo glede na trenutno stanje in po potrebi letala preusmerijo z načrtovane optimalne poti zaradi drugih letal v bližini. Opisan model kmalu ne bo več zmožen zagotavljati dovolj prepustnosti zračnega prostora za vsa letala, ki bi želela leteti.

Naša raziskava je delček v mozaiku napovedovanja trajektorij letal in optimizacije zračnega prostora. V prihodnosti si bodo letala izmenjevala podatke o zračnih poteh s kontrolo na tleh in bodo letela po načrtu, ki bo optimiziran tudi glede na ostali promet. Ker je zračni promet zelo reguliran, vsaka sprememba vzame ogromno časa. Do predvidenih sprememb moramo uvesti majhne izboljšave v okviru trenutnega sistema, s katerimi bomo bolje napovedovali trajektorije, ki bodo omogočale načrtovanje in optimizacijo zračnega prometa ter povečanje propustnosti zračnega prostora.

Dejanske poti letenja letal snemamo z radarji in jih hranimo za poznejšo uporabo. Z novimi radarji Mode-S lahko dobimo z letal tudi nekaj vremenskih podatkov. Podatke o letalskih zmogljivostih izračunamo iz shranjenih letalskih poti. Obogatimo jih še z vremenskimi podatki in načrti letov. Načrti letov vsebujejo pomembne informacije o

tipu letala, prevozniku, načrtovani poti in še mnogo drugega. S tem dobimo veliko podatkovno bazo znanja o preteklih letih. Ko pričakujemo nov let, v podatkovni bazi poiščemo lete, ki so podobni temu, ki ga pričakujemo. Če znamo poiskati lete s podobnimi letalnimi karakteristikami, lahko napovemo zmogljivosti prihajajočega leta in lahko izračunamo načrtovano trajektorijo leta. S trenutno uporabljanimi metodami za izračun vedno napovemo enako trajektorijo za isti tip letala in isto pot, ker imamo na voljo le nominalne vrednosti za določen tip letala. Nominalne vrednosti so določene tako, da so najboljši približki letov, ki so jih imeli na razpolago snovalci sistema. Leti v našem zračnem prostoru pa so drugačni. Naš cilj je napovedati boljše vhodne parametre za izračun trajektorij s pomočjo vedenja o shranjenih preteklih letih in izračunati trajektorije, ki bodo bližje dejanskim potem letenja.

Z našo rešitvijo upoštevamo vidike, kot so upravljavec letala, končna destinacija, čas letenja, itd., in vsakič napovemo drugačno trajektorijo, ki je prilagojena točno določenemu letu. Našteti atributi ne vplivajo neposredno na let. Končna destinacija, na primer, določa dolžino leta in s tem vpliva na to, koliko goriva bo na krovu letala. Več goriva pomeni večjo težo in drugačne letalne lastnosti. Podobno lahko sklepamo, da letalske družbe letijo različno. Nizkocenovni prevozniki običajno vozijo potnike z manj osebne prtljage, kar vpliva na težo. Vsi ti in podobni dejavniki niso lahko merljivi, a vplivajo na letalske zmogljivosti.

Da bi našli lete v podatkovni bazi, ki so najbližje napovedanemu letu, uporabljamo strojno učenje. S predpostavko, da leti s podobnimi lastnostmi letijo podobno, pričakujemo, da bomo napovedovali točnejše trajektorije kot s statičnimi modeli in nominalnimi parametri. Preizkusili smo mnogo algoritmov strojnega učenja za to vrsto podatkov in našli najprimernejše. Prilagodili smo standardne algoritme strojnega učenja za naše potrebe in za veliko količino podatkov, ki jih imamo.

Napovedi strojnega učenja smo namesto nominalnih vrednosti vnesli v najbolj uveljavljen model za izračun trajektorij. Metode, ki za izračune uporabljajo le tip letala, se redno uporabljajo v letalstvu, a jim primanjkuje zmogljivosti, da bi se prilagodile posameznemu letu. Taka statična in toga uporaba je po našem mnenju glavni vzrok slabih napovedi.

Rezultati kažejo, da so naše napovedi, ki so prilagojene posameznemu letu, natančnejše. Pokazali smo, da so rezultati naših metod primerljivi z najboljšimi standardnimi metodami strojnega učenja.

Rešitev je narejena kot storitev, ki ji uporabniki lahko pošljejo podrobnosti o letu in

dobijo nazaj prilagojene parametre o predvidenih zmogljivostih tega leta. Ker so parametri v enaki obliki kot v najbolj uporabljanem modelu Base of Aircraft Data (BADA), lahko obstoječe aplikacije uporabijo storitev namesto nominalnih parametrov. S tem bi izboljšale svoje napovedi le z majhnim posegom. Metode izračuna trajektorij lahko ostanejo nespremenjene. Dobile bi le boljše vhodne parametre in bi zato nudile točnejše izračune trajektorij.

Ključne besede: trajektorije letal, BADA model, strojno učenje

ABSTRACT

Air traffic is facing great challenges for the future. The economic crisis has brought a burden of cost savings, while the increase of traffic requires investments in research and development to find new paradigms for safe operations. One of the most important aspects in all future plans is better trajectory calculation, or better knowledge where the aircraft is going to be at a certain time. When positions are known, the planning can optimize flying paths to be cost efficient and safe, which is very important as the traffic becomes denser every day. Aircraft operators are planning flight paths with minimum costs, but they are not optimizing them for conflicts with other aircraft, and for airspace optimizations. Air traffic control and airspace restrictions are taking care of that. Soon, this present model will not provide enough throughput for all aircraft that want to fly.

Our research is putting a stone in the mosaic of trajectory prediction and airspace optimization. In the future, aircraft will share data about their planned paths with air traffic control and aircraft in vicinity. Since air traffic is a highly regulated and expensive business, it takes a very long time before changes are implemented. Until then, we have to find alternative ways for better trajectory predictions, which will allow us to plan and optimize traffic, and to increase throughput.

The ground control records the data about actual flight paths acquired by radars. Some weather data can be also acquired with a new generation of Mode-S radars. Pure aircraft performance data are enriched with weather and flight plan data into a joint knowledge database. For every new flight, we search in the database for flights similar to the incoming one. If we know how similar flights behaved in the past, we can predict the performances of a new flight, and can calculate the planned flight trajectory more accurately. Our goal is to predict trajectories better than using static models of aircraft performances. With existing prediction methods we predict for the same type of aircraft on a specific path the same trajectory every time. In that way, we have a

prediction that deviates the least from the majority of flights. On the other hand, we predict a trajectory that does not fit any flight.

With our approach, we want to take into account other factors such as aircraft operator, final destination, time of flight, etc., and every time predict a different trajectory suited to fit exactly to the considered flight. Operator and similar attributes are all factors that do not influence the flight directly. The destination, for instance, determines the distance of flight and therefore determines, how much fuel is on-board. More fuel means more weight and different flight characteristics. Similarly, we can assume that each operator operates airplanes differently than others, or carries different type of passengers that have usually more or less luggage than others. All these factors are not very well measurable, but they do affect flight performances.

We use machine learning to find the flights in the database that are the closest to the one being predicted. With the assumption that flights with similar features flight similarly, we expect to predict more accurate trajectories than with static models and default parameters. We tested many machine learning methods and found the ones that perform the best on our data. We also adapted standard machine learning algorithms for our needs and large amounts of data.

We have used machine learning predictions instead of static nominal values in widely used trajectory calculation model. The methods using only aircraft type are widely used in aviation, but they lack the capability to adapt to each flight individually. In our opinion, such rigid and static usage of aircraft type is an important cause for poor predictions.

The results show that our predictions methods using individually customized predictions are more accurate than predictions based on aircraft type. We have shown that our methods are comparable with standard machine learning methods.

The solution that we propose, is deployed as a web service, to which users can send flight details and get back parameters suited for a particular flight. Because the parameters are in the same form as in the widely used Base of Aircraft Data (BADA) model, legacy air control applications could use this service instead of static BADA database, and improve their trajectory calculations. In that way, a minimal change of the air control applications is needed. Trajectory calculations can remain unchanged, but with better input parameters, they can predict more accurately.

Key words: aircraft trajectories, BADA model, machine learning

ZAHVALA

Med študijem in raziskovalnim delom sem bil včasih v dvomih, če mi bo uspelo. Z doktorskim študijem sem se seveda ukvarjal kot novinec in v začetku si nisem predstavljal, kaj vse me čaka. Zato sem zelo hvaležen svojemu mentorju prof. dr. Francu Solini, ki me je vodil skozi vse čeri in preizkušnje. Korak po korak me je vodil od naloge do naloge in skrbel, da me obilica dela ni naenkrat zasula in mi vzela vse volje. Ko sem bil v zadregi in nisem vedel, kako in kam, ko sem bil prepričan, da mi naslednji korak ne bo uspel, je vedno našel prave besede, da me je vzpodbudil k delu in usmeril moj kompas k pravemu cilju. Veliko delo je opravil pri objavi vseh člankov in pripravi tega besedila s pomočjo pri piljenju jezika, da teče bolj gladko in razumljivo. Za vso pomoč sem mu zelo hvaležen. Brez nje mi nikoli ne bi uspelo.

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Z mnogimi sodelavci sem lahko razpravljal o svojih rešitvah, jih preverjal in dobival nove ideje ter nasvete v plodnih razpravah. Na tem mestu bi se posebej zahvalil Bobu, ki je sploh prvi dal idejo o temi in področju raziskovanja. Posebna zahvala gre tudi Eriku Štrumbliju, ki je pomagal z naduse koristnimi nasveti in napotki o pomembnih detajlih raznih metod strojnega učenja, ter doktorski komisiji z Markom Robnik Šikonjo na čelu, ki je podala pomembne pripombe in napotke, da je delo postalo še boljše.

Veliko večino dela sem seveda opravil doma. Vseskozi sem torej imel veliko podporo družine, ki je potrpežljivo čakala, da sem med delom našel čas tudi zanjo. Žena Tanja je marsikatero opravilo morala opraviti namesto mene. Za vso to dolgotrajno podporo sem domačim neizmerno hvaležen. Brez nje ne bi prišel nikamor.

Kot govori pesem na začetku, je jasno, da za takim delom ne more stati le en človek. Tu sem omenil le najbolj zaslužne. Zahvalil bi se torej tudi vsem drugim, ki so mi pomagali na različne načine od majhnih uslug, vzpodbujanja, zanimanja o napredku, moralne podpore in drugih oblik pomoči.

Hvala vsem!

— Marko Hrastovec, Ljubljana, junij 2018.

CONTENTS

<i>Povzetek</i>	<i>i</i>
<i>Abstract</i>	<i>v</i>
<i>Zahvala</i>	<i>vii</i>
<i>1 Introduction</i>	<i>1</i>
1.1 Near Future Improvements in Air Traffic Control	2
1.2 Far Future Improvements in Air Traffic Control	2
1.3 The Motivation for This Dissertation	4
1.4 ATM Systems Operational and Functional Constraints	5
1.5 The Goal of The Dissertation	5
1.6 Operational and Functional Constraints for The Proposed Solution .	7
1.7 How Can The Proposed Solution Be Used in Practice	8
1.8 Benefits of The Proposed Solution	9
1.9 Scientific Contributions	10
1.10 Thesis Outline	11
<i>2 Overview of The Problem and Related Work</i>	<i>13</i>
2.1 BADA Model	14
2.1.1 Structure of The BADA Model	16
2.1.2 Future of BADA	17
2.2 Trajectory Calculation	18
2.3 Regulation, Legislation, Metrics, and Plans for Future Air Traffic . .	21

2.4	Machine Learning and Data Mining for Trajectory and Aircraft Performances Prediction	24
3	<i>Data Gathering and Processing</i>	29
3.1	Process Overview	30
3.2	Test and Sample Period	30
3.3	Data sources	31
3.3.1	Radar Data	31
3.3.2	Flight Plan Data	33
3.3.3	Weather Data	34
3.4	Preprocessing	38
3.4.1	Extracting Aircraft Performances	38
3.4.2	Extracting Airline Procedures Parameters	41
3.5	Creating And Maintaining a Multidimensional Database	46
4	<i>Selecting a Suitable Prediction Algorithm</i>	49
4.1	Prediction Requirements	50
4.1.1	Predictions With Two Databases	51
4.2	Manual Feature Reduction Before Prediction	51
4.3	Evaluation of Various Machine Learning Methods	53
5	<i>Data Mining Based Prediction Algorithm</i>	63
5.1	Description of the Applied Algorithm	64
5.1.1	Feature Ranking	67
5.2	Classification of The Applied Feature Reduction Algorithm	75
6	<i>Results</i>	77
6.1	Evaluation of Results And Testing Methods	78
6.2	Time Calculation	79
6.3	Evaluated Prediction Methods	79
6.4	Brief Comparison of All Tested Methods	81
6.5	Comparison of the Best Methods From Each Group	85
6.5.1	Aircraft Performances Tables	85
6.5.2	Airline Procedures	96
6.6	Report on Usage of Attributes in Our Algorithms	106

6.6.1	Aircraft Performances Tables	106
6.6.2	Airline Procedures	109
6.6.3	Evaluation Against Standard Attribute Selection Method RReliefF	112
7	<i>Conclusions</i>	115
7.1	Quantification of Expected Improvements	117
7.2	Potential Usage of Proposed Solution	119
7.3	Future Work and Improvements	121
A	<i>Razširjeni povzetek</i>	125
A.1	Uvod	126
A.1.1	Razvoj zračnega prometa v bližnji prihodnosti	126
A.1.2	Razvoj zračnega prometa v daljni prihodnosti	126
A.1.3	Motivacija za to disertacijo	128
A.1.4	Operativne in funkcionalne omejitve sistemov za kontrolo zračnega prometa	129
A.1.5	Cilji doktorske disertacije	129
A.1.6	Operativne in funkcionalne omejitve predlagane rešitve	131
A.1.7	Kako lahko predlagano rešitev uporabimo v praksi	132
A.1.8	Prednosti predlagane rešitve	133
A.1.9	Znanstveni doprinos	134
A.2	Pristopi strojnega učenja in rudarjenja podatkov	134
A.2.1	Pred-procesiranje	135
A.2.2	Viri podatkov	136
A.2.3	Združevanje, obogatitev in hranjenje podatkov	139
A.2.4	Primerjava standardnih metod strojnega učenja	140
A.2.5	Opis našega algoritma za napovedovanje	141
A.3	Rezultati	142
A.3.1	Model letalskih zmogljivosti	143
A.3.2	Model letalskih procedur	144
A.4	Zaključek	145
A.4.1	Pričakovane izboljšave	145
A.4.2	Možne uporabe predstavljenih rešitev	146

A.4.3 Izboljšave in razvoj v bodoče 147

Bibliography 149

Introduction

Air traffic is facing big challenges to optimize flight paths, cut costs, and increase traffic with higher level of safety. The most busiest airspaces and especially airports are already at their limits.

In the future two main directions are going to be pursued to gain progress and to accommodate the demand for traffic growth and lower costs per flight [1, 2].

1.1 Near Future Improvements in Air Traffic Control

First, the development and optimization of present technologies should produce results with lower investments and earlier implementation. The main concept of the present clearance based operations, which is in use since nineteen thirties, is that air traffic is control the air situation by giving clearances to pilots. Since the first radars for civil air traffic were installed in nineteen fifties, the methods were constantly improved and many additional tools for increasing traffic throughput were introduced. Some tools like MTCD (Medium Term Conflict Detection) enable air traffic controllers to plan traffic further in the future and provide the means to handle higher capacity of traffic. Another group of improvements provide more accurate instruments and air situation overview to air traffic controllers, which allow a reduction of separation minima. An example of such an advance was the introduction of better pressure sensors enabling reduced vertical separation minima (RVSM), which allows aircraft to fly closer together and increase the throughput in that way.

There is still room for improvement in the present mode of operations. One of such improvements is more accurate trajectory calculation and prediction in order to plan traffic more closely together and to minimize separation. Air traffic controllers will benefit from new tools developed in that direction and will be able to increase their capacity even further.

1.2 Far Future Improvements in Air Traffic Control

In the second phase, we will need a larger leap. That shift in operations will require a lot of funds and stakeholders are not willing to finance it until the improvements of the present systems and operations are exhausted. The new concept of operations will involve new ways of communication between aircraft and ground controls to exchange data about planned trajectories. With these data, new mode of operations will be possible, which will be based on 4D trajectories. 4D trajectory is a flying path of an aircraft,

which defines the points on its path with 3D position and time. A move to trajectory based operations is a big step. It requires air navigation service providers (ANSP) to invest into their air traffic management (ATM) systems to support new functionalities for trajectory based operations. On the other hand, the aircraft operators (airliners) will have to upgrade their avionics to support new ways of communication. In a highly regulated business like air traffic, changes such as these can take decades. Until innovations in trajectory based operations are mature enough and prove to bring tangible benefits the stakeholders will not invest. Some estimations do not foresee the first applications with trajectory based operations until 2035 [1, 2].

The plans for future air traffic in Europe and the USA concentrate on trajectory based operations as one of the main drivers that allow predicted air traffic increase with a drop of cost per flight at the same time. Europe's project is called Single European Sky ATM Research (SESAR) [3], while the USA counterpart is called NextGen [4]. The main goals of these two projects are to modernize air traffic and to make safe and efficient transition for the future demands of air traffic increase. In Europe, the developments are progressing at various levels. European bodies are preparing legislation, which directs the involved parties (air navigation service providers, airports, airline operators, etc.) to a common goal of modernizing equipment and procedures. Eurocontrol, the organization of European air navigation service providers, is developing services and technologies for the whole Europe. Europe has been defragmented from 67 airspace blocks into nine functional airspace blocks (FABs) where common development is being introduced to increase efficiency. Practically all segments will have to deal with trajectory prediction and calculation sooner or later.

Nevertheless, trajectory based operations and advanced 4D trajectory calculations are a concept of operations, which is relatively far in the future, and we do not know all the details yet. Dixon [5] states in the memorandum about timely actions needed to advance the NextGen progress that: "Continued delays, however, in developing requirements and in making key program decisions will slow NextGen's progress. A recent NextGen portfolio analysis, commissioned by the JPDO (Joint Planning and Development Office), already shows that some NextGen automated air and ground capabilities originally planned for 2025 may not be implemented until 2035 or later and could cost the Government and airspace users significantly more than the projected cost estimate of \$40 billion."

1.3 The Motivation for This Dissertation

Before we get major improvements from the SESAR and NextGen projects, we should also concentrate on improving the present clearance based operations and systems supporting air traffic control. Our main motivation is to give air traffic controllers tools, with which they will be able to work more efficiently in a short time and with gradual small investments. We cannot wait to get the new systems with advanced methods and expect they will bring revolutionary improvements. The present economic situation is not in favor of big investments with revolutionary improvements, which will not be available any sooner than a decade from now.

Air traffic controllers will be able to plan and manage traffic more efficiently when they will be able to predict flight paths more accurately further in the future. The possibility to visualize flight paths gives air traffic controllers valuable tools, with which they can plan early. The earlier a possible conflict is identified, the smaller and less intensive maneuvers are needed to resolve it. With less intensive maneuvers and more optimal flight paths one can save fuel and minimize delays. It may not be much fuel for one flight, but for about ten million flights per year in Europe even very small savings scale to enormous amounts.

On-board computers on aircraft can calculate the trajectories pretty accurately. However, currently there are no means to download these data. This will be possible when trajectory based operations will take place. Since it is unclear when this is going to happen, we need to improve trajectory calculations without downlinked flight data.

Our motivation is to provide better inputs for existing trajectory calculations, which are currently used in air traffic control centers. Methods for trajectory calculation and prediction depend heavily on input parameters. In our case, the parameters are aircraft performances and weather conditions. By providing better inputs we can improve existing applications for trajectory calculations without the need for drastic changes, and with minimal costs.

There are many applications which calculate trajectories and depend on aircraft performances and weather data inputs. Our solution of providing better inputs for existing calculations represents inexpensive added value to the existing applications, which can be introduced rather easily.

1.4 ATM Systems Operational and Functional Constraints

ATM systems are a subject of strict certification procedures in order to assure safe operations. The change that we propose does not interfere with core functionalities of these systems. It provides only alternative inputs for certified and tested functionalities. In that way, the certification procedure tasks do not require full certification of new functions but re-evaluation of existing ones. The evaluation and certification process can be resource and time consuming, and therefore very expensive. Our solution is cost effective also in this aspect.

It is also important that the method provides inputs that work satisfactory for all flights. Safety is equally important for frequent as for rare flights. We cannot afford that prediction would work significantly worse for flights, which are rare and would be overly influenced by predictions for the most common flights. That is why all flights must be taken into account for prediction and the data used for prediction shall be automatically updated with all new flight data.

1.5 The Goal of The Dissertation

The sources of aircraft performances can be provided in many forms. The simplest is in the form of static tables with performances for various configurations for each aircraft type. More advanced presentations use physical formulae which describe forces acting on the aircraft.

We predict trajectories with a widely used physical model, Base of Aircraft Data (BADA) model, and with our methods. Some of our prediction methods try to tune the BADA model with customized input parameters to provide better predictions, while some other methods that we propose, ignore the physical model and take only the collected data to predict aircraft performances.

Irrespective of the method for determining aircraft performances, we are facing the problem that aircraft do not fly identically, and that depends on a multitude of factors.

A static table of performances can be calculated for a particular aircraft mass, and for a given set of parameters describing aircraft's maneuvers. Static tables provided by BADA are generated with nominal values. Nominal values are selected by BADA to minimize the error for various configurations of aircraft mass and practices how to operate given aircraft. These nominal values are calculated according to the flight samples available to BADA creators, and may be different for our requirements. For

any other configuration, a new static table would have to be generated.

Using physical formulae, aircraft mass and other parameters can be used in calculations to get more accurate performances. However, air traffic control centers do not have access to information about flights that would enable them to use exact parameters for calculations. They can only guess or use the provided nominal values. But with nominal values, one can only calculate the same values as provided in static tables.

Instead of nominal values, we need to get input values that will enable us to calculate performances, which will result in trajectories closer to the real ones.

The data that are available for air traffic control centers are the ones that enable air traffic controllers safe and efficient aircraft guidance through their airspaces. First, air traffic controls surveil the airspaces and get surveillance data that tell, where the aircraft are. Second, for every flight passing the airspace, air traffic controllers get basic information from flight plans. A flight plan has to be filed in by every flight, and tells where the flight is coming from, where it is going, which flight route it is taking, etc. Finally, there are weather data, which help to predict aircraft performances and flight times. All the data are described in detail in Section 3. We collect all these data into one big database, which stores information, on how the flights behave in our airspace.

The main targets to use the results of this dissertation are ATM systems, which calculate predicted times over points for aircraft that they control. More accurate predictions allow more precise planning, and take off some load from air traffic controllers. When predicted times are more accurate, the need to have additional communication for aircraft handover conditions between sectors is lower and traffic throughput can be higher.

Other potential users are simulators, which are needed to train air traffic controllers. They generate trajectories to simulate traffic. When aircraft in the simulators behave like real aircraft, they provide more realistic environment and behavior for training.

It will take some time before trajectory data from aircraft will become available to air traffic control. In the meantime, we will have to find other ways to improve our calculations.

Our assumption is that, if a flight was following a particular pattern in the past, there is a great probability that it will follow the same pattern in the future. An aircraft of the exactly same type can climb significantly different when flying on a regular line with business passengers than when transferring holiday tourists to a distant location. Distant location requires more fuel on board and tourists tend to carry heavier luggage.

With aircraft performances models, cases like this can be distinguished, if we have enough information about a given flight. Our proposal is to predict the unknown aircraft parameters to provide a better guess of the trajectory and allow predictions closer to the reality.

We record how aircraft are flying and extract performances from every flight. We enrich the acquired performances also with the corresponding flight plan data.

Our main hypothesis is, that by data mining this huge database about past flights, we can obtain better parameters for calculations of trajectories.

Although some data in the database are not indicative of aircraft performances directly, they still offer some relevant information. For instance, the aerodromes of departure and destination determine the flight distance and indicate the amount of fuel needed. The amount of fuel influences the take-off weight directly. There are many other flight parameters. Some of them give more clues on how the aircraft are going to fly than others. Our goal is to identify those parameters, which can help in finding flights with similar flight characteristics. In that way, we can predict aircraft performances of individual flights and consequently calculate more accurate trajectories.

1.6 Operational and Functional Constraints for The Proposed Solution

Using collected data we can start with predictions. The requirements for the predictions indicate, which learning methods are more suitable. The main requirements for the data collection and prediction are:

- the prediction algorithm shall use the latest data;
- the knowledge database shall be updated daily with no manual interventions;
- the machine learning shall not require human checks or manual reviews of learnt knowledge;
- the predicted data shall be compatible with current state-of-the-art prediction model in order to make an easy transition.

The main focus for the whole knowledge accumulation, processing, learning, and prediction process is to be fully automatic. Maintenance costs shall be low and users, who are not familiar with machine learning, shall be able to maintain it.

These prerequisites have driven us away of some classical machine learning algorithms for various reasons. When new data arrives it shall be used for the next predictions. Without a learning phase the algorithm can use the data, which are being updated regularly. If a learning phase is used, the learnt knowledge should be checked every time. This is a time consuming and costly operation.

The prediction should not predict well only for the most common attributes or the most frequent flights. It is important that prediction process will not treat rare flights as outliers and predict the trajectory of a more frequent flight for them.

Since new types of flights can arrive any day, new attributes can appear anytime in our database. Therefore, we decided to use an approach based on instance based learning, which improves predictions for new types of flights gradually and by itself when they start to fly regularly. Most other machine learning methods require in such circumstances a new learning phase. But to use algorithms, which require a learning phase, one has to detect new unknown attributes and concept drifts first, and then initiate a new learning process to learn from new data.

One of our most important goals is to design a system that is relatively easy to replicate and implement. In this way, we can expect that other potential users would follow our example and implement a system for their airspace that will provide them with better trajectory calculation accuracy as offered by their present system. If complex machine learning algorithms are used, that require a lot of fine tuning during the implementation, there is a much greater possibility that reproducibility can become a challenge.

1.7 How Can The Proposed Solution Be Used in Practice

Our main goal is to improve the state-of-the-art trajectory calculation accuracy, which is used in the majority of ATM systems. Instead of using default input parameters, we propose to use machine learning to customize the input parameters for individual flights.

These kind of improvements can bring large benefits to air traffic in general. Air speeds are already quite accurate and we will not get much more accurate predictions of times over points on the route. However, we showed that climb and descent predictions can be improved significantly. Vertical maneuvers are not so desirable as pilots want to climb to cruising level as quickly as possible and stay there for as long as possible. When we predict climbs and descents more accurately, we can allow pilots to stay on

cruising levels for a longer time. Continuous climbs and descents would be more easily achieved if air traffic controllers would be able to identify with more detail where and when the aircraft should perform maneuvers, and how much time the maneuver is going to take. In that way, we could also determine with better certainty whether a climbing or descending aircraft will be in conflict with other aircraft flying in vicinity.

We propose that the systems keep their present methods for trajectory calculations. The prediction service should provide customized parameters to enable the legacy applications to work the same way as they do now.

We estimate that the investment in changing only the source of input parameters, would be much lower than the replacement or improvement of entire existing systems.

To make predictions widely accessible they can be offered as a web service. Because prediction is simple, all that is required, is to establish a knowledge database with data about flight performances and a web service, which uses that database for predictions.

1.8 Benefits of The Proposed Solution

Let us take an example of a flight section with an actual duration 100 s. If the BADA model estimate is 120 s, and our prediction is 110 s, we declare that as a 10% improvement. In this case the error drops from 20% to 10%, which is a 50% error improvement. However, the prediction is for 10 s better, which is 10% of the actual flight section duration. Therefore, the prediction is improved for 10%.

With the described methodology, we can expect improvements for air speeds on cruising level only up to 1%. For air speeds in climbs and descents, the improvements are better - from 1% to 3%. We have achieved the greatest improvements in climb and descent rate predictions. For climbs we can expect 2% to 10% improvements, while for descents even 10% to 20%.

Billions of Euros have been invested in Europe solely in software for air traffic control systems and the lifetime of such systems is at least 20 years because of such high investments. To wait for the systems to become outdated and be replaced with new ones with better trajectory calculation will take too long and probably the trajectory prediction will not be much better in newer versions. It is also unrealistically to expect that existing systems will change the trajectory prediction method.

Around 300.000 flights pass through Slovenian airspace in a year. If we assume that we can save just a few Euros per flight due to better flying paths and shorter delays, we can expect millions of Euros in savings per year just in the Slovenian airspace. This

sounds good for a fairly low investment. If we scale it to a larger airspace and higher traffic volumes, the savings can be much higher.

Global emissions from international aviation transport account for about 1% of total anthropogenic CO₂ emissions. However, the influence on climate change may be significantly larger due to the combustion of jet fuel at high-altitudes [6]. One of three factors for reducing the emissions of international aviation are beneficial changes in air traffic management [7]. Our proposed solution optimizes flight trajectories resulting also in pollution reduction. This is especially important because emissions from international aviation are not under international policy control.

1.9 Scientific Contributions

The primary goal of this dissertation is to propose a better method for trajectory calculation that could fit into existing software systems currently used in air traffic control. If the general constraints of existing legacy systems and the general way of how these systems are operated would not be taken under consideration, the possibility that the results of this thesis would have any actual relevance for air traffic industry would be practically zero. The most important contribution of this thesis is a new concept of trajectory calculation which is individually tailored to each flight. We show in the thesis that predicting trajectories, based on the data of past flights that are collected by air traffic control centers can, in fact, give better results than the current state-of-the-art method.

Other contributions of this work are as follows:

- a new innovative way of acquiring weather data,
- piecemeal assembly of data from three separate sources to get one combined knowledge database, which can be used for analysis, learning and prediction of aircraft performances,
- estimation of aircraft performances based on similar flights from the past,
- prediction of aircraft performances based on indirect attributes without a complex physical model,
- a new innovative way to provide dynamic input parameters for a particular flight to the static BADA model enabling more accurate trajectory calculations,

- the system was tested on five years of real data from Slovenian airspace with approximately 1.500.000 flights.

1.10 Thesis Outline

The rest of the text is organized as follows. Chapter 2 is an overview of the main fields of research, and outlines main developments in these fields, describes views for future of air traffic, and points out regulative and legal requirements and constraints. In Chapter 3 the data sources, and preprocessing of data are described in detail. Chapter 4 defines prediction requirements, describes attributes and shows how various machine learning methods behave on a data sample. Chapter 5 describes methodologies, procedures, technologies, and solutions used for our solution. Chapter 6 shows how the applied solutions perform on real traffic data. The results are interpreted and compared to state-of-the-art solutions being used in air traffic control applications. Finally, the text finishes with Chapter 7, which puts the work in the perspective of usability and outlines potential improvements with future work on the topic.



*Overview of The Problem and
Related Work*

The main task of air traffic control is to handle the traffic in a conflict free way. Many conflict detection resolution and avoidance tools are being developed to help air traffic controllers to maintain safe and fluent operations. Every conflict resolution and last minute avoidance maneuvers are leading to unneeded fuel consumption, passenger discomfort, and delays. More accurate trajectory predictions are the main motivation for our research. They are important for tools being used now and even more important for future air traffic development.

2.1 BADA Model

Currently, the most commonly used source of aircraft performances is Base of Aircraft Data (BADA) model developed and maintained at European Organisation for the Safety of Air Navigation (EuroControl) Experimental Centre (EEC). It is based on mass-varying, kinetic approach that models an aircraft and underlying forces that cause aircraft motion. In the BADA model aircraft are grouped according to their general, operational, performance, configuration and speed characteristics. However, same aircraft types are not equipped identically and various airline companies have their own best practices on how to fly efficiently. The BADA model cannot take into account all these particularities.

The BADA model is currently at version 3. Subversions are published regularly to introduce new aircraft types and to adjust and correct the parameters. Currently, the 3.13 version is the latest BADA version [8–11] and includes data for 519 aircraft types. For 194 of these aircraft type, data are provided directly. For other 325 aircraft types (synonym models), the data are specified to be the same as the one of the directly supported aircraft types. Usually many different aircraft models (and the same model with different versions) fly under the same aircraft type. They have different performances. Based on the availability of performance data, the BADA developers decide which aircraft model to use. If performance data are available for more models, the decision is based on the usage in the European airspace.

According to the coverage report [12], the version 3.12 provides 90% coverage of aircraft types operating in Europe, and the majority of aircraft types operating across the rest of the world. In the percentage of actual European traffic, 99.92% of European air traffic is covered by the types in BADA 3.12. The rest of 0.08% are the aircraft of the remaining 10% of aircraft types not covered in the model. Version 3.13 covers even more aircraft models, but the coverage report is not available.

As mentioned earlier, the model is based on a kinetic approach. The aircraft performances calculation is described in Base of Aircraft Data (BADA) Aircraft Performance Modelling Report [13]. First, data about aircraft are gathered from Aircraft Operation Manuals (AOM), which are usually not precise enough and provide data for only one speed schedule. If possible, AOMs are substituted with aircraft performance engineering programs that provide a high quality aircraft performance reference data, which allow generation of data for a complete range of aircraft operating conditions. A secondary source of information is Jane's All The World's Aircraft [14], which is published annually. Jane's is suitable for providing information such as maximum weights, dimensions, etc., but it does not provide reference climb or descent profiles. Reference profiles from various sources are gathered together and inserted into the database. Along with the reference profiles, sample trajectory profiles are also provided for each aircraft type. The minimum number of trajectory profiles is seventeen (thirteen for climb, three for descent and one for cruise). All profiles and other characteristics of aircraft like maximum altitude, maximum speed, aerodynamic surface area, stall speeds, etc. are stored in the database. When data are gathered, the Matlab based identification process called BEAM calculates BADA coefficients. The problem is identified as a non-linear coupled multivariate parameter estimation problem. However, it can be split into several linear sub-problems whose sub-optimal solutions progressively incorporate more reference data and estimates coming from other sub-problems until the global optimal solution is achieved [13]. For the aerodynamic drag, engine thrust and fuel consumption generalized models are introduced that are valid for all aircraft types. The solution relies on the well-founded and powerful technique of least squares linear fitting. The objective is to make integrated BADA trajectories closest to the sample trajectories obtaining the best fit in the sense of root mean square errors (RMSE). The output of this process are the performances tables for a particular aircraft type. After extensive validation and cross checks the data are ready for publication.

The current BADA model demonstrates the ability to predict aircraft performances with a mean RMS error in vertical speed lower than 100 fpm (fpm = feet per minute) and a fuel flow error less than 5%, for the range of aircraft normal operation. In that way, the model provides trajectories that provide minimum error on average.

2.1.1 Structure of The BADA Model

The BADA provides three kinds of models. The first, Operations Performance Model is based on Total Energy Model (TEM). TEM equates the rate of work done by forces acting on the aircraft to the rate of increase in potential and kinetic energy. With the help of formulae provided, very accurate trajectories can be calculated if the aircraft intention is known and if important details about the flight are known, like take-off weight, power used for climb, etc.

Since aircraft fly differently, the designers of BADA developed Airline Procedure Model, which defines the set of parameters, which are used to characterize standard airline speed procedures for climb, cruise and descents. The BADA User Manual acknowledges the fact, that the way aircraft are operated, varies significantly in function of specific airspace procedures and operating policies of locally dominant airlines. Airline Procedure Model helps in such cases providing different input values for various operators or practices. However, BADA developers cannot provide all these different parameters so they put a default company in Airline Procedure Model. We believe, that one of the reasons for having only default values is also operators reluctance to have their best practices published in airline procedure model. After all, their best practices are considered as a competitive advantage in relation to other operators. That means that users are left with default input values for TEM producing trajectories, which are not the ones that are actually flown. Users should create their own values for Airline Procedure Model suited to their geographical or operator particularities to have more realistic trajectories.

With using default values in TEM we can calculate aircraft performances on predefined altitudes and weather conditions. BADA Performance Table Model does exactly that and provides pre-calculated lookup tables of true airspeed, climb/descent rates and fuel consumption at various altitudes for all aircraft types included in BADA [8]. Many legacy applications for air traffic control and simulations, which are still in use, use these tables, and it will take a while before they will be replaced with routines using more advanced trajectory calculation methods.

The BADA model provides a very good model for trajectory prediction. The main problem of BADA, in our opinion, are the default values which represent the smallest error for majority of flights, but no aircraft actually flies like that. There is a very interesting book *The End of Average* from Todd Rose [15] describing this problem.

An example from the book describes that USA army had unexplained high rate of accidents caused by pilot errors. At its worst point, seventeen pilots crashed in a single day. The research showed that cockpits, which were designed for body dimensions of an average pilot, did not fit a single one because not even a single pilot had dimensions of an average pilot. The same, in our opinion, applies for flights. We should try to calculate trajectories with different input values for each individual flight and try to fit them better than using average defaults from BADA for all.

2.1.2 Future of BADA

The developers of the BADA model have identified the need for better accuracy for the new SESAR systems. Since 2005 some informations about Base of Aircraft Data (BADA) 4 model were published by Gallo, Navarro, Nuic and Iagaru [16] and Nuic et al. [17, 18]. The new model provides better accuracy and lays the ground for accurate 4D trajectory calculations needed in future systems. For now, access to BADA 4 is much more strict [19] requiring a signed hard copy license, no organisation-wide or multi-purpose license, proof to be able safeguard confidentiality and usage only for permitted use. It is being advertised as the most accurate model, which will enable development of air traffic toward trajectory based operations and the basis for flight objects concept in Single European Sky ATM Research (SESAR) [3]. BADA 4.0 introduces many new features like operations model with different aircraft instructions and accurate models for different types of power plans covering the complete flight envelope under atmospheric and wind conditions. However, the model is still based only on physical characteristics and ignores all factors, which we are trying to incorporate into our machine learning model. In fact, the authors say that except for some details, the same modeling process (data preparation, identification, validation) as is used for BADA family 3 was applied for development of BADA family 4. The development is funded by Boeing Research and Technology Europe. According to the coverage report [12] the BADA version 4.1 provides a coverage for 67.80% of the current aircraft types operating in European Civil Aviation conference (ECAC) area.

The comparison between BADA 3 and 4 is being presented by authors of the BADA, Poles, Nuic and Mouillet [20] in 2010. While BADA 3 covered almost all aircraft models BADA 4 consisted of a validation set of 25 aircraft types in 2010. The coverage of aircraft types by BADA 4 is closely related to the availability of high quality aircraft performance reference data. At the moment, this kind of data exists only for major

manufacturers. However, BADA 4 model has better support for different aircraft operations and flight phases. For all the new features the computational model is more complex and needs accurate inputs from manufacturers. It is difficult to get these inputs especially for older aircraft types. BADA 4 strict licensing policy most probably comes from the agreement between BADA developers and aircraft manufacturers. In 2010 they published the following information: “The negotiations with aircraft manufacturers are currently on-going to define the terms and conditions for use of BADA outside of EuroControl” [18].

In our opinion, the model will be able to use its full potential when flight intent or planned trajectory will be downlinked. Until then both BADA versions can only calculate trajectories that produce minimum errors on average.

In 2013 an open source project called BlueSky ([21]) started under the guidance of Jacco Hoekstra and based on experience with a simulation tool called the Traffic Manager ([22]). This project can use the BADA model but it can also use its own aircraft model for air traffic simulations for users without a BADA licence. Metz [23] extended BlueSky with an internal aircraft performance model which is based on publicly accessible information about aircraft. This guarantees that BlueSky remains an open source project. The internal flight dynamics model is structured similarly to the BADA model, and the same algorithms are used within BlueSky for both.

2.2 Trajectory Calculation

Porretta, Dupuy, et. al. [24, 25] suggest a novel 4D trajectory calculation method based on BADA performances. The flight plan provides points where the aircraft will fly and estimated times over trajectory change points. The aircraft intent information acquired from a flight plan is summarized in a simple set of instructions called a flight script. Flight script emulates the aircraft control system with maneuvers to follow the planned flight path. Based on the time from the flight plan, the flight script is followed using BADA model with adjusted speeds. Speeds are adjusted in order to follow the times from the flight plan. Authors have compared the predicted trajectories with real traffic and the results show better results than two representative existing methods.

Schuster, Ochieng and Porretta [26] are taking the studies from Porretta and Dupuy [24, 25] further with the estimation of winds. Similarly as we do, they use the winds measured by the aircraft and not from the numerical weather models. Authors do not reveal how the wind measurements were obtained from aircraft. They only state

that the measurement is available every sixty seconds. More accurate winds help in trajectory calculations which are better in this case. However, since the measurements are available every sixty seconds they calculate the trajectories for only sixty seconds in advance. They do not share the measurements and use them for all the flights in the same area. Since they are using direct wind measurements, it is unclear why the temperature measurements are not used. It is unlikely that only wind measurements are available and temperature measurements are not.

When calculating 4D trajectories with a physical model, the algorithms need to know, how the aircraft is going to fly. López-Leonés, Gallo, Navarro and Querejeta [27] have developed a formal language called the Aircraft Intent Description Language (AIDL). The AIDL provides the necessary elements to unambiguously formulate aircraft intent. The alphabet of AIDL contains instructions that capture the individual commands and guidance modes available to direct the motion of an aircraft. The AIDL grammar rules define the possible combinations of the instructions. With AIDL the trajectory is described prior to computation process.

Gallo, Vilaplana, Navarro, Francisco and Nuic [28], and Gallo [29] state that the accuracy of the computed trajectories do not depend only on the trajectory computation infrastructure and its integration capabilities, but also on the input received from the associated aircraft performance model, the operational instructions defining each trajectory, the initial conditions and the atmospheric data. The Trajectory Computation Infrastructure (TCI) presented in the papers [28, 29] was developed by Boeing Research & Technology Europe (BR&TE). The papers present a trajectory computation that accepts either BADA 4 or BADA 3 aircraft performance model. It requires a set of operational instructions to compute any trajectory segment called Aircraft Intent Description Language (AIDL). These instructions represent the minimal indivisible pieces of information that capture basic commands, guidance modes, and control inputs at the disposal of the flight deck to direct the aircraft behavior. Each instruction closes an aircraft degree of freedom (throttle, elevator, or combined rudder and ailerons) during a given amount of time, upon which it is replaced by another instruction. The trajectory calculation integrates a system of differential equations describing the aircraft motion in vertical plane, together with the algebraic equations defined by the aircraft intent. The result is the computed trajectory.

Gillet, Nuic and Mouillet [30] use historical radar data to generate more realistic aircraft trajectories for simulation purposes. Simulators often generate trajectories which

do not reflect real flight scenarios. Trajectories that use operationally tuned parameters can improve the accuracy of aircraft modelling. They gather the same data as we do and store them in a database. When they extract averages for similar flight behavior, they can select aircraft type, operating airline, airport and flight range. For each such category, several operational parameters can be identified from the statistical analysis: average climb, cruise and descent speeds, altitudes where changes in speed occur, time taken to perform those changes, etc. They are used to make custom profiles for BADA according to the operated airport, aircraft type, operating airline, flight phase and flight range.

The authors Glover and Lygeros [31] propose a stochastic method for modeling 4D trajectories. They use a novel method, which uses BADA as a source of aircraft performances and wind as stochastic random field. Authors use flight plan data for planned route extraction and BADA performances to calculate flying path. They do not use other attributes from the flight plan.

The article of Jiuxia and Jun [32] makes an overview of development of trajectory computations from 1960s until today. It splits the flight into seven phases (take off, departure, climb, cruise, descent, arrival, and landing), and discusses mainly the generation of trajectory in cruise.

Natchev and Heidger [33] present trajectory computation algorithms considering two different sets of requirements. Short term model for trajectory computations is important for all kinds of tools used by air traffic controllers like short term conflict alert (STCA), minimum safety altitude warning (MSAW), area proximity warning (APW) and other tools for maintaining fluent and safely separated traffic. They usually use live surveillance data as main input. Another type of calculation is a long term model, which is mainly used by Flight Data Processing Systems (FDPS). FDPS's main source are not surveillance data. They calculate trajectories for the whole flight from the flight plan content (flying route, aircraft type, etc.), and atmosphere prediction. They may or may not adjust the trajectory based on surveillance data.

Vilardaga and Prats [34] present a method to plan suboptimal aircraft trajectories that have to meet time requirements at specific navigation points. With strategic 4D trajectory planning, the optimized trajectory plans could be produced which would minimize delays, reduce fuel burn and avoid the need for separation maneuvers at a tactical level. For strategic planning on such a scale, accurate aircraft performances for each flight are essential to predict the trajectories as accurate as possible, and estimate,

if paths with restrictions are possible to fly. In the future, aircraft could download such calculated trajectories and fly them. With pre-planned traffic, a larger throughput could be achieved than with ad-hoc conflict resolution used now.

2.3 *Regulation, Legislation, Metrics, and Plans for Future Air Traffic*

Trajectory prediction has evolved into a collection of disparate methods with differences in approach, data requirements, performance, capabilities and design. The paper by Mondoloni and Swierstra [35] introduces cooperation of Federal Aviation Administration (FAA) from USA and Eurocontrol. Action Plan 16 [36–41] tries to establish common trajectory prediction capabilities. It seeks to provide common trajectory prediction capabilities through the execution of nine points like common terminology, requirements for aircraft performance data, sensitivity analysis, validation, etc. The paper also introduces common trajectory prediction structure. The paper states, that it is practically impossible to get aircraft performances from manufacturers for specific trajectory prediction needs. Trajectory prediction structure presented does not foresee any other inputs to the aircraft performance library than the ones from aircraft manufacturers.

One of the points of Action Plan 16 mentioned by Mondoloni and Swierstra [35] is an evaluation of performance. Mondoloni, Swierstra and Paglione [42] propose common metrics for trajectory calculation performance. They define key performance areas: accuracy, confidence, speed, stability, reliability, uniformity and synchronization. A useful framework for structuring metrics introduces input, output, outcome, impact (IOOI).

Vilaplana, Gallo, Navarro, and Swierstra [43] present the effort of Action Plan 16 to harmonize trajectory prediction. Each trajectory prediction implementation is tailored to specific needs. That makes them difficult to compare since they lack consistency. To achieve consistency it is essential that, besides using similar estimates of meteorological conditions and aircraft performance, the various trajectory predictions share a common view of the way, in which the aircraft will be operated over the extent of the prediction period, i.e. of the aircraft intent. The paper identifies the need for a formal language for the common description of aircraft intent in the context of trajectory computation. Such a language, denoted as Aircraft Intent Description Language (AIDL), would allow expressing the aircraft intent with different levels of detail within a single standard

unifying framework. The paper also states that the best solution would be, for aircraft to communicate to the ground its intent as a 4D profile.

EuroControl has developed a data structure and database for trajectory prediction evaluation within Action Plan 16 project. Paglione, et. al [44] present a harmonized database and evaluation tools.

Another outcome of Action Plan 16 is a paper from Avello, Idris, Vivona, and Green [45]. They describe a set of tools, methodology, and metrics of key performance indicators developed for the analysis of different aircraft performance models approaches. Two major methods for trajectory prediction exist. Kinetic performance models are based directly on underlying physics governing the flight through the forces of thrust, drag, lift and weight. On the other hand, kinematic models use only the key performance elements such as Rate Of Climb (ROC), Rate Of Descent (ROD), as a function of the external parameters affecting it. Kinetic models provide a potentially higher level of fidelity, while kinematic models are often accurate enough with simpler and computationally less demanding procedures. The paper proposes methods, metrics of Key Performance Indicators (KPIs) for objective analysis of all kinds of Aircraft Performance Model (APM) approaches. The methodology proposes a three steps evaluation of the accuracy of any aircraft performance model. The first step consists of evaluating the performance of each model of interest over the flight envelope. The second step of the methodology aims at evaluating the accuracy of any APM. Finally, the third step completes the process by performing a sensitivity analysis of any model performance parameter.

International organizations, which are responsible for development of air traffic, have started projects to support traffic increase in a safe and efficient way. In Europe, the main driver for changes is Single European Sky ATM Research (SESAR) [46]. SESAR Joint Undertaking [3] is a public-private partnership where industry and states have joined their efforts to modernize air traffic. European Council Regulation (EC) 549/2004 [47] lays down the framework for the creation of the single European sky. Among other regulations, that followed this one, the Council Regulation (EC) No 219/2007 [48] and Council Regulation (EC) No 1361/2008 [49] form the joint undertaking in the form of a public-private partnership.

The main goal is to give the community a high-performance air traffic control infrastructure, which will enable safe and environmentally friendly development of air transport. One of the goals of SESAR is to migrate to trajectory based operations.

According to Enea and Porretta [50], four significant technological improvements will have to be installed and used in order to start with trajectory based operations (TBO). First, the flight managements systems (FMS) on board of aircraft will need to have more advanced features. One of the features is controlled time of arrival (CTA) which enables the aircraft to arrive at a predefined point at negotiated time. For that to achieve, FMS will have to receive wind data and other constraints to be able to calculate accurately. The second requirement comes naturally from the first one. In order to provide the FMS with up to date information, data communication between aircraft and ground for sharing trajectory and other important data will have to be established. Third, more advanced surveillance capabilities based on automatic dependent surveillance (ADS) will be used. The satellite based technology will be used on the ground for surveillance and on board of the aircraft for augmented traffic situational awareness. And the last prerequisite to enable 4D TBO is the implementation of Decision Support Tools (DST) for air traffic controllers to keep their workload within acceptable levels maintaining the current level of safety with increased traffic.

Eurocontrol, as the representative of states, is following the call to action by the European Commission to move forward with the implementation of Single European Sky. It has developed the concept of centralised services (CS) [51], as a way of helping to improve performance and competitiveness. The essence of the centralised services idea is that there are a number of air navigation services that could be run more efficiently at a central, network level. Eurocontrol has identified initial nine centralised services as candidates to make most sense to implement them on a pan-European basis. The centralised service number two (CS2), which is connected directly to our research, is called 4D Trajectory Flight Profile Calculation for Planning Purposes Service (4DPP) [52].

The cost benefit analysis figures presented in detail for all the nine centralised services estimates that 150 to 200 million € yearly cost reduction for the airspace users is possible. The contribution of CS2 (4DPP) is estimated at 8.2 million € savings in yearly operating costs and 54 million € savings in investments costs. If all 63 European centers would need to implement a complete trajectory based system to calculate all trajectories from pre-departure to the time when they enter their airspace, this would generate high costs across the network and would make consistency difficult to achieve. Therefore, it is suggested to operate a central 4DPP system making constantly available all data to the air navigation service providers, airports and airspace users, using

the emerging interoperability standards.

The presentation of 4DPP says, that everybody computes 4D trajectories independently of each other, with their own focus, and with limited data available to them. As a result, actors have inconsistent and/or inaccurate trajectory information, while in the end only one trajectory will be actually flown for each flight. This situation reduces confidence in predictability and has a significant negative impact on the quality of ATM planning. Instead, a consistent trajectory must be used by all actors. The objective of 4DPP is to provide accurate and consistent trajectories for planning purposes across the full area of interest. Planning activities extend from long-term planning to short-term and tactical planning and include post-operations analysis. Depending on the nature of the planning activity, the inputs, the timeline, the required accuracy and response time for trajectory calculation can vary considerably.

Several interoperability standardisation initiatives are currently on-going (e.g. SESAR Flight Object ED-133 [53], ICAO FIXM [54–56], etc). These standards and will enable the exchange of trajectory information between interested parties.

2.4 Machine Learning and Data Mining for Trajectory and Aircraft Performances Prediction

In their paper, Sun, Zhang and Cai [57] introduce a new method for 4D trajectory generation for simulation purposes. Their method learns from historical radar data, which are processed to generate traffic flow for each flight line. The model distinguishes different aircraft types and generates a flight path based on historical data on the same flight line. Since the radar plots are scattered due to radar inaccuracy, they smooth the line to achieve a better state estimate. After being smoothed, the positions of trajectories at each normalized sample period are obtained. Each flight has its own positions and they need to be interpolated to get all flights with same periods. When these smoothed and interpolated points on flight path are acquired, the flight path is generated. Due to characteristic of continuity and smoothness of a trajectory, the cubic spline interpolation is used in this step to get a full flight path. Comparison with real flight data shows a good matching.

Similarly as Sun et al. [57], de Leege, van Paassen and Mulder [58] use machine learning methods to predict trajectories along one particular landing procedure of 45 nautical miles length. Authors distinguish two aircraft types for learning - heavy and medium. The input data for learning were collected for two months. They used three

machine learning methods: generalized linear models, support vector regression and artificial neural networks. The first two methods performed marginally better than artificial neural networks, and authors decided to present the results from the simplest one, which is generalized linear method. Trajectory prediction calculates trajectory from first approach navigation point along significant points to the runway threshold. In total, seven points are calculated. Model inputs are: aircraft type, aircraft ground speed and altitude over initial point and winds. The model produces trajectories with approximately 5 s error on the last 15 nautical miles and 20 s error on 45 miles trajectory. The model was also tested to schedule flights entering the approach procedure. In practice, controllers use a standard separation between aircraft to achieve conflict free approaches to the runway. With model calculated approach schedule the capacity was increased by four aircraft per hour. The accuracy of predictions is satisfactory to improve the approach throughput.

Kun and Wei [59] are taking a similar approach as we do with one of the models. They are similar in the context of ignoring aerodynamics and using radar data. The method consists of two phases. First, they predict total flying time based on historical data only and present the status of traffic flow and winds, based on linear regression method. After the total flying time is calculated, they predict trajectory based on same flights taken in the past. The second phase of prediction adjusts the trajectory based on real-time radar data after the flight takes off. If time at certain waypoint on the flight route is not correct, times over following waypoints are adjusted according to the error recorded. The same method of real updates is proposed to be used in Eurocontrol's centralised service 4DPP [52] mentioned in 2.3. The authors don't use any additional data about the flight that might help them identify similar flights. The prediction is always based on identical flights from the past.

Cheng, Cui and Cheng [60] use data mining for air traffic flow forecasting. Their model is a hybrid of neural networks and statistical analysis. The model was fed with three months of incoming traffic data. The proposed prediction model was tested on air traffic flow collected by the Air Traffic Control Command Monitoring System (ATCCMS), which aims to give early conflict alert and advice of short-term air traffic flow management to human controllers in the Beijing center. Through the analysis, the air traffic flow was classified into seven categories corresponding to daily difference in a week, which were trained and forecasted separately.

La Fablec and Alliot [61] deal with the problem of unavailable data with neural net-

works. Similarly as all other attempts, they face a lack of information about flight, such as take-off weight, thrust, drag, lift, etc. These informations are simply not available to the ground control systems. They collect recorded trajectories for each type of aircraft and feed them into a neural network model. They use the model then to predict the trajectories based on accumulated knowledge. The neural network was trained with 142 trajectories, then predictions were performed on 50 non-learned trajectories. First, they predict a climb or descent time by knowing the aircraft type, starting altitude and final (requested) altitude. At aircraft take-off, the algorithm adjusts the prediction based on real flight data. The results show that neural networks are more efficient than existing non-parametric methods and that they outperform techniques used in operational systems. The prediction is based on aircraft type, requested flight level and later on real time radar measurements.

Hadjaz, Marceau, Savéant and Schoenauer [62] use machine learning for the climb phase of an aircraft. Their Covariance Matrix Adaptation Evolution Strategy (CMA-ES) optimization algorithm tunes five selected flight parameters, and thus improves the accuracy of the model. The first part predicts trajectory based on BADA default values. The results show that the flight parameters should be tuned according to actual flight performance of each individual flight. The second part then tunes the parameters based on real-time radar data with CMA-ES optimization algorithm. The results are much better when corrected with real-time data. However, without knowledge of aircraft intent, the prediction improves only for the short term. For 2 and 5 minutes in advance the results are better, but for 10 minutes the prediction is not very good any more. Authors state the need of transmitting relevant on-board data to the ground for improving the trajectory predictability. We are all aware of that fact, but flight crews are not in favor of sharing their information. Until international organizations (European Commission, FAA, ICAO) make the transition to new technologies mandatory, we have to make the best of what we have available now.

Crisostomi, Lecchini-Visintini and Maciejowski [63] use a novel approach for short-term trajectory prediction used in Short Term Conflict Alert applications. STCA is an application, which warns controllers of potential mid-air collisions. Authors combine two methods: Monte Carlo and worst-case to detect possible conflicts. The prediction is performed in real-time as it updates its values on every radar update. Monte Carlo method predicts most probable trajectories, while worst case method on the other hand predicts trajectories to test for possible conflicts.

A thorough overview of air traffic control (ATC) systems from the perspective of machine learning is done by Rehman [64]. It concentrates on keeping a safe distance between aircraft while preserving maximum throughput. The machine learning concept is presented for the whole ATC system with formal description called Z notation on a high level. This attempt is claimed to reduce complexity by decomposing it into its critical components. The author admits that the formal definition lacks details, because it would lose intuitive understanding. The description is useful for understanding complex system like ATC. We believe, ATC systems as a whole are not mature enough to be treated as one machine learning model.

Alligier, Gianazza and Durand [65–67] deal with the same problem of unavailability of exact data that would enable reliable ground trajectory calculations. The authors estimate mass and thrust, which are crucial in trajectory prediction of a climbing aircraft. The aircraft mass is estimated from a few points of the past trajectory measured with radars, and the thrust law is calculated with machine learning from a training set of trajectory records. Using these input data, the computed trajectory is better than BADA model based calculation using a single common mass per aircraft type.

Tastambekov, Puechmorel, Delahaye and Rabut [68] have taken an interesting approach for a mid-term conflict detection (MTCD) tool. The described method searches for similar trajectories from the past in the terms of shape and time with k nearest neighbours algorithm. Then, the linear functional regression model is used on already flown part of the trajectory and similar trajectories to predict the remainder of a flight. The method does not use any physical or aeronautical parameters for prediction, and uses a departure and destination from flight plans as a distance criteria.

Weitz [69] was investigating uncertainties that influence trajectory predictions. The most influential parameters for the uncertainty are: wind, temperature, aircraft mass, speed and navigation performance. The article shows that accurate meteorological conditions and knowledge about aircraft enable the calculation of more realistic trajectories.



Data Gathering and Processing

3.1 Process Overview

For the whole process of acquiring data and prediction, three main data sources are important. They are all available to air traffic control centers and are:

- radar recordings,
- flight-plan data,
- and weather data.

We gather data from all three main sources on a regular basis and preprocess them to be suitable for our use. The overall process is shown in Figure 3.1.

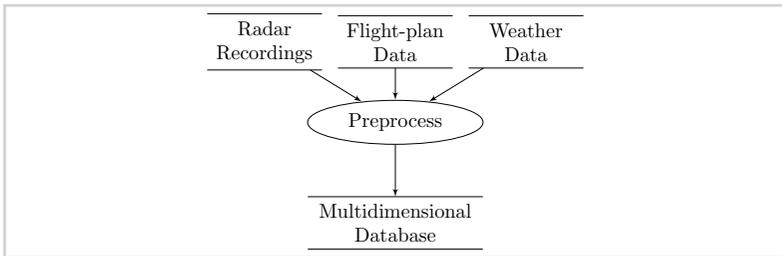


Figure 3.1: Data are gathered from radar recordings, flight plans and weather data.

3.2 Test and Sample Period

We have started to collect the data from all sources, in a form that is usable for preprocessing, in February 2011. Our knowledge database is growing since then every day. We call the period since February 2011 the sample period. The airspace, where we can gather data, is the Slovenian airspace extended over neighbouring airspaces where radars used by Slovenia Control can detect aircraft.

We chose the flights from January to December 2015 to be our test set. For approximately 265,000 flights from the test set we have predicted the aircraft trajectories using several different methods based on the data collected in the sample period and compared them with the actual recorded performances of each flight. More details about the comparisons and evaluation of results can be found in Section 6. The interval of one year encapsulates all seasonal changes. In Slovenian airspace the low winter traffic is almost two times lower than during the summer peaks. The earliest test predictions

for January 2015 were already based on almost four years of accumulated knowledge in the period from February 2011 to December 2014. Until the beginning of 2015 there were already 1.250.000 flights in the database.

Because the database is updated daily, the predictions, which do not involve learning, always use the accumulated knowledge until the current day. These daily updates are necessary because on any day new aircraft types, operators, destinations, etc. can appear. For predictions, that means that the yesterday's traffic can already be included in predictions for today. In that way, some test predictions were using samples until that date. For instance, predictions for 15 June 2015 were using samples in the knowledge database from the February 2011 to 14 June 2015.

3.3 *Data sources*

As mentioned earlier, samples are gathered from three main sources described in the following sections.

3.3.1 *Radar Data*

The first source of data are aircraft positions measured by radars. On every rotation, a radar records new aircraft positions of each aircraft within its range and sends them to the air traffic control center. Typically, the turn rates of radars are between 4 s and 12 s. An aircraft position from the radar is called a plot. Radar errors, at the limits of their ranges, can be up to 2.5 nautical miles. With accuracies like these, we would not be able to calculate aircraft performances from the radar recordings. The radars are simply not accurate enough, and we would have to implement error elimination and smoothing. For safety and availability purposes there are always at least two radars covering each portion of airspace. Radars are not synchronized and send data as they detect aircraft in the air. Such disorganized and unsynchronized feeds of radar data with variable accuracy are problematic for air traffic control. To overcome all these problems, tracker software is used. This software receives raw radar plots and effectively minimizes radar measurement error to generate smoothed flight tracks [70]. Trackers combine data from multiple radars and calculate projected positions of aircraft by taking into account radar accuracies, flight capabilities, etc. Figure 3.2 shows how a tracker would estimate aircraft position based on inputs from two radar's inaccurate measurements. Usually, some kind of filters such as Kalman filter or particle filters are used to eliminate errors and project most probable aircraft positions [71, 72]. The positions that come out of

a tracker are in fact not the positions given by radars. They are projected positions for the time of track creation based on all the inputs. Aircraft positions generated by tracker are called tracks. The main difference between plots and tracks is that plots are radar measurements representing a point in space taken at a certain time, while tracks are projections of aircraft positions for the predicted time. Unlike plots, tracks also have vector information with directions and sizes representing ground and vertical speeds. These smoothed tracks from trackers are far more accurate than individual radar measurements and are the source for our calculation of aircraft performances.

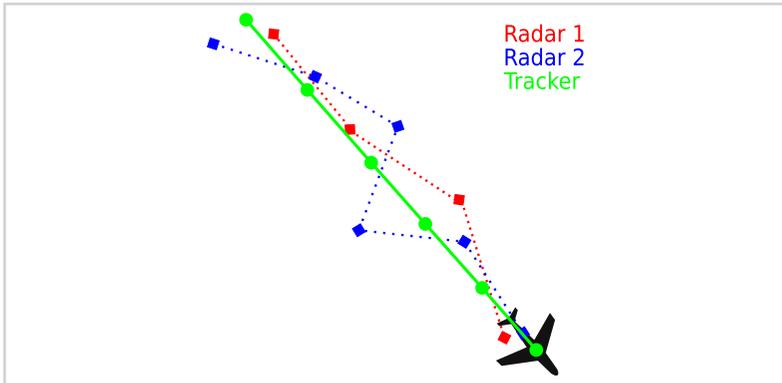


Figure 3.2:
Smoothing flying
path and elimi-
nating radar errors
with tracker.

The error in radar measurements is related to lateral position of aircraft. For aircraft's altitude the secondary radars are getting the altitude report from aircraft, while lateral position is determined from radar rotation (azimuth) and aircraft's distance from the radar (range). However, azimuth and range can provide only two dimensions of a three dimensional position. The third dimension is provided with the so called secondary radars, which interrogate aircraft for identification and altitude. For that purpose, the aircraft have to actively respond to secondary radar's interrogations with on-board equipment. On the other hand, primary radars do not need aircraft's response, but they cannot get the altitude, and can therefore calculate only approximate position. Only when altitude is acquired, the three dimensional position can be calculated from azimuth, range and altitude.

Trackers output aircraft positions on regular intervals independent of radar rotation times. In Slovenian air traffic services center, currently the tracker interval is

4.8 seconds long.

For our test period, the tracker used in Slovenian air traffic control outputs approximately 30 to 80 million aircraft positions every month. That is around 100.000 to 300.000 aircraft positions per day. The number of positions changes with the amount of traffic.

In the test period, there were over two billion aircraft positions gathered from tracker for preprocessing. At the limits of radar coverage, faulty reception caused by obstacles or reflections of radar signals can appear. In such cases, extracted aircraft speeds can be wrong. Since the amount of data is large and the errors are rare, we have not performed special error detection for such cases. Detection and deletion of such data would improve the quality of knowledge data.

3.3.2 Flight Plan Data

Every pilot (or her/his company) has to submit a flight plan to air traffic control before the flight. The pilot also has to make sure that all traffic control centers, which are on the planned flight route, get the flight plan. Eurocontrol members have a centralized service called Initial Flight Plan Processing System (IFPS), which takes the burden of distributing flight plans off pilots and sends the flight plans via the Aeronautical Fixed Telecommunication Network (AFTN) to all interested parties. Flight plans hold a lot of important information about the flight:

- aircraft identification,
- aircraft type,
- aerodrome of departure,
- aerodrome of destination,
- planned route with altitudes and speeds,
- planned time of departure,
- planned duration of flight,
- aircraft equipment,
- type of flight,
- flight rules,
- etc.

A radar track without flight plan information is just a track with position and speed. Air traffic control systems do the correlation of tracks and flight plan data to provide aircraft identifications and other important data for the air traffic controllers. Without flight plan data, the capacity of airspace would be significantly lower because air traffic controllers would know little about the tracks presented on air situation displays.

The extracted performances from the radar tracks and correlated flight plan data are the main sources of information for our data mining. We say that we enrich aircraft performances with flight plan data in our preprocessing phase. This process of enriching is actually adding attributes or features from flight plans to the aircraft performances. Using these ensemble of data for predictions is, in our opinion, one of the greatest added values accomplished in this research. Such a record in that database is called a fact. Every attribute enriching the aircraft performance represents a dimension or a feature. In the prediction phase, we extract the performances from the database based on their features.

Until the sample period, around 1.2 million flights with flight plans were preprocessed along with their performances. For every flight plan, the radar tracks were examined and aircraft performances extracted from the flying trajectories. Typically, hundreds of aircraft positions are recorded for one flight plan.

3.3.3 Weather Data

The third important source of information are weather data. Radars record aircraft positions relative to their fixed position on the ground. Therefore, we can only extract ground speeds from radar data. However, we mainly use air speeds.

Winds determine the difference between ground and air speeds. In order to calculate air speed from radar extracted ground speed, we need to subtract wind speed from the ground speed ($\overrightarrow{air\ speed} = \overrightarrow{ground\ speed} - \overrightarrow{wind\ speed}$). Speeds are, in this case, always represented as vectors with size and direction. Figure 3.3 shows the relations between air, ground and wind speed. It is obvious that wind speed and its direction are needed to calculate air speed from the radar track.

Winds can be very powerful especially at high altitudes and can have significant influence on lateral movements. It is not unusual to have winds with speed of hundred knots or more. Commercial aircraft fly at approximately four hundred knots on their cruising levels. With tailwind of hundred knots, the ground speed would be hundred knots higher (500 kts), and hundred knots lower (300 kts) with the opposite wind. As



Figure 3.3: Calculating air speed from ground speed

we can see, knowing the right winds is very important for calculating trajectories.

Another important weather information is air temperature. Lower temperatures mean more dense air and better lift, while higher temperatures provide less lift because of thinner air. The vertical movements of aircraft depend on temperature and it is important to know the right values to estimate the correct performances. Aircraft performances are usually provided for ICAO standard atmosphere [73] or the International Standard Atmosphere (ISA). Air density changes with altitude, temperature and humidity. In order to calculate the correct performances at various altitudes, atmosphere temperature and pressure need to be known.

In the BADA model, the total energy model uses atmosphere conditions in its formulae to calculate accurate performances for each section of a flight. In aircraft performances model, for example, aircraft performances are also provided for temperatures 10 °C or 20 °C above or below ICAO standard atmosphere. We calculate two types of aircraft performances data. They are described in Sections 3.4.1 and 3.4.2. For aircraft performances, we need to store the offset from the ICAO standard atmosphere with every recorded performance to be able to classify them later in the prediction process. For total energy model, we need to use the atmosphere conditions in order to get the correct values of airline procedure model.

To be able to extract performance values and airline procedures parameters from tracks as accurately as possible, we need exact winds and temperatures from the locations where the aircraft are flying. There are two main sources of weather data available.

The first source are weather predictions from numerical weather prediction (NWP) models provided by environmental agencies. Environmental agency feeds its numerical weather prediction models with weather measurements. These measurements come from various sources. The classical sources are ground stations, but informations from higher altitudes are needed. Radiosondes, which climb to high altitudes and measure weather on their way are one of the standard sources of high altitude weather measurements. For many years they were the only reliable source of high altitude atmosphere

data. Later, satellite measurements became available but they are very inaccurate in comparison to radiosondes.

Aircraft would be a very good source of high altitude weather data, if they could measure weather conditions. In fact, they can. When an aircraft is flying, it can measure:

- its air speed with Pitot's tube,
- vector of ground speed with inertial navigation system or GPS and
- the magnetic heading, which gives information about the direction of air speed.

With the measured vectors of ground and air speed, the on-board equipment can calculate the wind speed vector. Wind speed is calculated by subtracting air speed from the ground speed very similarly as we are calculating air speed as shown in Figure 3.3.

One of the first to use meteorological measurements on aircraft was the Aircraft Meteorological DATA Relay (AMDAR) project [74–76] started in the seventies of the previous century. The aircraft participating in AMDAR have special equipment installed for sending the meteorological measurements via radio or satellite links to the ground stations. Every message sent via satellite link costs money and airline companies are not fond of buying additional equipment, which will then produce costs with every message. Ground stations distribute the measurements via dedicated meteorological communication lines called WMO Global Telecommunication System (GTS). However, as of November 2014 only 40 airlines were participating in this project and 14 of them are European. There are many more aircraft flying in the air, which could also contribute their meteorological readings.

Similar to the AMDAR project, we have started a new way of collecting aircraft meteorological measurements. The new generation of secondary radars called Mode S (Mode Select) radars can get various information from the aircraft. Mode S transponders on board of aircraft have access to the data bus where the meteorological data are available. If the radar is configured to request the weather data, the transponder will fetch the measurement from the bus and send it to the radar. There are several important advantages of Mode S acquired measurements in relation to AMDAR. There is no special equipment required on board of aircraft. Some aircraft already send their data via standard avionics equipment. Since there is no special equipment required, the aircraft return the data whenever the radars request it, at no additional costs. If the

radar requests the weather measurements on every turn, the frequency of data is higher than in AMDAR project, where data at the same frequency would produce enormous costs and would occupy the communication lines. In the AMDAR project, the on-board software smooths the data and sends them at regular intervals to the ground. On the other hand, Mode S radars collect actual measurements, so smoothing and error correction has to be done on the ground.

Slovenia Control and The Slovenian Environmental Agency are the first in the world to routinely collect and use this type of data, which is acquired from the aircraft with the help of radars. Thanks to Slovenia Control and its radar specialist Rado Križ, the Mode S radars in Slovenia are configured to interrogate aircraft for meteorological registers. The new data path and data quality are described in detail in [77–80]. The Slovenian Environmental Agency has also assimilated the new source of data into their numerical weather prediction model. The model had to be adapted for a new source of data, which provides large amounts of data at a higher frequency than other sources. It has been proven that this new source of weather data has a positive effect on weather predictions [79–81]. In other countries there has been a great interest in this project. Unfortunately, it is not everywhere possible to configure radars in that way. The Czech Republic is the first to follow our example and we expect others to do so, too.

Two important characteristics allowed us to use the weather data from aircraft in our preprocessing. First, they come in larger quantities than other measurements, and second, they come all the time. Radiosonde data for instance come only once or twice a day.

All these positive factors convinced us to use the Mode S acquired data directly for our aircraft performances calculations. We generate geographically located vertical atmosphere profiles with a Kalman filter as described in [78]. We use then these profiles for air speed calculations and ICAO standard atmosphere offsets. If data from the aircraft are not available for the vertical profile creation, the numeric weather prediction for aviation is used. As mentioned earlier, this numeric weather prediction also uses measurements from the aircraft to make better predictions. Both sources of weather data are accurate enough to use them for air speeds extraction.

The studies by Strajnar [77], and Hrastovec and Solina [78] show that aircraft measurements accuracies are very good. For winds, the vector error is around 3-6 knots. For weaker winds the direction measurements are less accurate, while for stronger winds the strength of the wind can have a larger error. The error in temperature measure-

ments are also shown to be small (around $0.5\text{ }^{\circ}\text{C}$). In our calculations, these errors are negligible especially because we use averaging and smoothing, which make these errors even smaller.

In Slovenia two radars are currently configured to fetch the weather measurements. The number of measurements for a three hour period varies from no data at nights to over 20.000 during the day. At nights there is usually not enough aircraft derived data, so the weather predictions from environmental agency are used. For the day, we mainly use our own generated wind and temperature tables.

Even without Mode S derived weather data, weather predictions for aviation are quite accurate, especially for high altitudes, where winds are more stable. Therefore, weather predictions are sufficient to extract accurate performances from flights. However, since Mode S measurements were available, we were able to get even better weather data in this way.

3.4 *Preprocessing*

In order to make the data usable, some data preparation needs to take place. Preprocessing is a process where data from various source are being gathered, decoded, and stored. The data in its raw form are not suitable for usage in machine learning. The next stage of preprocessing extracts information from all sources and joins them in one big database. We call this database a knowledge database.

There are two main models for which we extract performances. These two models are used in applications to calculate trajectories. Both are described in detail in the following Sections 3.4.1, and 3.4.2.

3.4.1 *Extracting Aircraft Performances*

For extracting aircraft performances, we ignore the physical model in the proposed solution and calculate raw performances for every portion of the flight. Aircraft fly differently on different altitudes or in different weather conditions, so we have to dissect flights into small portions where we assume that the aircraft are flying with the same performance. BADA performance tables provide pre-calculated values from their TEM using default companies as the input parameters for aircraft behavior. An excerpt from such a table is presented in Table 3.1. The example shows true air speeds for cruises, climbs, and descents. For climbs, the rates of climbs are shown for low, nominal and

high aircraft mass. For descents, the calculated rates of descent are presented. The fuel burn values are also a part of aircraft performances tables, but are not shown here.

Table 3.1: Excerpt from BADA performance table without fuel burn columns for aircraft type Boeing 747-8F (B748) from BADA 3.13 for temperature ISA+10

FL	cruise TAS	climb				descent	
		TAS	ROCD			TAS	ROCD nom
			lo	nom	hi		
...
100	294	392	4552	2825	2262	392	1943
120	303	403	4299	2645	2101	403	1996
140	397	415	4038	2460	1935	415	2049
160	409	427	3771	2269	1765	427	2101
180	421	440	3496	2073	1590	440	2152
...

FL: flight level (altitude in 100 feet)

TAS: true air speed in knots

ROCD: rate of climb or descent in feet per minute

We extract values similarly as they are presented in Table 3.1. The difference is that we do not extract three climb values as we get only one from the trajectory. Anyway, the air traffic control applications usually do not know, which one to select. So they select nominal.

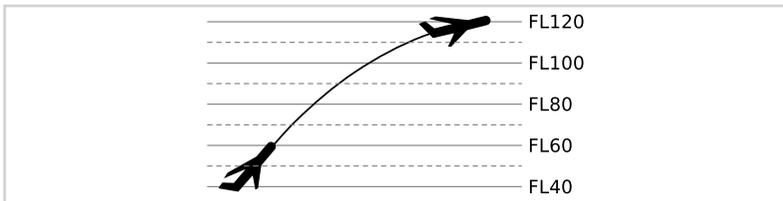
The preprocessing extracts performances from aircraft positions. We calculate different aircraft performances for various flight phases. For climbs, we calculate climb rates and air speeds. For descents, we calculate descent rates and air speeds. For cruise phases we can calculate only air speeds.

Cruising phases are usually significantly longer than climb and descent phases. One reason is that aircraft stay longer in cruising phases of a flight. Another reason is, that we need to calculate aircraft performances for individual altitudes. Aircraft performances change with the altitude. Therefore, we cannot provide a climb rate for the entire climb from the airport to the cruising altitude over an altitude of several kilometers. The algorithm dissects the flight into segments of altitudes and calculates the climb rates for each of them. For instance: rate of climb for flight levels¹ FL120, FL140, FL160,

¹ Flight level is an altitude of flight in hundreds of feet where the aircraft are flying with the altimeter pressure setting of ICAO standard atmosphere 1013.25 hPa [73]. Usually it is labeled as FL (FL180 = 18.000 feet at

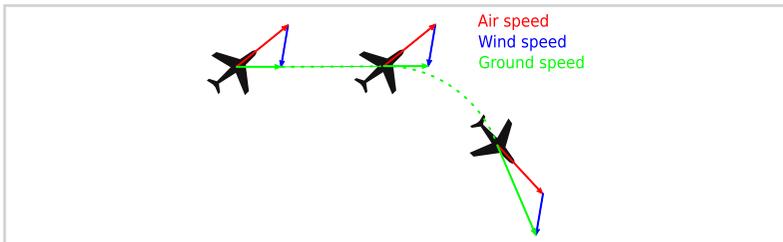
FL180, FL200, FL220, etc. These portions are typically short and we cannot calculate the climb or descent rate for the whole maneuver, because we need performances for different altitudes. The number of extracted performances for a flight can be a single air speed for a cruising phase over the whole airspace or up to sixty climb or descent rates with accompanying air speeds. Figure 3.4 shows a climb going through more BADA altitude classes and their borders.

Figure 3.4: Classifying altitudes and calculating rates for each class



For ground speeds, there is also one aspect to take into account - turns. Turns are dissected into smaller parts, where they are considered as straight flights. With this method, more accurate air speeds are extracted for shorter sections, because ground speed may change significantly when aircraft changes direction. Figure 3.5 shows how a turn, despite the same air speed and the same wind speed, affects the ground speed of an aircraft. Detection of turns is performed with the help of tracker outputs. Tracker distinguishes turns from straight flights and puts information about them into tracks. We use these fields in tracks to process turns, because trackers use sophisticated algorithms to detect and properly process turns.

Figure 3.5: Extracting air speed in turns



We assume all extracted performances to be constant. When an aircraft accelerates or decelerates in an observed flight phase the algorithm for calculating the performance

ICAO standard atmosphere).

uses the times of the first and the last measured positions and calculates the average performance for the section. In this way, the average performance over the measured flight phase is calculated. We have decided not to detect accelerations and decelerations in movements, because it would not have been reliable enough and portions of flights with changing speed would have to be treated differently. The assumption of constant movement results calculates average speeds on accelerated flight sections. For our purpose this approach is sufficient.

Since we assume constant speeds, the calculation is simple after we isolate sections of flights. The speed is $\frac{ds}{dt}$, where ds is the difference in path and dt the difference in time for that path. For vertical maneuvers, the distance is the change in altitude to extract climb or descent speeds, while lateral distances are used for ground speeds.

As shown in Table 3.1 for ISA+10 °C, BADA performances tables are pre-calculated for predefined temperature deviations from standard ISA atmosphere. We need to store the temperature deviation in our extraction, too. With every enriched performance we store the temperature deviation in order to use only relevant performances later for prediction. The performances recorded in significantly different atmospheric conditions cannot be the basis for an accurate prediction.

The prediction generates a very similar table to the one presented in Table 3.1. It does not provide more values (low, nominal, high) as BADA does, but only one, which is supposed to be closer to the reality than any of the values provided by BADA.

3.4.2 *Extracting Airline Procedures Parameters*

Another way to extract aircraft performances is by estimating the parameters that govern the total energy model. BADA total energy model needs inputs from airline procedure parameters in order to calculate the trajectory. These input values come in a form of aircraft mass and standard speeds. Extracting airline parameters should therefore produce values that fit into a table such as Table 3.2 and, when used in TEM, produce trajectory calculation as close as possible to the real flight path.

We extract actual performances from the recorded trajectory in the same way as for aircraft performances tables described in the previous paragraph. Then we use the TEM formulae in the opposite direction than for trajectory calculation. In this case, we have the trajectory and we need to estimate the parameters of TEM model. The input airline procedure parameters for TEM are mass and default speeds as presented in Table 3.2. These are:

Table 3.2: Airline procedure parameters for a default company for aircraft type Airbus 320 (A320) from BADA 3.13

mass	climb			cruise			descent		
	lo cas	hi cas	mc	lo cas	hi cas	mc	hi cas	lo cas	
LO	310	310	0.78	250	310	0.78	0.79	300	300
AV	310	310	0.78	250	310	0.78	0.79	300	300
HI	310	310	0.78	250	310	0.78	0.79	300	300

mass: LO \approx 39-51 tonnes, AV \approx 52-64 tonnes, HI \approx 65-77 tonnes
cas: standard calibrated air speed in knots
mc: standard air speed in Mach

- m - aircraft mass,
- $V_{cl,1}$ - standard climb CAS between 1,500/6,000 and 10,000 feet,
- $V_{cl,2}$ - standard climb CAS between 10,000 feet and Mach transition altitude²,
- M_{cl} - standard climb Mach number above Mach transition altitude,
- $V_{cr,1}$ - standard cruise CAS between 1,500/6,000 and 10,000 feet,
- $V_{cr,2}$ - standard cruise CAS between 10,000 feet and Mach transition altitude,
- M_{cr} - standard cruise Mach number above Mach transition altitude,
- $V_{des,1}$ - standard descent CAS between 1,500/6,000 and 10,000 feet,
- $V_{des,2}$ - standard descent CAS between 10,000 feet and Mach transition altitude,
- M_{des} - standard descent Mach number above Mach transition altitude.

The first TEM formula to use is the one for rate of climb or descent. According to the BADA User Manual [8] the forces acting on the aircraft are expressed as follows:

$$(Thr - D) \cdot V_{TAS} = mg_0 \frac{dh}{dt} + mV_{TAS} \left(\frac{dV_{TAS}}{dh} \right) \left(\frac{dh}{dt} \right) \quad (3.1)$$

where the variables are:

² Mach transition altitude is the geopotential pressure altitude at which calibrated air speed (V_{CAS}) and Mach speed represent the same true air speed (TAS)

Thr	- thrust acting parallel to the aircraft velocity vector	[N]
D	- aerodynamic drag	[N]
m	- aircraft mass	[kg]
h	- geodetic altitude	[m]
g_0	- gravitational acceleration	[9.8m/s ²]
V_{TAS}	- true air speed	[m/s]
$\frac{d}{dt}$	- time derivative	[s ⁻¹]

As can be observed from Eq. 3.1, some values, like aerodynamic drag, are determined by the aircraft type. Other values, like aircraft mass and speed, are the ones that are changing and affect how the aircraft is flying. These are the values that we try to estimate from the recorded trajectory, and later predict them in the prediction phase.

TEM Eq. 3.1 can be rearranged for different scenarios. We need to identify the phase of flight from the recorded trajectory and use the right formula to estimate the required aircraft parameter.

With speed and throttle controlled, Eq. 3.1 is used to calculate the change of altitude in time, which is the rate of climb/descent expressed as $ROCD$:

$$\frac{dH_p}{dt} = ROCD = \frac{T - \Delta T}{T} \left(\frac{(Thr - D) \cdot V_{TAS}}{mg_0} \right) f(M) \quad (3.2)$$

where additional variables from the previous formula are:

$ROCD$	- rate of climb/descent	[m/s]
H_p	- geopotential pressure altitude	[m]
T	- standard atmosphere temperature	[K]
ΔT	- difference from standard atmosphere temperature	[K]
$f(M)$	- a function of Mach number	[]

We can rearrange Eq. 3.2 and get the formula for mass:

$$m = \frac{T - \Delta T}{T} \left(\frac{(Thr - D) \cdot V_{TAS}}{ROCD \cdot g_0} \right) f(M) \quad (3.3)$$

One should be able to just input the right values into Eq. 3.3 to get the estimated mass of an aircraft. However, it is not as simple as it looks. The drag D in Eq. 3.3 is a function of mass and velocity. Therefore, we cannot calculate the mass from Eq. 3.3 directly. We would need to extract mass from drag too and rearrange the equation. Instead, we use, in our dissertation, a bisection-like method to get the estimation of mass.

In the iterative method we take a number of masses in regular intervals between minimum and maximum aircraft mass. Then we calculate $ROCD$ for these masses with Eq. 3.2, and see which one is the closest to the measured $ROCD$. We repeat the iteration with smaller steps around the best mass estimation. In each step we get the mass estimation with $ROCD$ that is closer to the measured $ROCD$ of a given flight. When the calculated $ROCD$ differs less than ϵ from the measured one, we stop and use the mass that produced the closest $ROCD$.

Beside mass, default speeds are used for trajectory calculations. Mass and default speeds form recommended speed procedures for use in TEM. With different sets of these parameters we calculate different trajectories. However, BADA always provides only airline procedure model parameters for a default company, which produce trajectories with the smallest average error for flights in Eurocontrol's database. With our calculation, we estimate an airline procedure profile for each flight and store it in a database.

Another method for mass estimation uses airline procedures model formulae for climbs and descents. These formulae determine calibrated air speeds for aircraft on different altitudes. For climbs, for instance, the following formula is used for jet engines at altitudes between 1,500 feet and 2,999 feet:

$$CAS = C_{V_{min}} \cdot (V_{stall})_{TO} + V_{DCL,2} \quad (3.4)$$

where

CAS	-	Calibrated Air Speed	[kt] ¹
$C_{V_{min}}$	-	Minimum Speed Coefficient constant from BADA model ²	[]
$(V_{stall})_{TO}$	-	Stall speed in take-off configuration	[kt]
$V_{DCL,2}$	-	Climb speed increment below 3000 ft	[kt]

For other types of engines, altitudes and for descents similar formulae are used with different constants and speed increments or decrements. All have in common the stall speeds $(V_{stall})_{TO}$ for take-offs and $(V_{stall})_{LD}$ for landings, which have to be corrected with mass correction factor $m_{corr} = \sqrt{\frac{m_{act}}{m_{ref}}}$, where m_{act} is actual mass, and m_{ref} is reference mass. When we multiply stall speed with mass correction factor from Eq. 3.4, we get

¹ kt = knots = nautical miles per hour = 1.852km/h

² $C_{V_{min}}$ the allowed speed in relation to stall speed (1.2 for take-off, 1.3 otherwise).

$$CAS = C_{V_{min}} \cdot (V_{stall})_{TO} \cdot \sqrt{\frac{m_{act}}{m_{ref}}} + V_{D_{CL,2}} \quad (3.5)$$

From Eq. 3.5, we can express actual mass m_{act} and we get

$$m_{act} = m_{ref} \cdot \left(\frac{CAS - V_{D_{CL,2}}}{C_{V_{min}} \cdot (V_{stall})_{TO}} \right)^2 \quad (3.6)$$

Equations 3.4, 3.5 and 3.6 are an example for a climb with a jet engine between 1,500 feet and 2,999 feet. For other engine types, altitudes and descents the formulae are a bit different but similar enough that the method remains identical. This method is not as reliable as the method extracting mass from rate of climb or descent described in Equations 3.2 and 3.3. It estimates mass based only on calibrated air speeds in climbs and descents. Using this method, we can use the formulae only for altitudes below 6,000 feet for jet engines, and below 1,500 feet for turboprop and piston engines.

As mentioned before, BADA always provides airline procedure model speeds for a default company with low, average and high take-off weights. Since users usually do not know the take-off weights, they use average mass and speeds from the airline procedure model. With our calculations we estimate the mass and speeds and store them in a database. We cannot always get all the values from one flight. From a particular flight we may calculate only mass and maybe one speed. From another, we get another speed and so on. Typically, we get climb or descent speeds and perhaps some cruise speed for departures and arrivals. There are also plenty of cases with only cruise Mach speed for overflights.

The calculations use meteorological data and estimations are calculated by taking atmosphere conditions into account. Different performances measured in different meteorological conditions may in the end result in identical mass or default speed. We have in this way normalized the calculated values since they are not weather dependent and can be used for any weather conditions during predictions. That is why we do not have to store temperatures or other meteorological conditions with airline procedures parameters, as they are not part of the data in BADA, too.

We have less facts in the database with airline procedures parameters, because we can estimate values for the whole flight and store one set of values per one flight. On the other hand, we can have lots of stored aircraft performances values per one flight, because we have to take smaller portions of flights. However, the smaller number

of facts is not problematic because all values can be used regardless of the weather, because the values are normalized during evaluation. On the other hand, for aircraft performances, only the values extracted at similar temperature can be used.

3.5 *Creating And Maintaining a Multidimensional Database*

When all performances and default airline procedure values are extracted with the help of weather data and enriched with flight plan data, they are stored in relational databases. The process is presented in Figure 3.6.

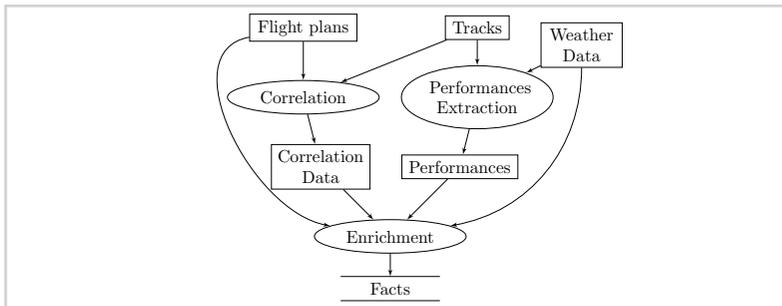


Figure 3.6: After extraction the performances are enriched with flight plan data they are stored in a facts database.

We have 10 million records of aircraft performances in the relational database for the interval from February 2011 to December 2014. On the other hand, the number of airline procedure values is much lower, because we only store one set of default values for each flight. The number of facts for airline procedures is ten times lower – 1.1 million for flights between February 2011 to December 2014. On average over 7.000 records are added every day in the aircraft performances and around 800 in airline procedures databases. On days with the lowest traffic, the number of new facts may be as low as 1.500 and on the days with high traffic over 14.000 facts can be collected for aircraft performances. For airline procedures, the numbers typically vary from around 500 to 1.600.

We have created our multidimensional databases with Microsoft Analysis Services from Microsoft SQL Server. This is a Microsoft implementation of multidimensional database called also Online Analytical Processing (OLAP).

All our methods for preprocessing and database updating are designed to be processed on a daily basis. They pick up where they stopped the last time. In that context

they are very robust. The interval of refreshments does not play any role. The pre-processing and database refreshing can be executed anytime. The process will proceed from where it has finished the last time.

Our prediction algorithms generate MultiDimensional eXpressions (MDX) queries and get the data from the database in an efficient way. Other architectures for storing this type of data, like relational database, would require much more resources and time to get the results. Optimizations and performance given by OLAP database give us the means to perform many queries during the prediction process and to implement a prediction method on top of it. There are estimates that MDX queries on an OLAP database can be up to 1000 times quicker than queries in a relational database for complex queries [82].



*Selecting a Suitable Prediction
Algorithm*

In order to find a suitable prediction method, one has to become first familiar with data, the processes by which one gathers the data, and finally, the requirements for prediction. Requirements define what do we expect from the data, how accurate it needs to be, how is it going to be accessed, how quick the data mining shall return the results, etc.

The requirements and good knowledge about the data define how the data mining methods are going to be implemented. Good investigation of data brings good data mining. Similarly, good requirements give little doubt about expected results. In this chapter we present the requirements, which were followed during the implementation in Section 4.1. Next, the ideas about feature reduction are presented in Section 4.2.

We have tried various methods for aircraft performances prediction suited for the database and storage technology used. To evaluate the performance of our algorithms, we have compared them with some standard regression algorithms presented in Section 4.3.

4.1 Prediction Requirements

We want our prediction to be used in real air traffic control systems. That means that the prediction should provide results in a reasonable amount of time. When a flight takes off or is rerouted, the trajectory calculation algorithm shall get new values from the prediction process instead of static nominal values. Route recalculation is an operation that needs to be performed when it is detected that the calculated trajectory does not correspond to the actual one. The actual trigger for recalculation depends on actual implementation, but typically happens a few times during a flight. The reason may be inaccurate original trajectory calculation or unplanned deviations, avoids, changed weather conditions, etc.

The trajectory calculation algorithms usually get aircraft performances data from pre-calculated static tables or pre-determined flight parameters. Our prediction has to provide a substitute for static input values with dynamic ones. When these dynamic values are used in trajectory calculation, they should lead to trajectory closer to the real one being actually flown.

The prediction shall be accessible as a service, possibly in a cloud. It shall be transparent whether the results are from a prediction or a pre-calculated table.

If more details about a flight are provided to the prediction service, better predictions shall be returned to the client. Even when no usable details about the flight are

provided to perform data mining, the algorithm shall return usable and meaningful aircraft performances. In the worst scenario, when there is no knowledge about similar flights in the database, the algorithm can provide nominal tables from the BADA model. That situation happens, for instance, when a flight with new attributes starts to fly in the airspace and there are no similar recordings in the database yet.

The service shall not require frequent manual maintenance. In fact, the maintenance shall be minimized, and all jobs shall be automated. The process of preprocessing and database updates shall also be automated in a manner that the database shall automatically gain new knowledge, which can be used in the prediction service, without the need to repeat the learning process.

The service shall be designed in a way that it can be easily expanded to a larger airspace, over more servers and for more clients or accessible in a cloud. In other words, it shall be scalable.

4.1.1 Predictions With Two Databases

As described in Sections 3.4.1 and 3.4.2, we collect two types of data. The prediction algorithms use the same flight plan derived attributes for both databases and predict different trajectory parameters from these databases. According to trajectory calculation method, the prediction shall provide parameters suitable for that method to be used directly in the calculation.

The prediction using database with aircraft performances shall predict the performances like true air speed, climb rate and descent rate in the form shown in Table 3.1.

The prediction using airline procedures database shall predict parameters like aircraft mass, calibrated air speed in cruise, climb or descent like presented in Table 3.2.

4.2 Manual Feature Reduction Before Prediction

According to Kantardzic [83] the application of feature selection and reduction of data dimensionality may be used in all phases of the data mining process for successful knowledge discovery. It has to be started in preprocessing phase, but on many occasions, feature selection and reduction are a part of the data mining algorithm.

In our case, features are flight plan attributes that characterize each measured and stored performance.

We have manually selected around thirty attributes for preprocessing. When the data are preprocessed and stored in a multidimensional database, the task of data min-

ing or prediction is the next step. From original thirty attributes coming out of the preprocessing phase, twelve were selected to be used in prediction. The selected attributes are considered as the ones that should actually have an influence on aircraft performances. The reasons to exclude a particular attribute are typically:

- The attribute is identical to already selected attribute.
- The attribute is rarely present in the data.
- The attribute does not come from the flight plan directly.

Finally, we selected twelve attributes to be used in the data mining process. They are presented in Table 4.1.

Table 4.1: Manually selected attributes for data mining

<i>Attribute</i>	<i>Description</i>
Aerodrome of Departure (ADEP)	Aerodrome where the flight starts
Aerodrome of Destination (ADES)	Aerodrome where the flight lands
Aircraft Type	The type of aircraft as received from the flight plan (Airbus 320, Boeing 737, etc.)
Arrival Hour	Hour of the day when the flight arrives to the destination
Departure Hour	Hour of the day when the flight departs from the airport
Entry Point	Point of entrance into Slovenian airspace
Exemption	Special statuses of flights (medical, state, vip, charity, training, air show, etc.)
Exit Point	Point of exit from Slovenian airspace
Flight Rule	Set of regulations for operating the aircraft (visual flight rules, instrumental flight rules)
Flight Type	Type of flight from flight plan (scheduled, non-scheduled, general aviation, military, etc.)
Operator	The operator operating the aircraft (Adria, Lufthansa, British Airways, etc.)
Week Day	The day of the week (Monday, Tuesday, Wednesday, etc.)

Along with the selected attributes from Table 4.1, additional attributes are used implicitly during the prediction process. They describe the conditions in which the aircraft fly. For aircraft performances prediction, these attributes are:

- temperature – the temperature, which determines air density and therefore influences aircraft performances,
- flight Level (FL) – aircraft performances change with the altitude and the data mining predicts for the defined altitudes.

If we do not know the aircraft type, we can still use other attributes to predict performances. However, for airline procedures in TEM formulae, the aircraft type is a mandatory input parameter. The minimum and maximum aircraft mass are determined by aircraft type and also the engine type determines, which formulae have to be used. So, for the airline procedures model, an additional implicit attribute is:

- aircraft type – the type of aircraft determining its physical characteristics with engine type.

We have come from over thirty attributes stored in a multidimensional database to under fifteen using a heuristic method of manual selection. The manual reduction can be classified as a preprocessing reduction, because it is included in a prediction algorithm as a prerequisite or a limiting condition.

4.3 Evaluation of Various Machine Learning Methods

With the set of manually selected attributes, which are going to be used for machine learning, we have grounds to evaluate various machine learning methods, and to find the most suitable ones for implementation.

We selected a smaller randomly selected dataset to evaluate various regression algorithms. In that way, we would compare different methods and see, which provide the best predictions for our data. With this comparison, we get a reference showing how well a particular method performs in relation to others.

A smaller dataset was selected also, because some implementations of standard machine learning methods were not able to use the whole amount of data. We have taken

only the year 2014 as the learning set and took 5,000 random record samples from year 2015 to test predictions for each individual BADA parameter.

We have developed some own prediction methods. The comparison also shows, how our methods perform in relation to standard machine learning methods.

We have tested several different implementations from families of standard algorithms using various settings to get the best possible results. We present here only the results of the best performing representatives from each family of machine learning algorithms that we have used:

- decision tables from software package WEKA
(<https://www.cs.waikato.ac.nz/ml/weka/index.html>),
- linear regression from software package Orange
(<https://orange.biolab.si/>),
- random forests from software package Orange
(<https://orange.biolab.si/>),
- classic k nearest neighbours (kNN) from software package CORElearn,
(<https://cran.r-project.org/web/packages/CORElearn/index.html>),
- locally weighted regression (LWR) from software package CORElearn,
(<https://cran.r-project.org/web/packages/CORElearn/index.html>),
- support vector regression (SVR) from software package e1071
(<https://cran.r-project.org/web/packages/e1071/index.html>).

We used two measures of predictive performance.

Mean Absolute Error Comparison

The first measure is Mean Absolute Error (MAE). It shows the average error between predicted and measured value and is presented in Equation 4.1

where $y_{p,i}$ is i^{th} prediction and $y_{m,i}$ is i^{th} measured value.

$$MAE = \frac{\sum_{i=1}^n |y_{p,i} - y_{m,i}|}{n}, \quad (4.1)$$

where the variables are:

MAE	-	mean absolute error
n	-	number of predictions
$y_{p,i}$	-	i^{th} predicted value
$y_{m,i}$	-	i^{th} measured value

Table 4.2 shows parameters used in aircraft performances model, which correspond to five basic parameters, from which we can calculate the predicted trajectory. These are air speeds in climb, cruise, and descent, and rates for climb and descent. Values are always given for a predefined altitude and weather conditions (temperature).

The first four rows in *emphasized typeface* present methods, which we have implemented. The first, *BADA 3.13*, is actually not a machine learning prediction. It uses BADA parameters as are given in the BADA model. This method is a reference, which shows, how good the predictions would be if did not use any prediction.

Methods *AC Type Average*, *FA With Relaxation*, and *DA Similarity* are k nearest neighbours methods, which are adapted to our use. The detailed description of algorithms is in Section 5.1. Description of each implementation is given in Section 6.5.1.

The following lines, in regular typeface, present standard regression methods. They are:

- Decision Tables
- Linear Regression
- Random Forest
- kNN (k Nearest Neighbours)
- LWR (Locally Weighted Regression)
- SVR (Support Vector Regression)

Table 4.2: Mean average error comparison of *our methods* presented in Section 6.5.1, and standard methods for aircraft performances model

Algorithm	Climb		Cruise
	Air Speed [kt]	Rate [ft/min]	AirSpeed [kt]
<i>BADA 3.13</i>	26	390	15
<i>AC Type Average</i>	18	317	13
<i>FA With Relaxation</i>	17	307	13
<i>DA Similarity</i>	20	322	14
Decision Tables	19	321	12
Linear Regression	18	305	12
Random Forest	19	317	14
kNN ¹	28	429	17
LWR ²	28	429	17
SVR ³	29	410	17

Algorithm	Descent	
	Air Speed [kt]	Rate [ft/min]
<i>BADA 3.13</i>	26	885
<i>AC Type Average</i>	20	425
<i>FA With Relaxation</i>	19	402
<i>DA Similarity</i>	21	415
Decision Tables	19	408
Linear Regression	19	401
Random Forest	21	426
kNN	24	460
LWR	24	460
SVR	24	431

¹ k Nearest Neighbours² Locally Weighted Regression³ Support Vector Regression

We can observe in Table 4.2 that methods, that we propose, have similar performance as the best performing standard machine learning methods.

Table 4.3 shows the same mean absolute error, but this time for airline procedures model. In this case, the parameters are not linked to altitude or weather conditions, because the model calculates adequate speeds with the help of the total energy model formulae for appropriate altitude and weather conditions. However, the parameters are linked to the aircraft type, because the aircraft type defines, which formulae must be used.

The comparison shows that machine learning method accuracies are close to each other.

Table 4.3: Mean average error comparison of *our methods* presented in Section 6.5.2, and standard methods for airline procedures model

Algorithm	Climb			Mass [kg]
	Low CAS [kt]	High CAS [kt]	Mach [M]	
<i>BADA 3.13</i>	55	23	0.03	4906
<i>AC Type Average</i>	15	13	0.03	4145
<i>FA With Relaxation W.</i>	13	13	0.02	3729
<i>DAW - Dispersion</i>	18	18	0.03	10023
Decision Tables	13	12	0.02	3770
Linear Regression	13	13	0.03	3766
Random Forest	13	13	0.03	3882
kNN ¹	15	15	0.03	4188
LWR ²	17	15	0.03	4336
SVR ³	15	13	0.03	4108
Cruise				
<i>BADA 3.13</i>	121	27	0.02	
<i>AC Type Average</i>	52	17	0.02	
<i>FA With Relaxation W.</i>	41	17	0.02	
<i>DAW - Dispersion</i>	53	23	0.03	
Decision Tables	42	17	0.02	
Linear Regression	41	17	0.02	
Random Forest	41	18	0.02	
kNN	50	18	0.02	
LWR	55	18	0.02	
SVR	49	17	0.02	
Descent				
<i>BADA 3.13</i>	55	22	0.03	
<i>AC Type Average</i>	19	16	0.03	
<i>FA With Relaxation W.</i>	16	15	0.03	
<i>DAW - Dispersion</i>	19	18	0.04	
Decision Tables	16	15	0.03	
Linear Regression	16	15	0.03	
Random Forest	16	16	0.03	
kNN	19	17	0.03	
LWR	21	17	0.03	
SVR	18	16	0.03	

¹ k Nearest Neighbours² Locally Weighted Regression³ Support Vector Regression

Root Relative Squared Error Comparison

Root Mean Square Error ($RMSE$), presented in Equation 4.2, is another measure of prediction accuracy. $RMSE$ is calculated as

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_{p,i} - y_{m,i})^2}{n}}, \quad (4.2)$$

where variables are the same as in Equation 4.1. This measure penalizes larger mis-predictions more than smaller ones. In that way, it gives a different view on prediction accuracy, but the values are not as intuitive as for MAE .

If we use the average value for $y_{p,i}$ instead of prediction in Equation 4.2, we can see how good we would predict, if we do not make any prediction but take just the average value. We label the $RMSE$ measure for average values $RMSE_{AVG}$. By dividing $RMSE$ with $RMSE_{AVG}$ we get the Root Relative Squared Error ($RRSE$):

$$RRSE = \frac{RMSE}{RMSE_{AVG}}. \quad (4.3)$$

When $RRSE$ is smaller than 1.0, the prediction has learned something from the data and predicts better than taking the average value. When it is bigger than 1.0, then the prediction is worse than using the average value.

Table 4.4 shows $RRSE$ for aircraft performances model. Again, we see that many machine learning models perform similarly. In such situations, taking into account reliability and ease of implementation, simpler methods seem to be a better choice than more sophisticated ones. It is always worth checking the simplest approaches. As the book *Data Mining Practical, Machine Learning Tools and Techniques* [84] says on page 83: “One of the most instructive lessons is that simple ideas often work very well, and we strongly recommend the adoption of a ‘simplicity-first’ methodology when analyzing practical datasets.” The same book on page 96 says for some other machine learning algorithms: “The moral is, always try the simple things first. Repeatedly in machine learning people have eventually, after an extended struggle, obtained good results using sophisticated learning methods only to discover years later that simple methods such as 1R and Naïve Bayes do just as well – or even better.”

The last comparison with standard methods in Table 4.5 shows $RRSE$ for the airline procedures model. Interesting in this table is the model “AC Type Average”. As mentioned in Section 6.5.2, this method just takes the average from the learning set.

Table 4.4: Root relative squared error comparison of *our methods* presented in Section 6.5.1, and standard methods for aircraft performances model

Algorithm	Climb		Cruise
	Air Speed	Rate	AirSpeed
	[kt]	[ft/min]	[kt]
<i>BADA 3.13</i>	0.783	0.971	0.842
<i>AC Type Average</i>	0.576	0.797	0.682
<i>FA With Relaxation</i>	0.560	0.810	0.688
<i>DA Smilarity</i>	0.659	0.823	0.816
Decision Tables	0.613	0.770	0.688
Linear Regression	0.559	0.732	0.676
Random Forest	0.576	0.766	0.757
kNN ¹	0.900	1.007	0.956
LWR ²	0.900	1.007	0.956
SVR ³	0.982	0.987	0.965

Algorithm	Descent	
	Air Speed	Rate
	[kt]	[ft/min]
<i>BADA 3.13</i>	0.984	1.865
<i>AC Type Average</i>	0.781	0.961
<i>FA With Relaxation</i>	0.762	0.913
<i>DA Smilarity</i>	0.834	0.937
Decision Tables	0.768	0.924
Linear Regression	0.760	0.907
Random Forest	0.822	0.967
kNN	0.971	1.028
LWR	0.971	1.028
SVR	0.980	0.998

¹ k Nearest Neighbours² Locally Weighted Regression³ Support Vector Regression

Because grouping samples on aircraft type matches grouping of subsets for machine learning models in airline procedures model, the “AC Type Average” relative error is always exactly 1.0, as it predicts the average. This means that taking the average is already significantly better than using nominal BADA values, but introducing some learning is even better. Again, we see that the best machine learning methods are pretty close to each other. However, all have problems to predict significantly better than the average. Some do even worse.



Table 4.5: Relative root mean square error comparison of *our methods* presented in Section 6.5.2, and standard methods for airline procedures model

Algorithm	Climb			Mass
	Low CAS	High CAS	Mach	
<i>BADA 3.13</i>	3.048	1.401	1.091	1.173
<i>AC Type Average</i>	1.000	1.000	1.000	1.000
<i>FA With Relaxation W.</i>	0.949	0.952	0.978	0.892
<i>DAW Dispersion</i>	1.338	1.464	1.648	3.046
Decision Tables	0.920	0.893	0.975	0.892
Linear Regression	0.891	0.928	1.001	0.914
Random Forest	0.896	0.914	1.033	0.900
kNN ¹	1.014	1.069	1.051	0.988
LWR ²	1.114	1.095	1.053	1.053
SVR ³	1.003	0.991	0.999	0.985
Cruise				
<i>BADA 3.13</i>	2.236	1.466	1.120	
<i>AC Type Average</i>	1.000	1.000	1.000	
<i>FA With Relaxation W.</i>	0.823	0.982	0.981	
<i>DAW Dispersion</i>	1.081	1.487	2.034	
Decision Tables	0.848	1.000	0.982	
Linear Regression	0.841	1.031	0.998	
Random Forest	0.843	1.035	1.028	
kNN	0.990	1.039	1.040	
LWR	1.096	1.043	1.053	
SVR	0.989	1.011	0.985	
Descent				
<i>BADA 3.13</i>	2.558	1.303	1.223	
<i>AC Type Average</i>	1.000	1.000	1.000	
<i>FA With Relaxation W.</i>	0.871	0.963	0.965	
<i>DAW Dispersion</i>	1.093	1.245	1.642	
Decision Tables	0.897	0.958	1.003	
Linear Regression	0.879	0.977	0.987	
Random Forest	0.905	0.995	1.007	
kNN	1.029	1.068	1.033	
LWR	1.109	1.061	1.052	
SVR	0.977	1.004	0.976	

¹ k Nearest Neighbours² Locally Weighted Regression³ Support Vector Regression

*Data Mining Based Prediction
Algorithm*

The comparison in Chapter 4 revealed, what can we expect from each prediction algorithm. Since we have experienced some issues with large amounts of data with some of the standard machine learning algorithms, we have implemented own methods in order to comply with all requirements presented in Section 4.1. Our algorithm for prediction is based on the k nearest neighbours method.

The following chapter describes the approach in detail.

5.1 *Description of the Applied Algorithm*

Our proposed algorithm of feature reduction is closely connected to k -nearest neighbours algorithm and is outlined in Algorithm 1. The nature of data makes it difficult to define a measure of distance between samples for various attributes. Do the flights with the same aircraft type have closer performances capabilities than the flights with the same aerodrome of destination? The answer to this question is dependent on the individual case, for which we have to make a prediction. For instance, at high altitudes in en-route airspace the rate of descent is dependent mainly on aircraft performances. On the other hand, when landing at an airport at lower altitudes the descent rate is dependent on the aerodrome of destination, where the approach procedures and instrumental landing systems dictate, how the aircraft must be flying there. This example shows that it is difficult to say that a given attribute is the most influential in general and for specific cases. The number of different flight situations also make it difficult to create a finite set of predefined combinations of attributes, which would be used in various scenarios. Therefore, we have decided that the importance of attributes shall be determined individually for every prediction, for each altitude and performance. That means that each prediction gets its own set of attribute preferences, which determine how the nearest neighbours will be selected.

The k -nearest neighbours algorithm is also called a “lazy” learning method [85]. The burden of computation is moved from the learning to the prediction phase and that is a drawback that we had to consider since predictions take more time. However, the applied method fits well with the data storage architecture, and, as it turned out, the predictions are not much slower.

As in many other cases, the k -nearest neighbour algorithm could not be used directly. We had to adapt it to our specific problem. First, the distance needs to be defined in order to find the k nearest neighbours. The distance in our case cannot be an Euclidean distance. Our measure of distance is the count of non-matching attributes for two

given flights, which is a standard distance measure for nominal attributes:

$$d_{x,y} = \sum_{i=1}^n [x_i \neq y_i] \quad (5.1)$$

where:

- $d_{x,y}$ - distance for similarity measure between flights x and y
- n - the number of attributes
- x_i, y_i - i -th attributes

With a distance measure like this, a lot of pairs have identical distances. However, all attributes are not equally significant in determining aircraft performances. It is not important only how many attributes are not matching, but also which are the ones that do match. Here is where the feature ranking comes in and helps to decide, which attributes will be discarded first.

Our task is to find the set of attributes, which locate the closest neighbours in terms of aircraft performances. With a good set of k nearest neighbours we can get a good prediction. If the selection of significant attributes is not good, we will not get the closest neighbours and the prediction will be poor. With these assumptions our problem of prediction reduces to the problem of finding the set of attributes that determine the set of flights exhibiting the closest aircraft performances. When the most significant attributes for finding the set of the k nearest neighbours will be used, the best prediction will be obtained. Therefore, our algorithm is actually an adapted k nearest neighbours algorithm.

Algorithm 1 first ranks the attributes. Then it searches the database for the records with matching all attributes. If there are not enough samples, the algorithm relaxes the search condition by removing the least significant attribute. With relaxed condition, more samples fit into the search results and the number of records is checked again. This condition relaxation eliminates attributes one by one until the number of matching samples is above the threshold. With a credible amount of samples the algorithm stops with a representative set and makes a prediction from it.

We have used the threshold of 10 samples in our experiments, which gives some level of trust and is not too demanding. The number was determined with experimenting trying to make sure that great majority of predictions will have enough samples, and that no single flights will be used for a sample. The nature of attributes reduction does not allow us to use an exact number of nearest neighbour samples. Sometimes the

Algorithm 1 Adapted k nearest neighbours algorithm sorts the attributes and eliminates lower ranked attributes until there are enough samples to make a credible prediction

Input: attributes values of a flight

Output: predicted aircraft performances

```

function GETPERFORMANCES(attribute values of the flight)
    sort attributes according to ranking criteria
    attrSet ← sorted attributes
    prediction ← ∅
    repeat
        currentPerformances ← sets of samples for the given attrSet
        for all performances in currentPerformances do
            if set of samples bigger than  $k$  members then
                calculate average performance of the given set
                prediction ← prediction ∪ {calculated average}
            end if
        end for
        attrSet ← attrSet \ {lowest ranked attribute}
    until all predictions calculated or attrSet empty
    for all missing predictions do
        if exists average behavior for aircraft type in the database then
            prediction ← prediction ∪ {average for aircraft type}
        else
            prediction ← prediction ∪ {nominal performance from BADA}
        end if
    end for
    return prediction
end function

```

elimination of an attribute rises the number of samples significantly. We may have only a few or no samples with a chosen set of attributes. Then, when we eliminate only one, we may get lots of flights matching a reduced set. Therefore, the number of samples used in prediction varies from 10 to thousands. It depends on the feature reduction order and on the frequency of similar flights in the observed airspace.

One of the approaches that we tried in our experiments was a manual selection of attributes. This can be considered as an expert guess or judgment, on which attributes should provide good results. However, one can only make one static selection of attributes in advance for all predictions. On the other hand, our approach makes a decision, which attributes to use, for every prediction separately.

One of the measures to evaluate and select attributes was the spread of the values. If a particular attribute is not important for the performance of the aircraft, the values of measured performances are spread more uniformly. On the other hand, if an attribute is important, the values should be concentrated more closely around the actual performance.

The various ranking methods that we have tested are presented in Section 5.1.1.

When a flight is new there are not enough samples in the database yet. This happens, for instance, when a new aircraft type starts to fly, or a new operator flies to a new location, etc. In that case the algorithm cannot get enough samples from the database to make a credible prediction. It then tries to get the average values for that aircraft type from the database regardless of other attributes. These aircraft type based averages are a kind of BADA substitute for the default company extracted from the database. They reflect how the aircraft are flying in the observed airspace just like BADA default company reflects their method to minimize the error for their database of flights. When completely new flight arrives into the airspace, the database does not have any data about it. In that case, no averages are available for the prediction. The algorithm relies to the last resort of the aircraft performances available – the BADA model nominal values. This does not happen to often, because the algorithm uses the updated database all the time. Every night, the flights from the previous day are added. It takes only a few flights and the database will have enough samples to make the next prediction based on own measured data.

5.1.1 Feature Ranking

As shown in 5.1 the algorithm's performance depends on, which attributes are eliminated first or how they are ranked.

Usually, the attributes are compared and ranked directly. We have used a different approach by comparing the values of aircraft performances that each attribute affects. In that way, the attributes are not compared directly, but rather their effect on the predicted values.

We have tried many different methods in feature ranking to find the one that performs the best. In some methods we evaluated each attribute by itself and assumed their independence. Although the attributes are not independent, the methods are efficient. Another ranking approach is to use feature similarity or some other comparison. With this methods, the attributes are compared and one of them is eliminated. Reduction continues until we have enough samples for the prediction, or there are no more attributes to compare.

In the following sections we present two ranking methods in detail.

Dispersion Ranking

The first ranking method that we are using is based on the dispersion of performance values that are dependent on the particular attribute. For the purpose of feature ranking we use standard deviation. Our assumption is that the attribute, which influences the performance the most, must have the values concentrated closer together than others. When the performance values, correlated with a given attribute, are concentrated closely together around one value, we can say that this attribute determines the performance. When the values are spread more evenly, we assume that the given attribute does not influence the performance so strongly. In other words, the performance is not affected by that attribute and we can safely remove it. Clearly, different dispersions cannot be compared to each other unless they are normalized to be comparable.

We have generated thousands of charts to visualize the influence of different attributes to a particular aircraft performance. Some samples of the charts are shown here to show their influence on aircraft performances (5.1, 5.2, 5.3, 5.4, 5.5, 5.6). Some of the chosen attributes should have no effect on the observed performances. However, it can be seen that there are some dependencies. It can also be seen that the same attribute with a different value can have a significantly different effect on the observed performance.

Figures 5.1 and 5.2 show the influence of attribute “ADES” (Aerodrome of Destination) on the expected rate of climb. We can observe in Figure 5.1 the rates of climb for the flights flying to destination “LIRF” (Rome Fiumicino Airport). The parameter “n” on the chart indicates the number of facts with the selected attributes that were filtered out and used to create the chart. 83872 samples were used for Figure 5.1. Figure 5.2 shows rates of climb for airport “EDDF” (Frankfurt Airport) with 74783 samples. If we don’t know anything else about the flight than the destination airport, we can

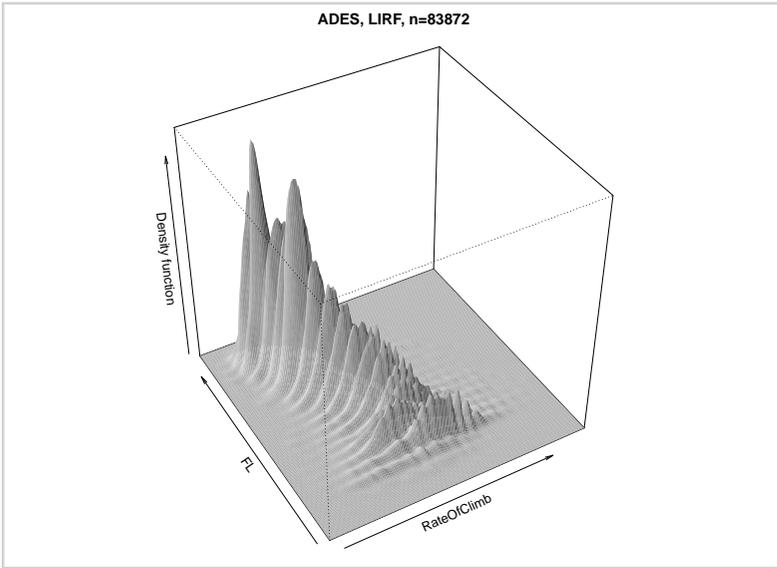


Figure 5.1: Influence of attribute ADES (Aerodrome of Destination) "LIRF" (Rome) on dispersed rate of climb. (n - number of samples, FL - flight level)

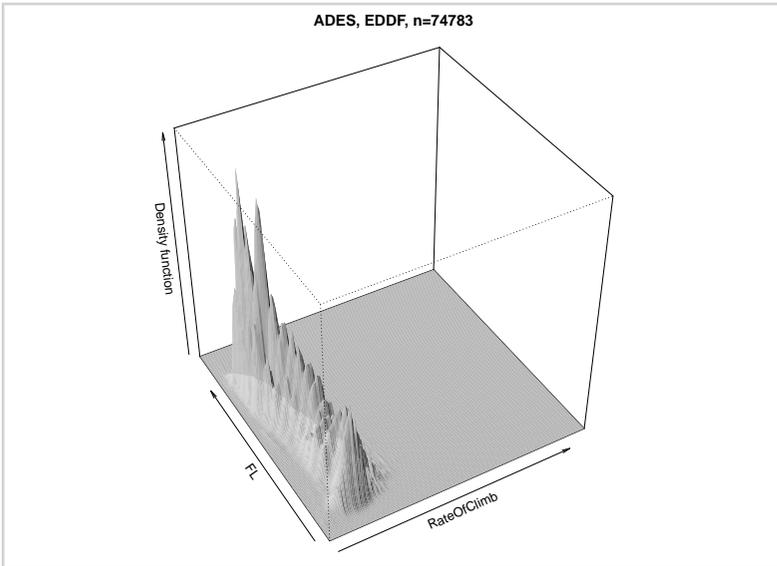


Figure 5.2: Influence of attribute ADES (Aerodrome of Destination) "EDDF" (Frankfurt) on concentrated rate of climb. (n - number of samples, FL - flight level)

already say that we would be able to better predict the rate of climb for a flight flying to Frankfurt.

Figures 5.3 and 5.4 show how different values of the attribute “Entry Point” can affect the air speed. Figure 5.3 shows the air speeds for aircraft entering our airspace at point “MAGAM” located on the Slovenian southeast border. A lot of aircraft entering on that border point depart from the nearby Zagreb airport. That is the reason why there are also air speeds recorded at lower altitudes. On the other hand, Figure 5.4 shows air speeds for aircraft entering at point “REKTI”, which does not have a major airport in the vicinity. At that point, there are practically no air speeds recorded at lower altitudes. The number of facts is much bigger for point “REKTI” showing that the number of overflights on high altitudes is higher than departures or landings on near airports. It can be seen that air speeds can be more dispersed on lower altitudes. On higher altitudes the aircraft have much smaller maneuverable space to change the air speed. The interval between stall and maximum air speed is closer on higher altitudes because of thinner air. That can be observed in Figure 5.4, where mostly speeds at high altitudes are recorded and they are concentrated over small intervals. The charts show, that calculating the air speed on higher altitudes is not as problematic as on lower altitudes. The times for overflights can be calculated more accurately than times for approaches, landings and climbs to cruising altitudes.

The last example of attribute dispersion are Figures 5.5 and 5.6 showing rates of descent depending on the attribute “Weekday of Flight”. Figure 5.5 shows rates for Saturdays (6). We can see that the values are spread over large intervals and have many local maximums that indicate the influence of other attributes. That is an expected behavior, because the day of flight should not affect the rate of descent. However, Figure 5.6 shows the rates of descents for Fridays (5), where the values are much more concentrated. This can be explained with the fact that on Fridays arriving flights mainly bring business passengers home. They use standard arrival procedures and instrumental landing systems (ILS) and use less diverse aircraft. On Saturdays, there are more charter flights and more non-professional flights by sport pilots that fly during weekends for fun.

All these examples of data distribution show that it is not wise to make a fixed ranking and use it for all cases of aircraft performances extraction and prediction. A standard deviation (σ) is an indicator of dispersion. In order to be able to compare dispersions of various attributes we normalize them by dividing them with the average

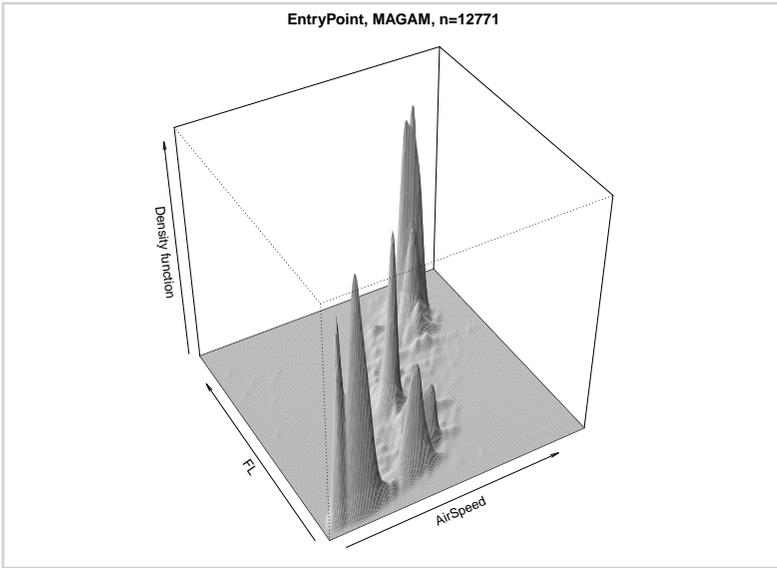


Figure 5.3: Influence of attribute entry point “MAGAM” on dispersed air speed. (n - number of samples, FL - flight level)

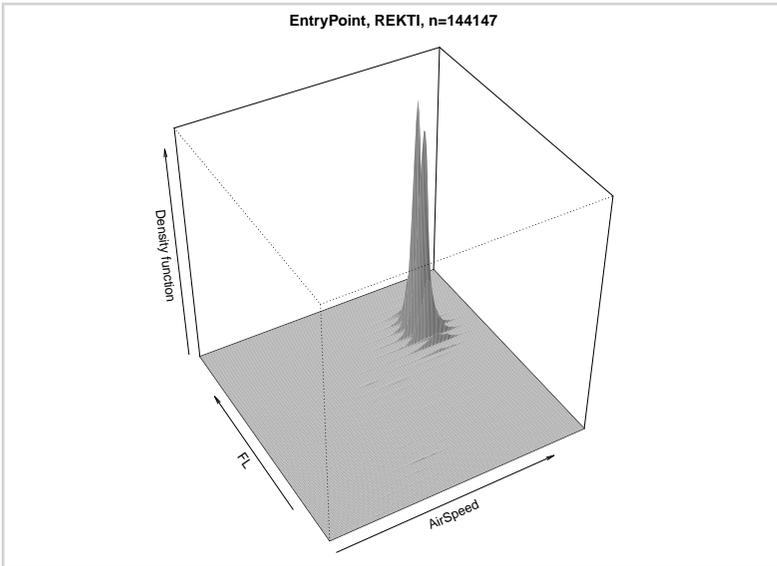


Figure 5.4: Influence of attribute entry point “REKTI” on concentrated air speed. (n - number of samples, FL - flight level)

Figure 5.5: Influence of attribute weekday of flight Saturday on dispersed rate of descent. (n - number of samples, FL - flight level)

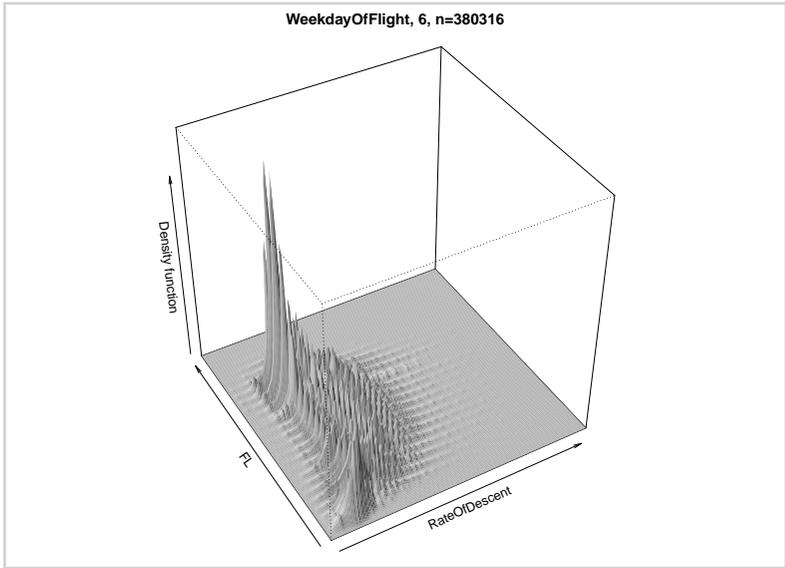
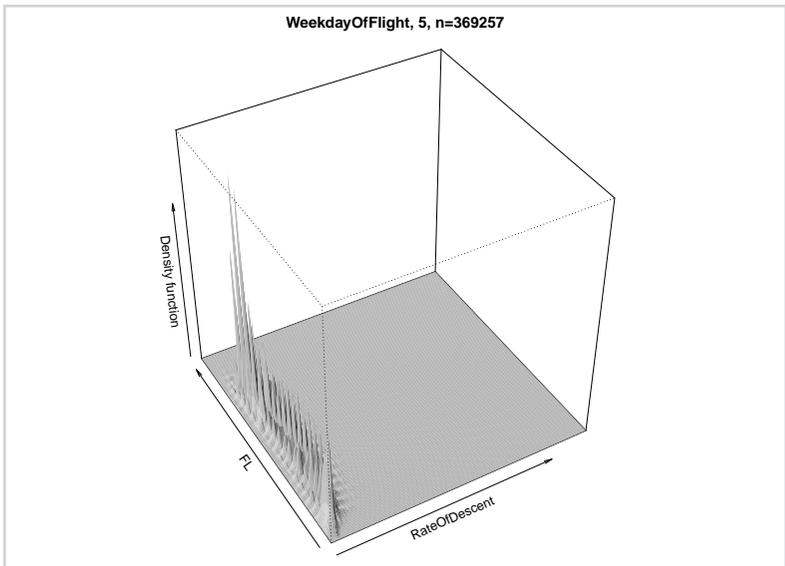


Figure 5.6: Influence of attribute weekday of flight Saturday on concentrated rate of descent. (n - number of samples, FL - flight level)



value (μ). The attributes are sorted according to their coefficient of variation σ/μ . If there are not enough samples of similar flights with all possible attributes, the attributes with the greatest spread are eliminated first. These are typically “Weekday of Flight”, “Hour of Arrival”, “Hour of Departure”, “Exemption”, etc. The detailed report on the ranking and attributes used for predictions is given in Section 6.6.

Since we took a naive approach, we do not consider dependences among attributes. We only measure the spread of each individual attribute and rank them according to it. It can be observed in Figures 5.1, 5.2, 5.3, 5.4, 5.5, and 5.6 that attributes are not independent. Local maximums on charts are representing the influence of other attributes. For instance, the local maximums on Figure 5.5 are probably showing different aircraft types along x -axis labeled “RateOfDescent”.

If the feature ranking would be done once, at the beginning in the preprocessing phase, and then used in all predictions, the calculation of dependencies between attributes would not present a computing problem. However, the feature ranking is done at least once per every prediction. In that case, the ranking of attributes can only be done with the assumption of their independence if we want to perform it in a reasonable time.

The feature ranking based on means and variances, as we are using it, has its weaknesses. The distribution of a performance with a particular attribute is not known. Therefore, the measure of the spread of the value at a specific attribute is not an ideal indicator. An attribute can be linked strongly to another attribute. In that case, the spread is wider as shown in Figure 5.5. In that case, the attribute would be ranked lower in the feature ranking procedure. However, the stronger attribute, which disturbs the spread of the lower ranked one, should be ranked higher.

Attribute Similarity Ranking

Mitra et al. [86] use feature similarities to reduce the feature set by keeping only the most significant of similar features. In that way, they remove the features that do not contribute to the prediction since there are other similar features. That gave us an idea how to make some kind of feature dependency or similarity checking without costly evaluations of all attribute combinations. Similarly as Mitra et al. select the features in their unsupervised feature selection, we use the attribute similarity in our application of feature ranking based on similarity.

The method is outlined in Algorithm 2. The similarity measure for two attributes

tells us how close are the predicted values for them. The closer the predicted values, more similar the attributes are. For example: Climb rates for aircraft flying the same distances should have similar values, because the amounts of fuel and weight of the aircraft should be more similar than for aircraft flying to other destinations.

Algorithm 2 Attribute similarity ranking algorithm

Input: set of all attributes of a flight

Output: set of attributes sorted in a way that elimination from the end eliminates first the attribute that is most similar to some other attribute

function GETRANKEDBYSIMILARITY(attribute values of the flight)

 sort attributes by numerical value

 attrSet \leftarrow sorted attributes

 returnSet $\leftarrow \emptyset$

while attrSet $\neq \emptyset$ *do*

 minDiff $\leftarrow \infty$

 minIndex $\leftarrow 0$

for $i = 0$ *to* count(attrSet)-1 *do*

if attrSet[$i + 1$] - attrSet[i] < minDiff *then*

 minDiff \leftarrow minDiff

 minIndex $\leftarrow i$

end if

end for

 returnSet \leftarrow returnSet \cup {attrSet[minIndex]}

 attrSet \leftarrow attrSet \setminus {attrSet[minIndex]}

end while

return returnSet

end function

The method extracts aircraft performances average for each attribute. The attributes are sorted according to the extracted averages. As they are sorted, it is easy to find the two attributes, that have the values closest together. At every step, the two closest attributes are selected and one of them is eliminated. The algorithm continues to remove the attributes until there are enough samples in the database to make a credible prediction, or until there are no more attributes.

5.2 Classification of The Applied Feature Reduction Algorithm

With all the prerequisites and requirements in mind, we try to classify the methods used for feature reduction during prediction. We will use the classification of feature reduction methods described in Chapter 2 of the book “Computational Methods of Features Selection” [87]. As mentioned before, features in our case are flight plan attributes.

Feature selection can proceed in two directions. We can start with an empty feature subset and add features until we are satisfied with the selection. That is a forward selection. We are doing it the other way around. We start with the full set of flight plan attributes and reduce them until we get a subset that is used for the prediction. This is called *backward selection*. There is also another detail – we rank flight plan attributes before we select them. The ranking helps with the decision, in which order the flight plan attributes are going to be removed. So *feature ranking* is implicitly embedded in every feature selection, unless features are selected randomly.

With feature selection we need to evaluate, which features are going to be selected and which not. We need to have some kind of checking procedure or measure, which tells when to stop eliminating the features and make a prediction based on the remaining ones. With a wrapper method, the feature selection is wrapped around the learning algorithms that will ultimately be applied. After each selection, the learning algorithm clusters the data and the evaluation procedure checks the results. The loop of selection, learning and evaluation is repeated until a suitable set of features is selected. On the other hand, the filter approach checks the data by itself and does not apply the learning algorithm. In that way, a suitable checking method has to be found to evaluate the selected subset. As the prediction algorithm does not check the results during prediction, we classify it as a *filter method*.

The global approach selects one subset of features for all cases while the local approach selects different subsets for different clusters. We do not select one attribute subset, because we select a different subset for each prediction. In fact, choosing the right subset of flight plan attributes for each prediction is essential part of our algorithm, so we declare our approach as *local feature selection*.



Results

6.1 Evaluation of Results And Testing Methods

As mentioned in Section 3.2, the database consists of accumulated knowledge from January 2011 to December 2015 and the flights being tested are all flight from year 2015. For year 2015 we have around 270.000 test flights. These flights are our test set and we have tried various prediction methods on them.

For every flight from the test period, we have predicted the aircraft performances and airline procedure values, and calculated flight times with predicted flight parameters. Figure 6.1 shows the entire test process. We have used various sources for the parameters for our flight time calculation procedure. The calculation procedure for the flight time was always the same, only the input values for aircraft capabilities were different.

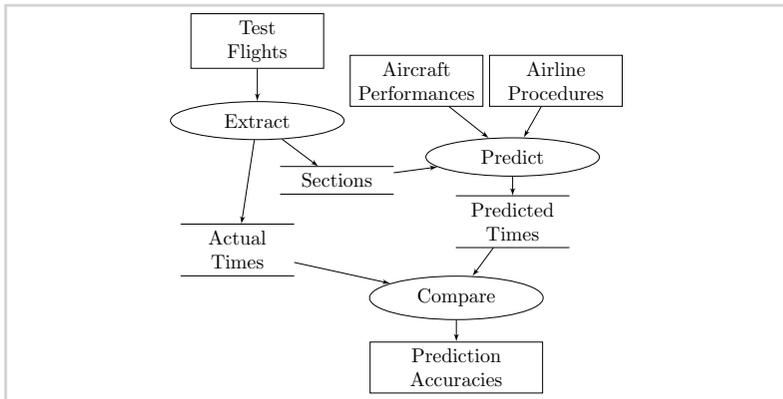


Figure 6.1: The procedure of evaluating prediction accuracies.

We have compared calculated times of flights with actual flight times taken from the recordings to evaluate the prediction errors. We have the actual flight recordings, from which we extracted the aircraft performances. These recordings serve also as a reference for actual flight times. The comparison of predicted and actual flight times for different prediction and calculation methods show, which method gives the best results.

For the measure of prediction accuracies we have selected mean absolute error (MAE) presented already in Chapter 4 with Equation 4.1.

The average error measure is useful because we can quickly identify the size of the

absolute value of prediction error and what error we might expect when predicting a particular value. Charts show prediction accuracies using this measure to visualize the prediction performance. A lower value means lower error and better accuracy.

6.2 Time Calculation

In our evaluation, we calculate, what is the expected time for a flight to fly from a starting point to an ending point with our predicted performances. The starting point is the start of radar detection and identification by radars and the ending point is the point, where the aircraft flew out of radar coverage or landed. We are not able to calculate the trajectories from take-off to landing, because the flights are typically longer than we are able to track them with our coverage. However, we are still able to monitor all elements of flights. There are very few flights, from which we are able to get all the phases. From some flights we get climbs, from others descents, etc. In the end we are able to evaluate all main flight sections.

The accuracies of predictions are not given in units of aircraft performances like knots for speed or feet per minute for climbs and descents. The accuracies are given in differences between actual and predicted flight times in number of seconds.

The algorithms for prediction and comparison divide the flight into sections similarly as for performances evaluation described in Section 3.4.1.

For air speed predictions we have included comparison of sections up to 45 minutes long. For climbs and descents the sections are shorter – up to 20 minutes. In all cases approximately 99% of flight sections are included in these time frames.

6.3 Evaluated Prediction Methods

We have implemented and tested many variations of prediction methods. They can be categorized in three main groups:

- predictions based on nominal values,
- standard regression methods,
- predictions using heuristic global feature selection during k nearest neighbours search,
- predictions using dynamic feature selection during k nearest neighbours search.

The first group are the reference methods with nominal values used for trajectory calculations. At the time of our research, five versions of BADA model 3 were available for us (3.09, 3.10, 3.11, 3.12, 3.13). We have tested all of them and the results are very similar since the BADA versions are close to each other. The calculation formulae are the same for all versions, which may not always be true for BADA. Sometimes some formulae are changed with a new version or even the parameter set may be altered. The versions that we used, differ only in various parameter values used for aircraft.

The second group are standard machine learning methods for regression. They have been evaluated and the results are presented in Chapter 4. For the detailed comparison of results in this chapter we present only the one that performed the best on our data – linear regression.

The third group of methods introduces k nearest neighbours methods with manually selected attributes. These are called static global feature ranks. It means that the order of feature reduction was defined identically for all cases. The methods presented with results from this group reduce the features by a fixed rank until there are enough samples in the database to get a credible average value for prediction. If there are not enough samples in the database, the aircraft type average from the database is used, and BADA nominal values are used, if there are even no samples for the predicted aircraft type. The features were selected and ranked as an educated guess with a goal in mind to find the features that influence the performances the most and provide the best prediction in majority of cases.

The last group of methods use dynamic feature ranking and selection with k nearest neighbours. They are described in detail in Section 5. When attributes are selected, the flights with the same attributes are extracted from the database and the average value of required performance is calculated.

All of the k nearest neighbours algorithms use the average values of aircraft performances accumulated in the multidimensional database. The calculation of the average values is independent from the algorithm used for prediction.

Some of the methods were chosen from the literature as being suitable and adapted to be used for our problem. On the other hand, we were improving our methods when getting more and more familiar with the data. Sometimes our own methods outperformed the ones adapted from other areas but many ideas for improving the algorithm that we tried, did not perform as good as expected. We present here only the ones which performed well enough.

6.4 Brief Comparison of All Tested Methods

The first comparisons briefly show how the same class of methods may differ. The charts, which present the accuracies, show the difference between actual and predicted times as described in Section 6.1. A lower value on the chart, means a better prediction quality and higher value indicates worse prediction. Below the charts are frequency histograms that show the number of predictions used for evaluation and their distribution. The frequencies show that the majority of sections are short, where the errors are the smallest.

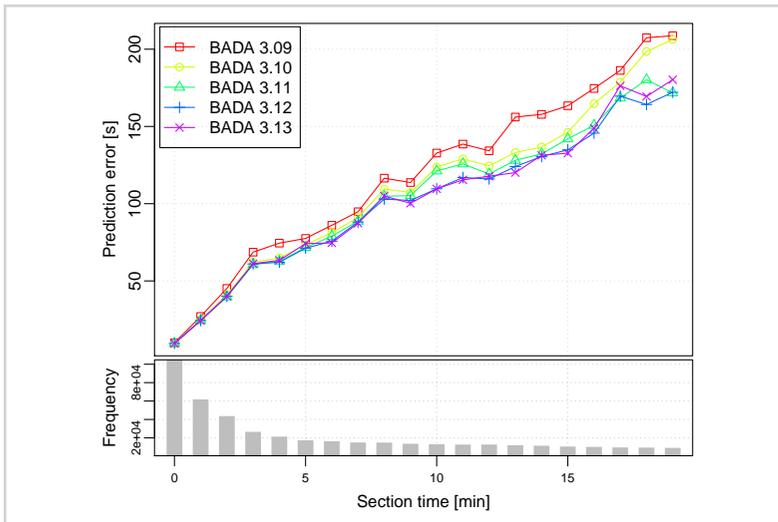


Figure 6.2: Average error for climb rate predictions using BADA total energy model with nominal values and default aircraft operator

The first group of methods are actually not machine learning or data mining methods. They show BADA model as a reference. When we compare BADA versions, that we tested, we notice slight improvements with newer versions. Figure 6.2 shows comparison of climb rate predictions using total energy model when nominal BADA values are used.

In the next group of methods with manually selected features we have made a few different ranks. One of them is using just one attribute – aircraft type. This method can be interpreted as an equivalent to BADA model. It behaves better than BADA in our case, because we have recorded the data in our airspace. Another method worth

mentioning is a method with four manually selected attributes:

1. aircraft type,
2. aerodrome of destination,
3. aerodrome of departure,
4. operator.

They are selected as the attributes, which should have the greatest influence on the performances. As shown in Algorithm 1, the method uses the provided feature rank. First, all the attributes are used to search for the average performance values. If there are enough samples, the extracted performances are used. For performances with a number of samples under the threshold, the operator is removed and samples are searched again. This feature removal continues until all performances are calculated, or until no more attributes are available. In the latter case, the BADA nominal performances are used.

Figure 6.3: Average error for descent rate predictions using fixed ranks with aircraft performances

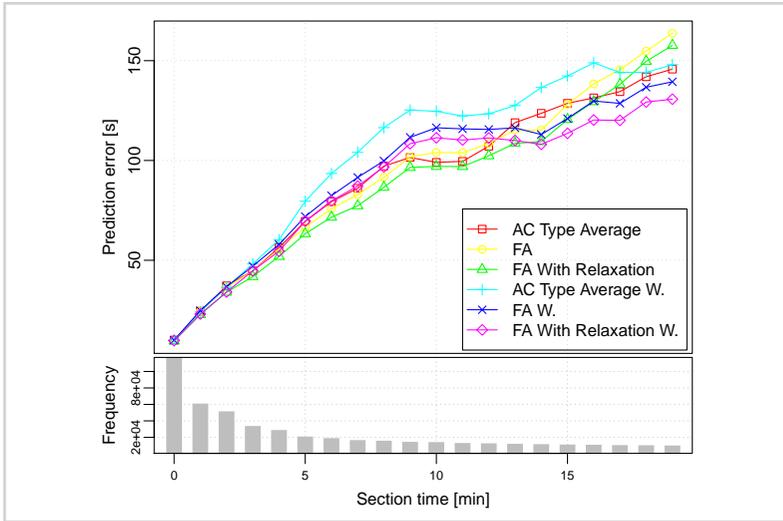


Figure 6.3 shows a comparison of methods using fixed ranks for descents using aircraft performance tables. It can be seen that methods with weighted averages tend to improve for longer sections. This is somehow expected, because longer sections contribute more to the average.

For the dynamic local feature selection during k nearest neighbours search, we have tried different strategies, which are described in Section 5.1.1. Methods using dispersion and attributes similarity proved to be good and have provided very similar results showing, that a well selected strategy can provide notably better results, but not a significant improvement.

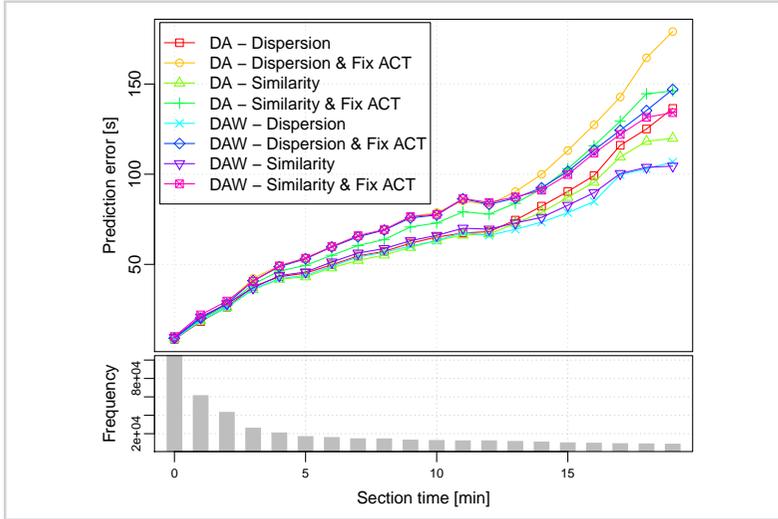
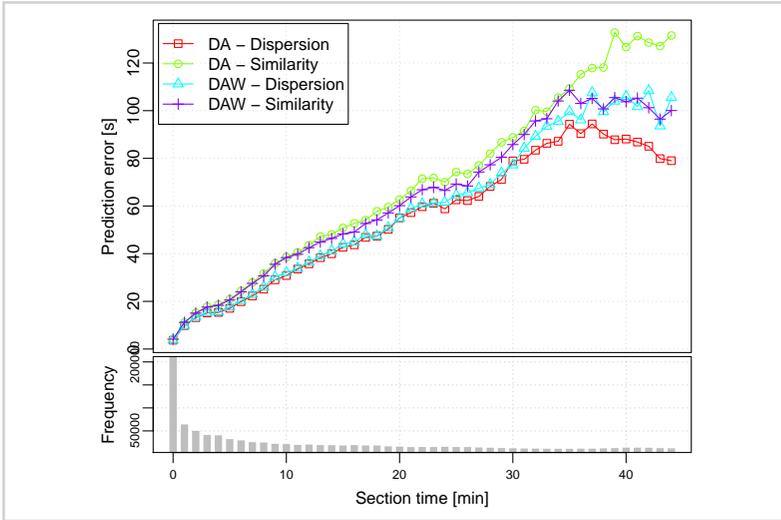


Figure 6.4: Average error for climb rate predictions using dynamic ranks with aircraft performances

Figure 6.4 shows a comparison of climb rate predictions using performance tables for different ranking methods. The algorithm searches for nearest neighbours with various ranking criteria. When using fixed aircraft type, the aircraft type is always ranked highest. In that case, only the samples of that aircraft type are always used for prediction. When aircraft type is not fixed, it is ranked as other attributes are. When looking for similar flights, the algorithm may decide, that other attributes have a higher rank and will use them for determining the nearest neighbours, which should determine the prediction. It can be observed that some algorithms may behave better when the aircraft type is not fixed. This can be explained with our original hypothesis that the same type of aircraft can fly differently, and that some other attributes, like destination, influence the performances too. We present eight different methods here. Label *DA* in charts stands for Dynamic Attributes, and label *DAW* stands for Dynamic

Attributes with Weighted averages. Each of them is then used with dispersion feature ranking and with ranking based on feature similarity.

Figure 6.5: Average error for air speed predictions using dynamic ranks with airline procedures



When using aircraft performances calculations, we can have the aircraft type as one of the attributes. When we predict with airline procedures (TEM), the formulae and their input parameters depend on the aircraft type. If the aircraft type attribute would have been removed, the prediction method would not be able to determine the correct formulae to be used. These are defined for aircraft types, and also other parameters that are used in calculations like drag, thrust, mass, etc., would not be defined. Figure 6.5 shows an example of air speed predictions using airline procedures calculations for different ranking methods. It shows only half of the dynamic attributes prediction methods presented in Figure 6.4 – the ones with aircraft type fixed.

6.5 Comparison of the Best Methods From Each Group

For the comparison of different methods we have selected the best representatives from each group of methods to be compared between each other. There is no clear winner that performs the best for all scenarios. For a particular performance parameter, one method is better than the other, while for another one the situation can be different.

In the following section, predictions with both databases are presented. Section 4.1.1 describes how all prediction algorithms are using two databases to predict other types of attributes.

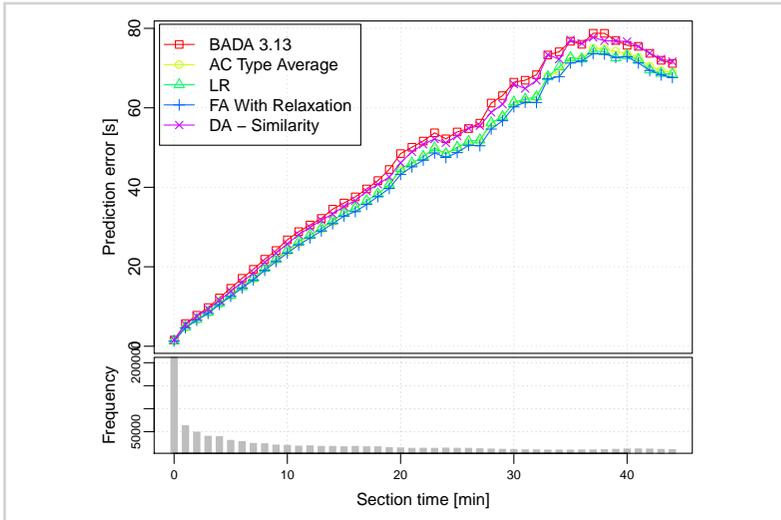
6.5.1 Aircraft Performances Tables

The first comparison shows how the methods behave for aircraft performances predictions. We have chosen five representatives for this group of charts.

1. The first method uses values provided by BADA performance tables. We have used the latest BADA version and the method is labeled *BADA 3.13* in the charts.
2. The second method is a kind of BADA equivalent from our database. BADA performance tables are generated in that way that nominal values are used and then the tables are generated for each aircraft type. Our method can generate identical tables. They are not generated from TEM formulae, but actual averages from our database. It is labeled *AC Type Average* in the charts.
3. The third method is linear regression as the best representative from standard regression methods. It is labeled *LR*.
4. The next method demonstrates how the predictions perform if we manually select a set of attributes. The set of attributes is listed in Section 6.4. This method is labeled *FA With Relaxation*. FA stands for Fixed Attributes.
5. The last method presented is one of the methods, which uses dynamic attributes selection. We have selected the method which ranks the attributes by similarity to other attributes for these charts. It is labeled *DA - Similarity*. DA stands for Dynamic Attributes.

The first Figure 6.6 shows how accurate the air speed predictions are. Air speed is the parameter that allows the smallest deviations from the actual air speed. The aircraft at cruising level have only a small range of speeds that allow it to fly safely, efficiently,

Figure 6.6: Average error for air speed during cruise predictions with aircraft performances



and economically. That is why the predictions of air speeds are also the closest to each other. However, we can still identify slight advantage of the fixed ranking methods and linear regression over BADA and dynamically selected attributes. Figure 6.6 also shows the number of sections with the corresponding length used in predictions. We can see that a great majority of sections are very short. However, there are still a lot of samples used for longer sections – almost 500.000. The lower part of charts presenting the number of samples are also used in all the following figures.

Figure 6.7 shows the structure of prediction errors. We can observe practically all errors to be under 10%. The great majority are close to 0%. Prediction of air speeds is not so problematic because the pilots also file in the air speeds in the flight plans. The systems calculating trajectories should also consider to take the speeds from flight plans for accurate lateral position predictions.

The next flight phase that we are trying to predict is climb. Figures 6.8 and 6.9 show prediction accuracies for air speed during climbs and climb rate for the same four prediction methods.

We can observe in Figures 6.8 and 6.9 that differences are bigger and the predictions are less accurate. The situation is similar for air speeds in climb and descent rates.

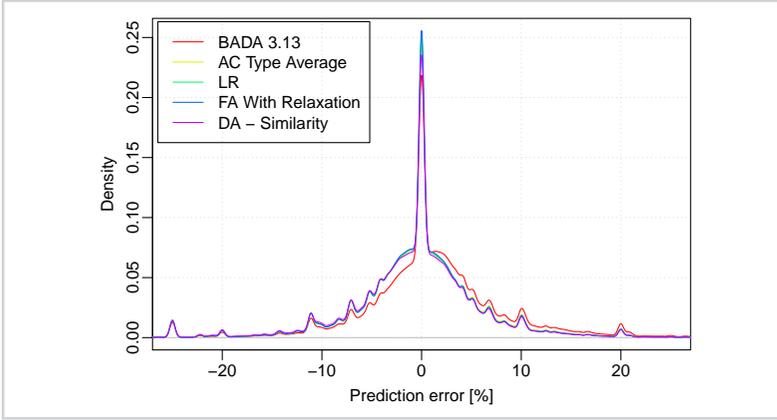


Figure 6.7: Error distribution for air speed during cruise predictions with aircraft performances

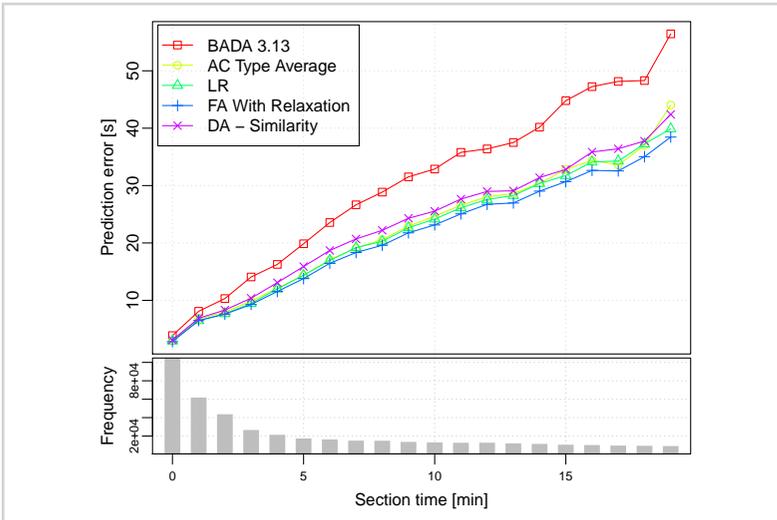
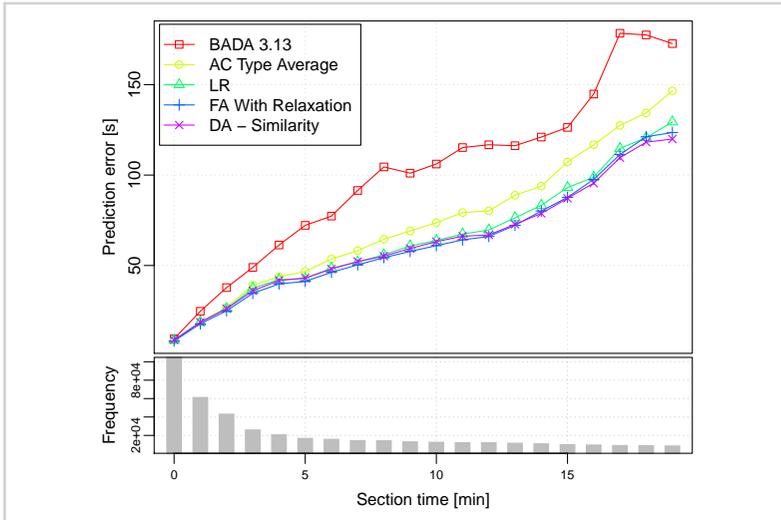


Figure 6.8: Average error for air speed in climb predictions with aircraft performances

Figure 6.9: Average error for climb rate predictions with aircraft performances



We have the worst prediction with BADA nominal values. Other methods are closer. However, there is a noticeable disadvantage for dynamic attributes at air speed and for aircraft type average for climb rates.

As the accuracy is lower, the error distribution in Figures 6.10 and 6.11 also show larger errors that are less concentrated around 0%. The distribution is still symmetric for methods taking values from the database. For air speeds in climb with BADA, the errors are shifted a bit to the right indicating that predicted times were shorter than actually flown, or in other words, the predicted speeds were larger than actually flown.

The last set of charts shows aircraft performances prediction methods for descents. Figures 6.12 and 6.13 show the air speed during descents and descent rate prediction accuracies. We can see here that BADA with nominal values is again performing significantly worse while all other methods show little differences between each other. Machine learning methods are still better than the method using just aircraft type. The difference is smaller, however, in some sections almost as big as for climb rates. The differences appear to be smaller because the vertical scale on the chart is much larger because of poor BADA performance.

Figures 6.14 and 6.15 showing error distribution reveal the main reason why BADA

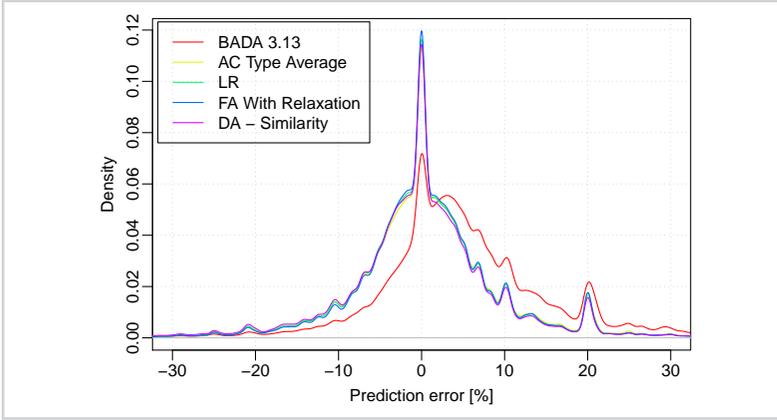


Figure 6.10: Error distribution for air speed in climb predictions with aircraft performances

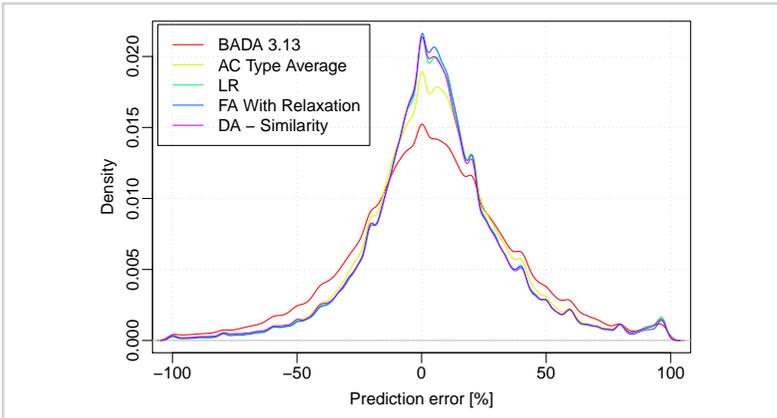


Figure 6.11: Error distribution for climb rate predictions with aircraft performances

Figure 6.12: Average error for air speed in descent predictions with aircraft performances

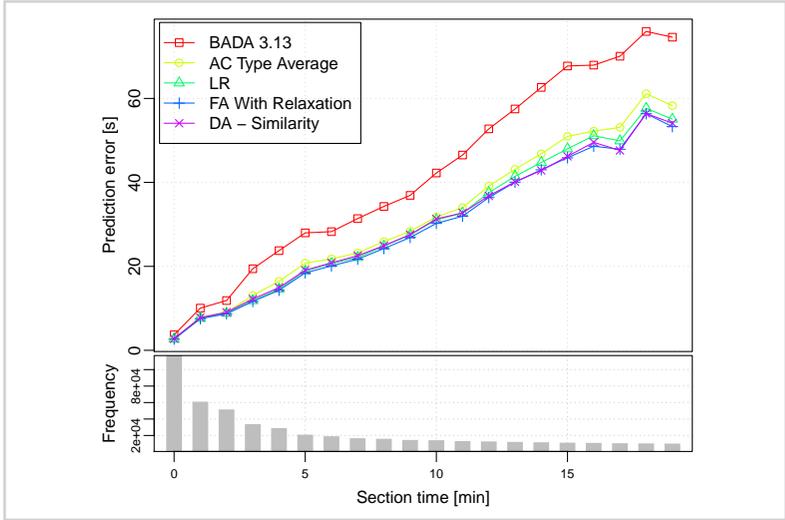
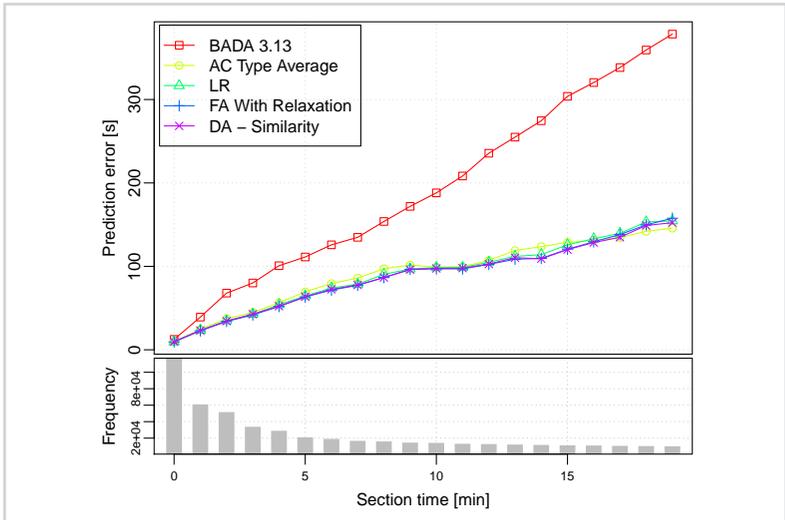


Figure 6.13: Average error for descent rate predictions with aircraft performances



performs so poorly at descents. We can see in Figure 6.15 that the majority of prediction errors are moved slightly to the right except BADA, which is moved significantly to the right and has another significant peak at around 70%. This move to the positive side means that the predicted times were shorter than the ones actually flown. The peak at BADA represents a large number of mispredictions of descent rates on altitudes around $FL_{360 \pm 30}$. On this altitude the tropopause (boundary between troposphere and stratosphere) is located. Different calculations are used in total energy model for troposphere and stratosphere. Since the tropopause is not very sharp and with a fixed border, it is difficult to determine, which formulae to use. BADA inputs are most affected here because the values were calculated using the total energy model, while other methods ignore the physical model and use recorded data from the database. The recorded data does not care about tropopause. It only provides averages for the selected altitude and temperature.

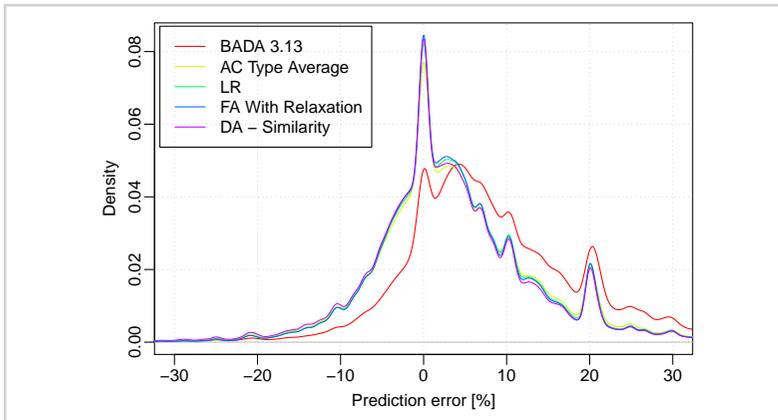
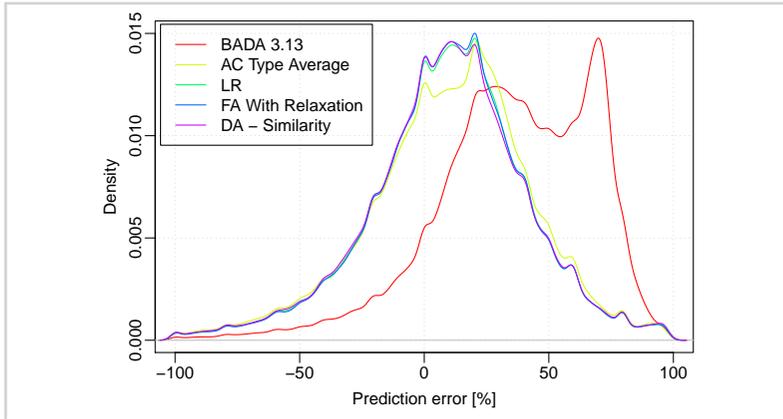


Figure 6.14: Error distribution for air speed in descent predictions with aircraft performances

To see for which parts of flight we can expect the best predictions, Figures 6.16, 6.17, and 6.18 show how the the accuracies are affected by altitude. The x axis in Figures 6.16b, 6.17a, 6.17b, 6.18a, and 6.18b shows prediction errors so that values on the left are better than the ones on the right part of the chart. The y axis represents the flight altitude.

For air speed in Figure 6.16b we can see that dynamic attributes are pretty unreliable at lower altitudes while aircraft type average and fixed attributes perform better. At

Figure 6.15:
Error distribution for descent rate predictions with aircraft performances



higher altitudes, where aircraft have a smaller range of air speeds, all methods are almost identical.

For climbs presented in Figure 6.17 BADA is again the worst performer. It is interesting to observe in Figure 6.17a that air speed predictions are more reliable on higher altitudes. On the other hand, climb rates in Figure 6.17b are better on lower altitudes. That trend for climb or descent rates versus air speed in climbs or descents is identical in all the following comparisons by altitude.

Figure 6.18 presenting descent prediction accuracies shows that the tropopause is indeed a problem when using the total energy model. Other methods, which ignore the physical model, also display larger errors on high altitudes, but they are significantly lower than with the total energy model.

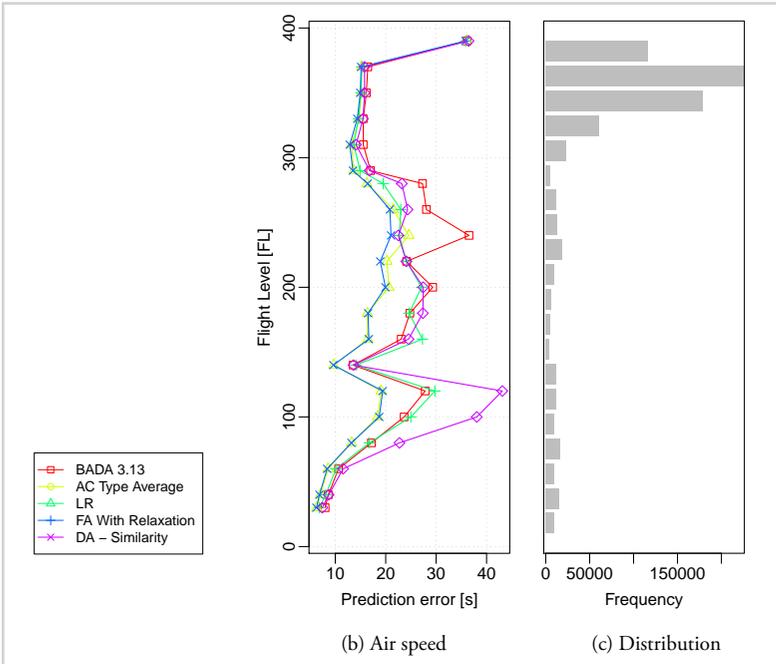


Figure 6.16: Air speed during cruise prediction error for aircraft performances in relation to altitude

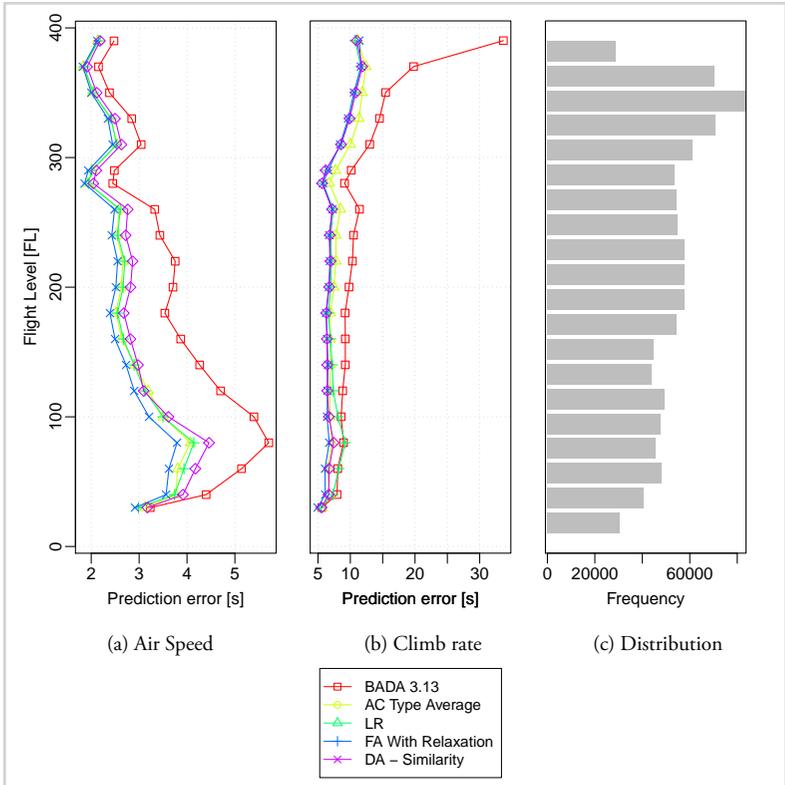


Figure 6.17: Climb phase prediction error for aircraft performances in relation to altitude

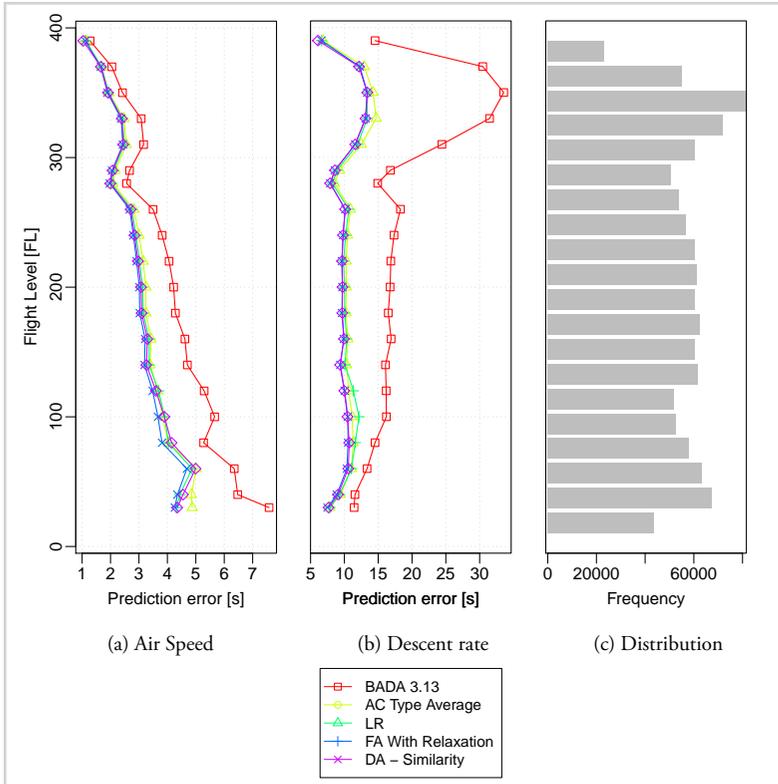


Figure 6.18: Descent phase prediction error for aircraft performances in relation to altitude

6.5.2 Airline Procedures

For predictions with airline procedures, the total energy model was used as described in Section 3.4.2. Because we imitate airline procedures parameters, we often call the methods using TEM formulae airline procedures prediction methods. The parameters predicted here are different than for prediction of aircraft performances. It turned out that prediction methods, that performed the best for aircraft performances, do not necessarily perform the best for airline procedures, too.

We have selected different machine learning methods for consideration here.

1. The first method is using values provided by BADA default company. The method is labeled *BADA 3.13* in the charts.
2. Similarly as for the aircraft performances, the second method is a kind of BADA equivalent from our database. The method is labeled *AC Type Average* in the charts.
3. The third method is the best performing representative from standard regression algorithms – linear regression. It is labeled *LR*.
4. The fourth method is again demonstrating how the predictions perform, if we manually select a set of attributes. In this case, it is the method using fixed ranks of attributes with weighted averages. The method is labeled as *FA With Relaxation W*.
5. A method using dynamic attributes that is performing the best for air speeds predictions is using dispersion ranking. It is labeled as *DA - Dispersion*.
6. The method that performed the best for air speeds was not suitable for climbs and descents. The method that we have selected is again using dispersion for ranking but employs weighted averages instead of regular ones. It is labeled *DAW - Dispersion*.

Figure 6.19 shows a comparison of predictions using total energy model and predicted airline procedures parameters for air speed. Fixed attributes and linear regression that work well for aircraft performance predictions, do not perform well with airline procedures. Their decline in accuracy is particularly observable on longer flight sections.

Very similarly as for aircraft performances, the accuracy for air speed using airline procedures predictions presented in Figure 6.20 show highly concentrated predictions with a minimal error. All methods show very similar distribution of errors.

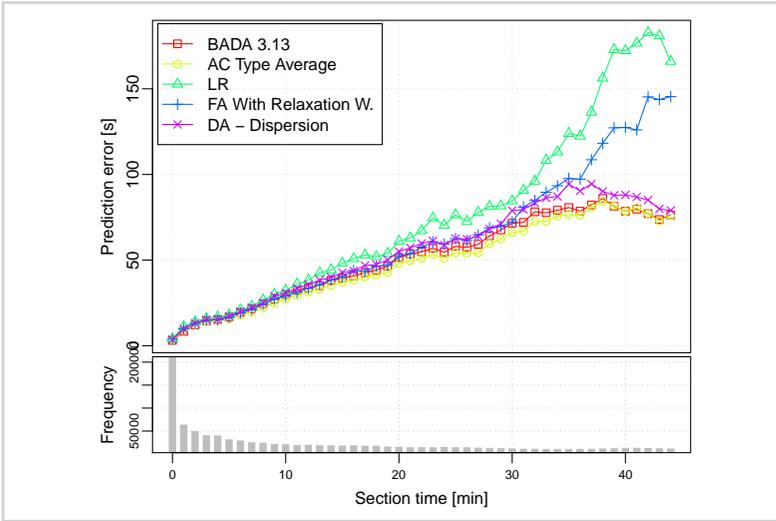


Figure 6.19: Average error for air speed during cruise predictions with airline procedures

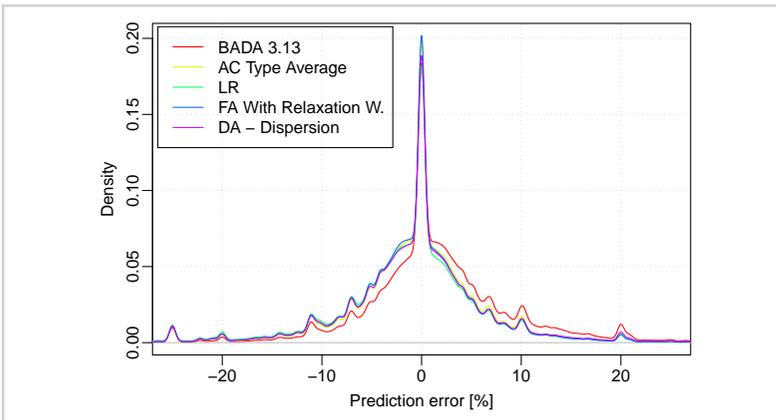


Figure 6.20: Error distribution for air speed during cruise predictions with airline procedures

Figure 6.21: Average error for air speed in climb predictions with airline procedures

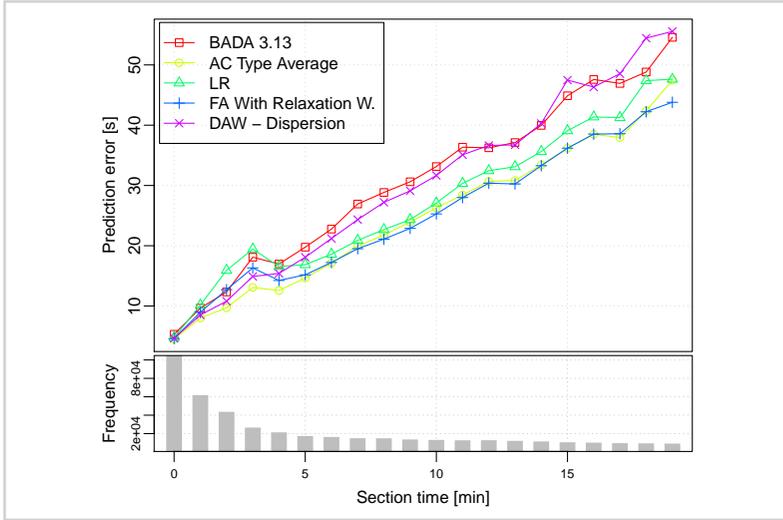
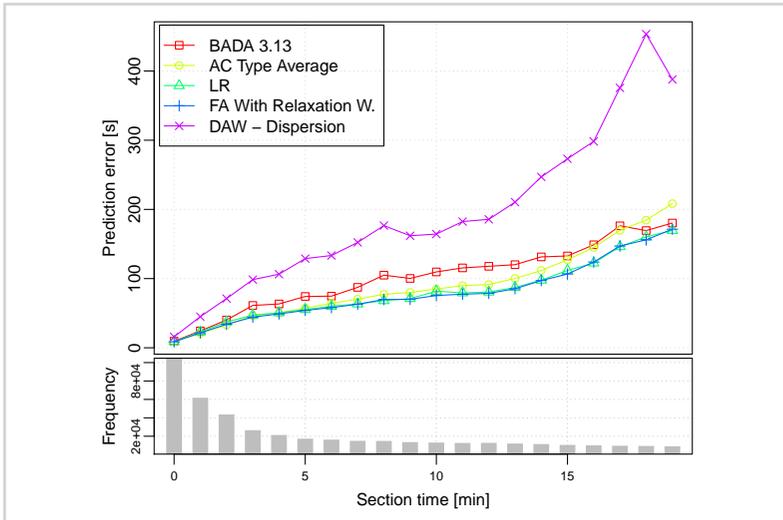


Figure 6.22: Average error for climb rate predictions with airline procedures



For climbs it is obvious that machine learning with dynamic attributes ranking shown in Figures 6.21 and 6.22 shall not be used. For air speed in climb in Figure 6.21 simple methods are better than BADA or machine learning with dynamic attributes. Climb rates in Figure 6.22 is one of the rare cases where dynamic attributes selection is significantly worse than other methods. However, simple learning with fixed parameters is still better than just using aircraft type average.

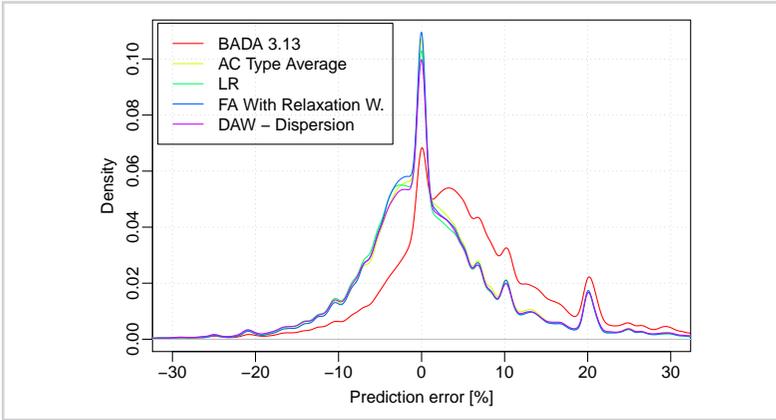


Figure 6.23: Error distribution for air speed in climb predictions with airline procedures

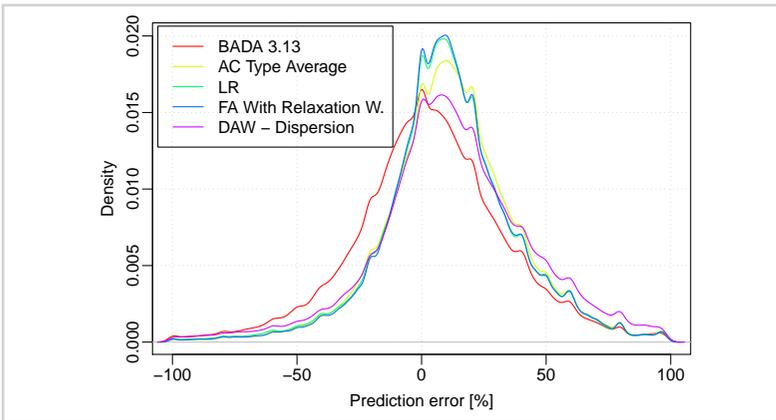


Figure 6.24: Error distribution for climb rate predictions with airline procedures

The distribution of errors in Figures 6.23 and 6.24 shows an interesting trend observable in many charts using airline procedures. The predicted values are higher than the ones actually flown. That causes the error distribution charts to move to the right. There is also a distinctive peak for air speeds in climbs and descents at 20%. These are flights departing or arriving to Ljubljana airport. The mispredicted air speeds are predicted very close to the airport, where speeds of aircraft are obviously smaller. For descents it is even more obvious as the concentration of mispredictions is concentrated on the area where instrumental landing systems guides aircraft to the runway and they are prepared for landing. The speeds there are lower and we could investigate how we use the landing configuration from TEM formulae. Obviously the aircraft are earlier in landing configuration than defined in formulae.

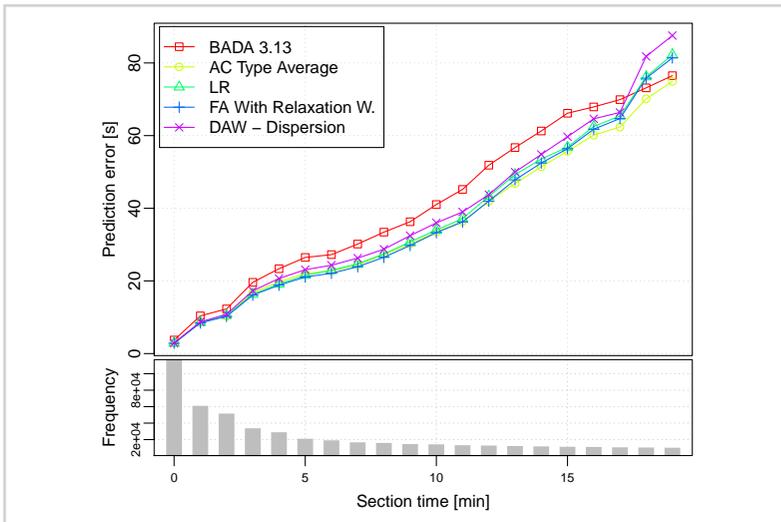


Figure 6.25: Average error for air speed in descent predictions with airline procedures

Descent rates are the last performance to test and we can see in Figures 6.25 and 6.26 the same situation that we have seen several times until now. BADA with nominal values is not very suitable for our airspace, while all other methods using the database with locally recorded flights fit the actual situation better.

Figures 6.27 and 6.28 show the distribution of errors for descents. Again, the total energy model dictates similar error distribution for all methods. Very interesting here

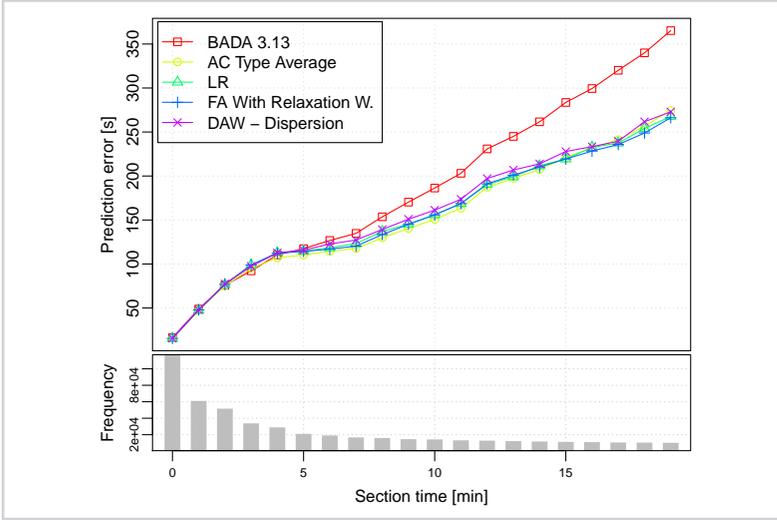


Figure 6.26: Average error for descent rate predictions with airline procedures

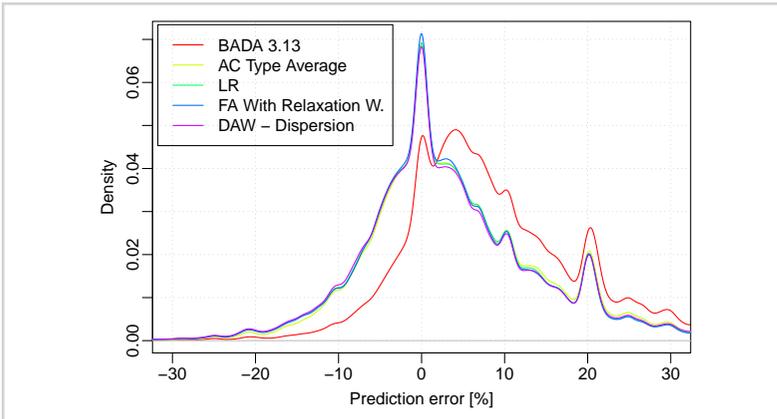
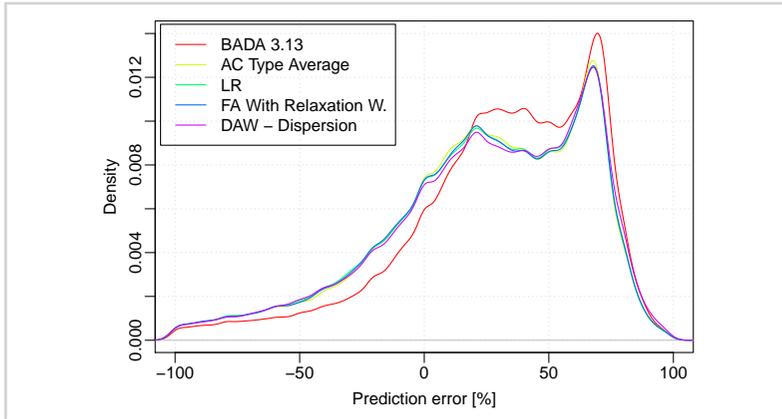


Figure 6.27: Error distribution for air speed in descent predictions with airline procedures

Figure 6.28: Error distribution for descent rate predictions with airline procedures



is the distribution of errors for descent rates shown in Figure 6.28. While for aircraft performances our prediction methods did not exhibit such a strong deviation to the right of the chart, in this case, all methods do. The explanation for this behavior is simple. All methods using airline procedures are using total energy model to predict the performances and all are affected by the tropopause altitude. With aircraft performance only BADA was affected, because the values for BADA values were produced from the values from the total energy model, while other methods successfully ignored it. Obviously the formulae above and below that area perform fine, therefore the equations are correct. It is just difficult to establish, which equations to use – for troposphere or stratosphere.

Figures 6.29, 6.30, and 6.31 display prediction accuracies vertically. Again, the air speeds predictions in Figure 6.29b are very accurate for high altitudes, while dynamic attributes ranking performs very poorly on lower altitudes.

For climb rates in Figure 6.30 we can see again that the dynamic attributes ranking shall not be used and fixed attributes methods are clear winners.

For descents in Figure 6.31b, all methods are unusable at high altitudes in comparison to methods ignoring the physical model.

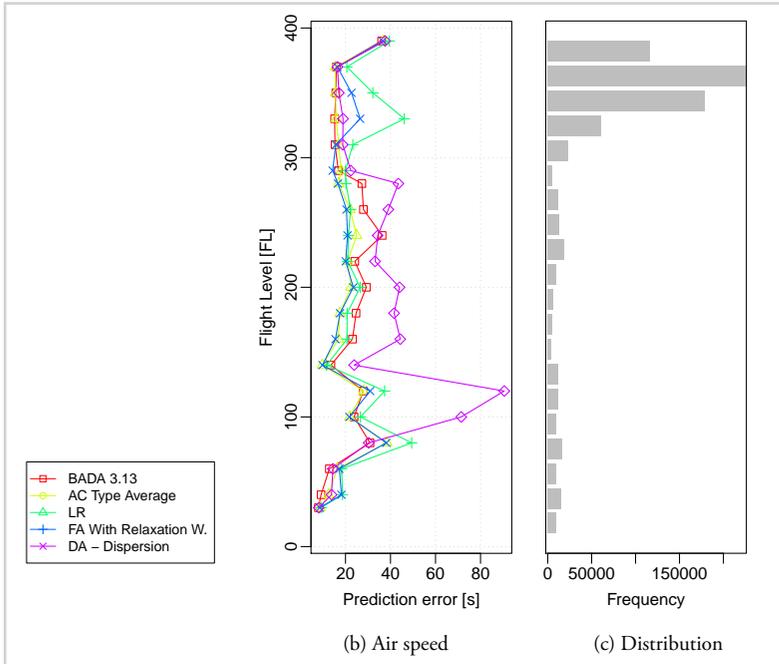


Figure 6.29: Air speed during cruise prediction error for airline procedures in relation to altitude

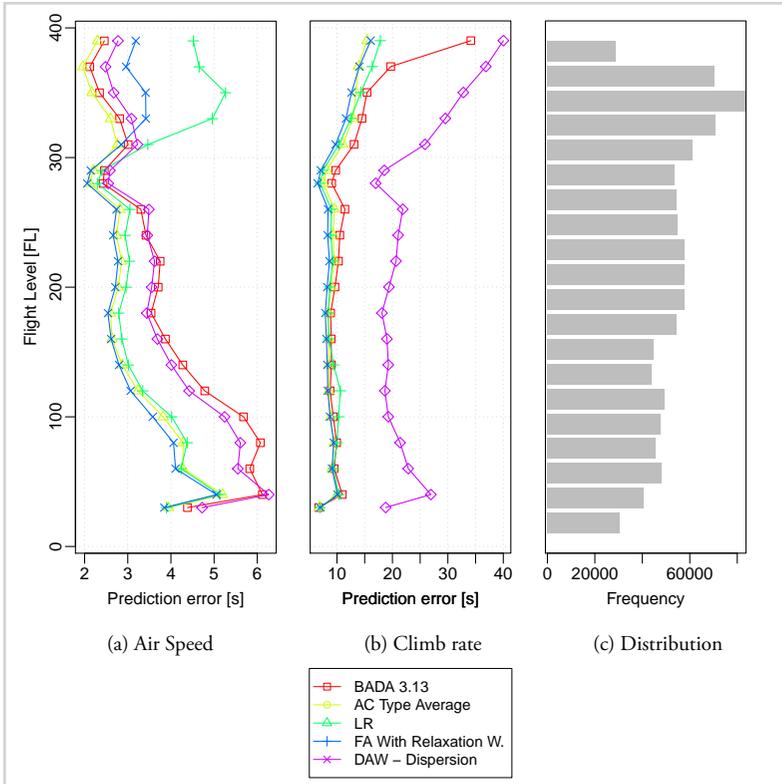


Figure 6.30: Climb phase prediction error for airline procedures in relation to altitude

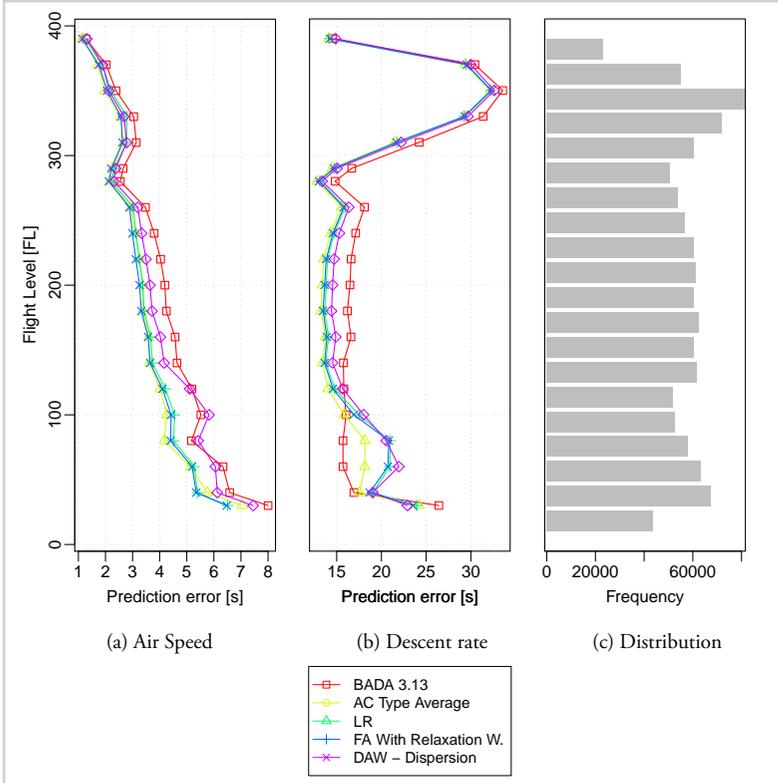


Figure 6.31: Descent phase prediction error for airline procedures in relation to altitude

6.6 Report on Usage of Attributes in Our Algorithms

To see why a specific method is better than other, we have to look how the attributes are ranked and used during k nearest neighbours searches. With analysis of attribute ranking we can identify, which attributes are ranked higher with the more successful prediction methods. When we gather all this knowledge, we can try to find more accurate methods or optimize current methods to work faster.

6.6.1 Aircraft Performances Tables

First we present the usage of attributes for aircraft performances model. As mentioned, we can compare only k nearest neighbours methods here as they rank attributes in different ways to get better results.

FA With Relaxation is the first method to analyze. Although it uses a fixed order of attributes, we can still investigate how many attributes have been used during predictions and how many samples were contributing to the predicted values. Using that, we can compare how dynamic attributes ranking methods are different from the fixed one.

Table 6.1: Number of attributes used and the average contributing samples for FA with relaxation prediction method used for aircraft performances

No. of Attributes	Usage Count	Average No. of Samples
1	537858	2025
2	550392	398
3	179247	92
4	3576569	286

Table 6.1 shows that most of the times all four attributes were used for predictions and 294 samples on average contributed to the predicted value. Since the order of attributes is fixed it also means that four attributes are always aircraft type, ADES, ADEP and operator. Three attributes include aircraft type, ADES and ADEP, two are aircraft type and ADES, and when a single one is left, it is always aircraft type.

It is also interesting to see that if four attributes did not provide enough samples, then three would also probably not. Table 6.1 shows that one or two attributes were used more times than three.

Table 6.2: Average rank and usage of attributes for DA - Similarity prediction method used for aircraft performances

Attribute	Average rank	Usage count
Aircraft Type	3.25	2972300
Operator	3.47	2932018
ADEP	3.81	2727160
ADES	3.83	2674849
Entry Point	4.57	2479941
Exit Point	4.71	2340603
Arrival Hour	5.02	2144349
Flight Type	5.02	2421920
Departure Hour	5.11	2115149
Week Day	5.54	1671230
Flight Rule	6.87	1612502
Exemption	6.92	1580324

Table 6.2 shows average ranks of every attribute for DA - Similarity method. For this method 125 samples contributed to the predicted value on average, and 6 attributes were used on average. Attributes are ranked from the first to the twelfth. That means that a lower rank number means a higher overall ranking of an attribute. As expected, the highest ranked attribute is aircraft type. Usage count column shows how many times the attribute was actually used for prediction.

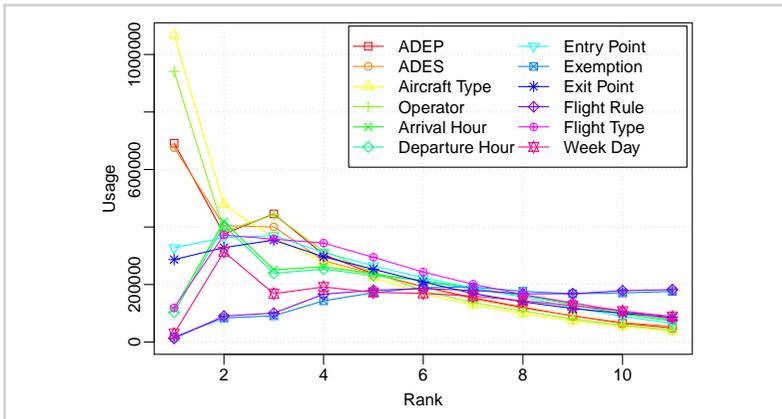
Table 6.3 shows how far did the relaxation of attributes go until there was enough samples to make a prediction. All attributes were never used, but just removing one single attribute was in a large number of cases enough, to have enough samples to make a prediction. On average, 29 samples were used in that case. The threshold for samples was always 10. That means, if the number of samples is below ten, the conditions are relaxed. Otherwise, the prediction is used. As expected, the number of samples rise as the number of used attributes is smaller.

Figure 6.32 shows some more detail. We can see that Aircraft Type is indeed the most frequently used highest ranked attribute. Operator attribute is close and then ADEP and ADES are almost identical. These four form the set of most influential attributes. In the middle of the set are the attributes that might also have some influence on the performances. At the end of the list are flight rule and exemption as the attributes with

Table 6.3: Number of attributes used and the average contributing samples for DA - Similarity prediction method used for aircraft performances

No. of Attributes	Usage Count	Average No. of Samples
1	366994	901
2	434190	163
3	434703	91
4	402850	64
5	371981	49
6	343586	40
7	314813	33
8	279742	30
9	236219	27
10	189304	26
11	1012673	29

Figure 6.32: Usage of attributes in DA - Similarity prediction method used for aircraft performances



the lowest ranks. Figure 6.32 also shows ranks up to 11. More attributes than 11 are practically not used as there are not enough samples in the database to predict based on all matching attributes.

6.6.2 Airline Procedures

For airline procedures model, we show how attributes were used and ranked with k nearest neighbours searches the same way as they are shown for aircraft performances in the previous section.

Table 6.4: Number of attributes used and the average contributing samples for FA with relaxation w. prediction method used for airline procedures

No. of Attributes	Usage Count	Average No. of Samples
1	688161	10463
2	671574	370
3	96023	92
4	1077885	437

For fixed attributes with relaxation, some attribute analysis is needed to be able to compare the method with dynamic attributes. Table 6.4 is very similar to Table 6.1. We can see again that most of the times all parameters have enough samples to provide a credible prediction. It is even more obvious here, that if four attributes are not enough, then three will probably not be enough too. Operators fly regular lines on scheduled flights. If we do not have samples in the database for an operator flying that line, it seems likely that we have no other operator flying the same route. This seems to be a pattern for less popular lines. It is perfectly logical, if there are passengers to fill one aircraft, other operators will not fly with an empty aircraft.

For DA - Dispersion, Table 6.5 shows average ranks and usage of attributes. For airline procedures, the aircraft type is fixed to be always in the attributes, because the TEM model implicitly includes aircraft type as described earlier in Section 3.4.2. For that reason, the average rank of aircraft type is 1.00. It turns out that all methods that produce good results rank, beside aircraft type, operator, ADES, and ADEP at the top. Usually, there is a group of similar attributes in the middle and then two or three attributes ranked significantly lower. Table 6.5 does not deviate from that pattern.

Table 6.6 shows how many attributes are used in the prediction and how many

Table 6.5: Average rank and usage of attributes for DA - Dispersion method used for airline procedures

Attribute	Average rank	Usage count
Aircraft Type	1.00	2570360
Operator	2.50	1849281
ADES	3.75	1269110
ADEP	3.78	1359021
Entry Point	4.91	1169834
Flight Type	4.95	1444875
Exit Point	4.96	1140828
Departure Hour	6.44	755346
Arrival Hour	6.74	773156
Flight Rule	6.95	1175879
Exemption	7.59	1033438
Week Day	7.67	718954

Table 6.6: Number of attributes used and the average contributing samples for DA - Dispersion prediction method used for airline procedures

No. of Attributes	Usage Count	Average No. of Samples
1	111614	251138
2	386767	3414
3	328720	1523
4	265128	581
5	214189	340
6	215432	218
7	184597	109
8	147260	63
9	129027	49
10	130663	37
11	456963	62

samples on average contribute to the prediction values for the prediction method DA - Dispersion with airline procedures. Again, we see the highest number of predictions made on all but one attribute used. There is also a significantly larger number of samples being used when only one attribute is left. The reason for that is the fixed aircraft type attribute, which always remains the last attribute used. When aircraft type is not fixed, the last attribute may be some other attribute and the number of samples is not as big in this case.

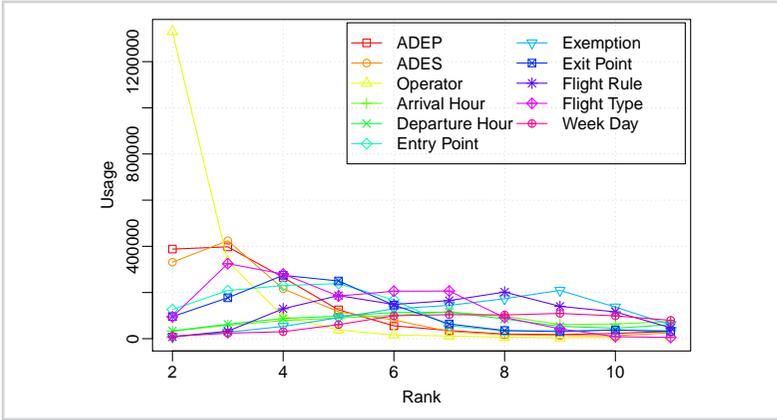


Figure 6.33: Usage of attributes in DA - Dispersion prediction method used for airline procedures

Figure 6.33 shows attribute usage with method DA - Dispersion. Because aircraft type is always ranked as number one, it is left out to show other attributes in greater detail. The operator is again the attribute that is ranked right after aircraft type. This confirms the BADA strategy that airline procedures profiles for individual operators should be created to increase accuracy. The profiles in this case are also locally dependent and therefore the ones used in our airspace would most probably not be suitable for some other airspace. Beside the fact that delicate private data would be revealed, that may be one of the main reasons why BADA developers did not issue airline procedures profiles for companies. They always publish just the default company.

6.6.3 Evaluation Against Standard Attribute Selection Method RReliefF

To see whether our attribute selection methods provide relevant information on attributes rank we compared it with standard attribute ranking method RReliefF [88, 89].

Table 6.7: RReliefF average attribute rank for aircraft performances model

Attribute	Average Rank
Aircraft Type	2.23
Operator	2.68
ADEP	4.38
ADES	4.71
Flight Type	5.22
Exit Point	7.15
Entry Point	7.34
Departure Hour	7.43
Arrival Hour	7.62
Exemption	9.25
Flight Rule	9.91
Week Day	10.08

We have grouped the samples in the same way as we did it for prediction. For aircraft performances we grouped samples according to altitude and temperature, and calculated the RReliefF rank of attributes for each group of samples. Average ranks of attributes shows us the overall rank, and is presented in Table 6.7.

When we compare these ranks with average ranks of our methods in Table 6.2, we can observe that the ranks are similar. The first group of most important attributes: aircraft type, operator, ADEP, and ADES, stands out as these have been ranked higher than others by both methods. In the middle, there are: flight type, entry/exit point, and departure/arrival hour. At the end are the least significant attributes: exemption, flight rule, and week day.

The greatest differences between our methods and RReliefF are in the ranking of attributes flight type and exemption. However, on overall, both ranks are similar and that confirms that our attribute ranking methods are comparable with a proven standard method, and can be used for aircraft trajectory predictions.

For airline procedures model, attribute ranks are not as consistent as for aircraft

Table 6.8: RReliefF average attribute rank for airline procedures model

Attribute	Average Rank
Aircraft type	1.00
ADEP	4.60
ADES	4.85
Operator	4.99
Exit point	5.44
Entry point	5.45
Departure hour	6.36
Arrival hour	6.55
Type of flight	6.60
Exemption	6.85
Weekday	7.09
Flight rule	7.21

performances model. We have grouped samples according to aircraft type and ranked each group with RReliefF for airline procedures modules again. The average ranks are presented in Table 6.8. For the same reason, as with ranks given by our methods in Table 6.5, the aircraft type is always ranked as the first attribute. The distinction between groups of attributes is not as clear as for aircraft performances model. Inconsistent ranks of attributes may indicate why the predictions in this model are generally worse than for aircraft performances model. The attributes seem less correlated with the values and thus more difficult to predict accurately.



Conclusions

7

Our main goal in this dissertation was to improve trajectory predictions and to make them more accurate than in current state-of-the-art trajectory calculation systems. We have shown that we can dynamically provide custom input prediction parameters for each flight, which are better than nominal values. Current state-of-the-art trajectory prediction methods do not have the means to get better input parameters than nominal ones. We have succeeded in making trajectory predictions better by calculating individually customized parameters for the state-of-the-art trajectory prediction.

Obtaining custom input parameters is the main problem for ATM users, because they do not have the means or knowledge to find out, which are the optimal parameters for their airspace.

The system that we have introduced is relatively simple to implement and is cost efficient. It does not require users to understand or manually extract parameters for their airspaces. Prediction service provides inputs for trajectory calculation in a form identical to nominal parameters. In that way trajectory calculation can remain unchanged. Only the input parameters are changed to provide better accuracy.

With better trajectory predictability we can expect cheaper and more efficient flights. If we can achieve savings of only a few Euros per flight, that would, with ten millions of flights in Europe per year, scale up to millions of Euros.

We have expected that machine learning methods would provide significantly better results than some of the simplest methods that we used by manually assigning fixed parameters. That was probably an unrealistic expectation. If the experts know how to evaluate attributes and how to use them to get a credible value we cannot expect that machine learning algorithms will come up with a magical recipe that will improve the predictions drastically. The main advantage of a machine learning approach is, in our opinion, to make better predictions much faster and cheaper, based on a large amount of data, and to take the burden of routine tasks off the human expert.

The majority of methods proved to be a better choice than the static BADA model. It is up to users to select the one that suits them well.

7.1 Quantification of Expected Improvements

The results show that the use of recorded flight data for aircraft performance prediction is a promising way forward. Figures 7.1, 7.2, and 7.3 show prediction improvements that we have achieved in relation to the BADA model version 3.13, for selected prediction methods. The percentage of improvement indicates how much the prediction time is better than nominal BADA 3.13 prediction according to the real flight time. The four representative methods compared to nominal BADA 3.13 are:

- AC Type Average, where average performances for each aircraft type recorded in our airspace are being used;
- Linear Regression, as the best selected method from standard regression methods;
- FA With Relaxation, where we have manually selected the attributes for all flights, which affect performances;
- DA - Similarity, where the algorithm decides dynamically for each flight separately, which attributes it will use to search for similar flights for the one being predicted.

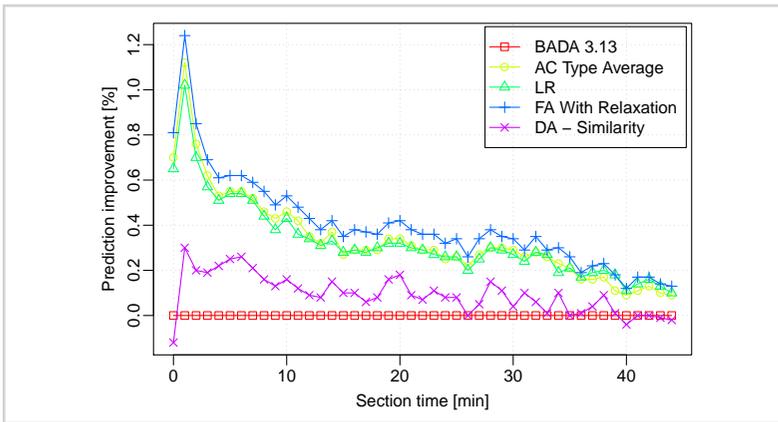


Figure 7.1: Expected prediction improvements with aircraft performances for air speed against BADA 3.13

Figure 7.1 shows that air speeds are already very accurate. We can expect a slightly larger improvement for air speeds in climbs and descents, but still not more than 3%.

Figure 7.2: Expected prediction improvements with aircraft performances for rate of climb against BADA 3.13

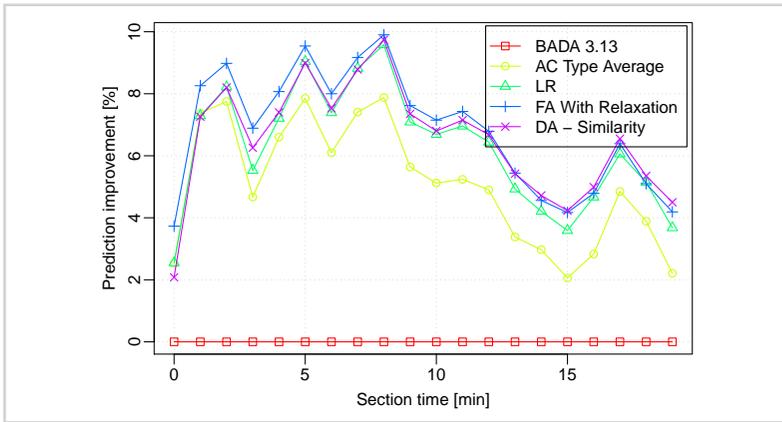
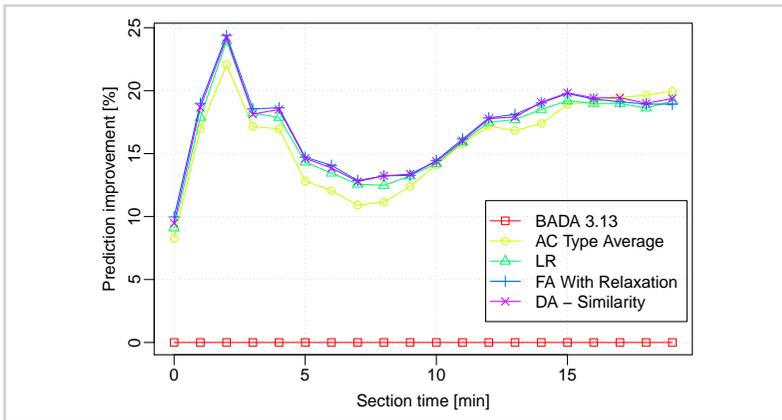


Figure 7.3: Expected prediction improvements with aircraft performances for rate of descent against BADA 3.13



For rates of climbs and descents the situation is different. As shown in Figures 7.2 and 7.3 the prediction improvements are significant and can go up to 10% for climbs and even up to 25% for descents.

The predictions using the BADA nominal values give the worst results because the model is made for a general case, and does not include local characteristics. We have implicitly invoked local characteristics with our knowledge database. In that way, we can predict customized physical TEM parameters without a deep knowledge about aircraft.

7.2 Potential Usage of Proposed Solution

Although we constantly compare our proposed solution with the BADA model, we are not proposing to replace it. The BADA model is much more than just a trajectory prediction application. Our solution provides an easier way to get customized input BADA parameters, which will lead to more accurate trajectory calculation when using BADA. BADA developers cannot provide input parameters for trajectory calculation for every user, because they do not have the information about their local characteristics. However, users also do not adjust their input parameters to improve their predictions since this is too complicated for the average BADA user. The important advantage that we propose is to provide custom parameters individually for each flight. Based on the concerned flight details one can get a lot of information that can help in fine tuning the parameters.

There is an essential difference how BADA creators use recorded flight data. They fine tune their model to keep the error of the model to be at minimum or, in other words, they model to fit the average. We, on the other hand, try to use the recorded data to get a better prediction customized exactly for the considered flight.

Another way to use the proposed method is to completely ignore the physical model and to predict trajectories solely on the recorded parameters from the database.

One can observe such a complementary approach in many other fields of computer assisted applications. One way is to try to understand and model the system being observed. The result is then a rule-based algorithm, where the behaviour of the system is modeled. Rule-based algorithms use inputs to apply proper rules of the model and in this way provide outputs. The other way is by ignoring the model and trying to record large amounts of inputs and outputs. Various statistical methods can be used, that given some input, try to deduce the outputs by analyzing these large amounts of

data. This is the approach that we have taken as the opposite of the BADA model, which tries to describe the exact physical model with all the forces acting on aircraft.

To make a rule-based algorithm requires a profound understanding of the system and an additional effort to program the algorithm that models the rules of the system. Any change of the design or behaviour of the system requires its reevaluation and redesign of the algorithm. On the other hand, statistically based algorithms usually do not require that, unless the change is really significant.

Combining both approaches, one can complement the weaknesses and strengths of both, to get better results than using just one approach. We believe that we are doing such a combination with providing statistically derived, customized input parameters for the TEM BADA model, which models rules and laws of aircraft movement.

Beside using our proposed approach for predictions we see also other benefits that might come from the acquired database. One could directly generate an airline procedure model input parameters for various operators from the historical data. It seems that this was also a plan of BADA creators, when they included a default company for each aircraft into their system. However, this parameter always remained just the default company. There are endless possibilities to study aircraft behaviour from various aspects with queries into the database.

All prediction algorithms are installed as a web service. Legacy applications using BADA values for trajectory calculation could use this service and get a substantially better predictions. All methods that we developed return performances in a format identical to BADA performance tables. In that way, one can, in legacy applications, simply replace the static BADA nominal values with dynamic parameters.

OLAP databases support cluster architecture and large amounts of data. They are optimized to provide quick answers to queries. The multidimensional database is designed to be easily expandable to a larger airspace. In our case, we were able to perform all the described tasks with a couple of desktop computers. With powerful servers and careful planning, expanding to a larger airspace should not be a problem. In that case, the predictions should be based on geographic position to support local operations characteristics. The databases are already designed to hold this information. The OLAP supports partitioning for such scenarios. Partitioning enables the distribution of the database and optimization of queries to work in parallel and to search only through the partitions which actually hold the data searched for. In that way, predictions with larger databases would not require more time to provide results.

A database holding data of a large airspace becomes a good candidate for a centralized service providing predictions to a wider audience. In Europe we have good experience with centralized services. Eurocontrol's Network Manager Operations Centre (NMOC), for instance, delivers core operational services across several domains in flow and capacity management, flight planning, etc. Eurocontrol is trying to introduce new centralized services [51], which would provide consistent and cheaper services across the whole of Europe. A proposal for a centralized service named "CS2: 4D Trajectory Flight Profile Calculation for Planning Purposes Service (4DPP)" [52] should bring a consistent 4D trajectory calculation for all Eurocontrol stakeholders. A service like that would use more advanced BADA TEM trajectory prediction. However, a database like ours could help in tuning the model and provide local or operator characteristics for even better performance. With centralized services, the 4D trajectory calculations would be more consistent and accurate in the whole European airspace at a lower price. There would be no need for every air traffic control center to invest money in software to calculate trajectories by themselves.

7.3 Future Work and Improvements

A complex system like the one described in this thesis opens many possibilities for improvements and future development. Let us introduce some of possible improvements and directions for future work, which we have identified during our work.

As expected from the beginning, air speed is the most predictable performance. Results show that predictions are the most accurate for air speed and we do not need improvements there. The main focus should be on climbs and descents.

A potential field, where the results of this research could be used, are performance based navigation (PBN) procedures. They are being introduced widely and are used to optimize airspace to allow easier operations with continuous climb and descents. In our view, this is one of the steps in airspace optimization that will eventually bring us to trajectory based operations. First, we need to have procedures that are optimized to take advantage of aircraft capabilities to reduce operations costs.

The accuracy of methods could be further improved by analysis of parameters used by these prediction methods. The attribute usage reports show, which attributes are used more frequently for successful methods. With detailed data from attribute usage reports we can analyze when the machine learning gets the best predictions.

First, the set of attributes can be changed. In that way, we could optimize the

attributes usage to a set that would allow good predictions and would not include features that do not contribute anything to a better prediction. We have deliberately include some attributes, for which we suspected that they do not affect performances. However, we wanted to show that the prediction algorithms identify and exclude such attributes. With a detailed analysis of each performance and the methods, we could use different prediction methods for different performances. There are also differences in the length of predicted sections. For shorter sections some of predictions are more successful than others.

A deeper analysis would also show, if there are different optimal numbers of contributing samples. With that information, the thresholds and the amount of data in the database could be adjusted. For some common aircraft or operator there would be enough to use the data for the last year. On the other hand, for some flight that occurs more rarely there might not be enough data in one year to make credible predictions.

We have taken the data that are available to air traffic control services providers. The airports, for instance, have more details about load on aircraft, take-off weight, passengers, etc. With that information the predictions could be improved even further. However, sharing that data is another task that is out of the scope of this thesis. Even if we managed to get the data from nearby airports, that would be less than 10% of traffic. Aircraft departing from London or New York and flying to Asia pass through our airspace. To get data from these airports exceeds the framework of this thesis. Similar conclusions can be done for aircraft operators. To exchange data between air traffic service providers and operators or aerodromes must be organized at least on European or best on even global level. Otherwise we could get a just handful of contributing partners. Unfortunately, activities with wider participation take years or decades to implement. This is also one of the reasons that we decided to use only the data that are available now. Even getting data needed for the proposed system within larger air traffic controls can be a great challenge, since data can be spread across different departments.

In our predictions we have calculated only times for individual flight sections related to our radar coverage. The sections that we were able to record with our surveillance equipment are the ones that we were able to test. The next step would be to upgrade this calculation to combine together all the sections (take-off, climb, cruise, descent, land) and to calculate aircraft positions with times for the whole flight path. However, this involves calculating the predicted flight path according to the flight plan and comparing it with actual paths flown. This encompasses a whole new dimension of

air traffic control clearances and other changes of the flight path, which are also not available. A flight plan is typically longer than the flight through a few flight sectors. In that case, it would also not be possible for us to check the accuracy of the calculations outside the range of our radars since the necessary data are not available to us.



Razširjeni povzetek

A

A.1 Uvod

Letalski promet se sooča z velikimi izzivi, ki vključujejo optimizacijo letalskih poti, nihanje stroškov in povečanje prometa skupaj s povečano varnostjo. Najbolj obremenjeni deli zračnega prostora in letališča so že na mejah svojih zmogljivosti.

V prihodnosti bodo izboljšave, ki bodo zadostile zahtevam za povečanje letalskega prometa ob manjših stroških na let šle v dveh smereh [1, 2].

A.1.1 Razvoj zračnega prometa v bližnji prihodnosti

Prva smer, ki bo dala hitrejša rezultata z manjšimi investicijami, poskuša izboljševati in optimizirati metode, ki so trenutno v uporabi. Prevladujoč koncept z dovoljenji, ki temelji na usmerjanju in navodilih kontrolorjev zračnega prometa s predstavo situacije v zraku, je v uporabi že od tridesetih let prejšnjega stoletja. Po uvedbi prvih radarjev za civilno uporabo v petdesetih se metode neprestano izboljšujejo in v tem času je bilo uvedenih veliko novih orodij, ki omogočajo varno povečevanje zračnega prometa. Ena takih orodij je srednjeročno odkrivanje konfliktov, ki kontrolorjem zračnega prometa omogoča načrtovanje dlje v prihodnost in jim nudi možnost upravljati z večjo količino prometa. Druga skupina izboljšav ponuja natančnejše instrumente in boljši pregled nad situacijo, kar omogoča letalom, da varno letijo bližje drugo drugemu. Primer takega napredka je bila vpeljava natančnejših višinomerov, ki dovoljujejo zmanjšano vertikalno razdaljo med letali in tako omogočajo večjo propustnost zračnega prostora.

Možnosti za izboljšave še niso izčrpane. Ena od možnosti je natančnejši izračun in napovedovanje trajektorij letal, kar bo omogočilo načrtovanje bolj zgoščenega prometa. Kontrolorji zračnega prometa bodo tako s pomočjo novih orodij lahko še povečali propustnost in zmogljivost.

A.1.2 Razvoj zračnega prometa v daljni prihodnosti

V drugi fazi bomo potrebovali večji preskok. Ta sprememba koncepta bo zahtevala veliko sredstev in trenutno vpleteni niso pripravljeni financirati takih sprememb, dokler ne bodo izkoriščene vse cenejše možnosti. Nov koncept bo vključeval drugačne komunikacijske poti med letali in kontrolami na tleh, ki si bodo izmenjevale načrtovane trajektorije. Z novimi informacijami bo možen drugačen način vodenja zračnega prometa, ki bo temeljil na 4D trajektorijah. 4D trajektorija je pot letala, ki določa točke na poti s 3D položajem in časom. Prehod na koncept vodenja s trajektorijami

je velik korak. Zahteva vložke v posodobitev opreme na strani kontrol zračnega prometa in na strani prevoznikov, ki bodo morali v letala vgraditi opremo za podporo te nove vrste komunikacije. V strogo regulirani dejavnosti, kot je zračni promet, se lahko take spremembe vlečejo desetletja. Dokler ne bodo inovacije v konceptu vodenja s trajektorijami obljubljele prijemljivih ekonomskih učinkov, vpleteni ne bodo hoteli investirati v novo tehnologijo. Nekatere ocene [1, 2] predvidevajo uporabo tega koncepta do leta 2035.

Načrti za zračni promet v Evropi in Severni Ameriki se osredotočajo na koncept vodenja s trajektorijami kot glavno gonilo, ki bo omogočilo predviden porast prometa z manjšimi stroški na let. Evropski načrt se imenuje "raziskave za skupno evropsko nebo" (Single European Sky ATM Research (SESAR)). V Združenih državah Amerike se podoben projekt imenuje NextGen. Glavna cilja obeh projektov sta modernizacija zračnega prometa in omogočanje varnega in učinkovitega povečanja zračnega prometa. V Evropi se spopadamo s temi izzivi na različnih področjih. Evropske ustanove pripravljajo zakonske okvire, ki vključujejo vse vpletene (ponudnike navigacijskih storitev, letališča, upravljavce letal, itn.) na pot k skupnemu cilju modernizacije opreme in postopkov. Evropska organizacija ponudnikov navigacijskih storitev Eurocontrol razvija storitve in tehnologije za celo Evropo. Evropa, ki je razdrobljena na 67 enot zračnega prostora, bo v prihodnosti zajemala le devet funkcionalno združenih blokov zračnega prostora. V teh blokih bo zagotovljen skupen razvoj, ki bo omogočal boljšo učinkovitost. Vsi segmenti bodo prej ali slej imeli opravka z izračunavanjem in napovedovanjem trajektorij letenja.

Koncept vodenja zračnega prometa osnovan na 4D trajektorijah je kljub vsemu še vedno precej oddaljen od dejanske uporabe. Dixon [5] trdi v poročilu o projektu NextGen: "Neprestane zamude pri razvoju zahtev in sprejemu ključnih odločitev bodo upočasnile NextGenov napredek. Nedavna analiza, ki jo je izvedel skupni načrtovalni in razvojni oddelek, že kaže, da nekatere avtomatizirane funkcionalnosti na tleh in v zraku, ki so bile načrtovane za leto 2025, ne bodo na voljo do leta 2035 ali celo kasneje, in bodo stale državo in uporabnike zračnega prostora bistveno več kot prvotno načrtovanih 40 milijard dolarjev."

A.1.3 Motivacija za to disertacijo

Preden bomo imeli na voljo rezultate projektov SESAR in NextGen, se moramo osredotočiti na izboljšave trenutnega koncepta vodenja z dovoljenji in sistemov, ki podpirajo vodenje zračnega prometa. Naša glavna motivacija je dati kontrolorjem zračnega prometa orodja, s katerimi bi lahko kmalu delali učinkoviteje z majhnimi in postopnimi investicijami. Ne moremo si privoščiti čakanja na nove sisteme z naprednimi metodami in pričakovati, da bo prinesli revolucionarne spremembe. Trenutna gospodarska situacija ni naklonjena velikim vložkom v drastične spremembe, ki bodo morda na voljo kasneje kot čez deset let.

Kontrolorji zračnega prometa bodo lahko načrtovali in vodili promet učinkoviteje, ko bodo lahko napovedovali poti letal dlje v prihodnost. Možnosti prikaza zračnih poti nudijo kontrolorjem zračnega prometa orodja, s katerimi lahko načrtujejo v zgodnejši fazi. Hitreje, ko identificiramo možen konflikt, manjši in manj intenziven letalski manever je potreben za njegovo razrešitev. Z manj intenzivnimi manevri in optimalnejšimi zračnimi potmi lahko prihranimo gorivo in čas. Morda za en let prihranek ni velik, toda za deset milijonov letov v enem letu, ki letijo v Evropi, se prihranki pomnožijo v velikanske številke.

Oprema na letalih zna izračunati trajektorije precej natančno, vendar teh podatkov trenutno ne moremo prenesti na zemljo. Šele, ko bo kontrola prometa zasnovana na trajektorijah, bo to možno. Ker ne vemo, kdaj se bo to zgodilo, moramo zdaj nekako izboljšati napovedi brez podatkov z letal.

Naša motivacija je zagotavljanje boljših vnosnih parametrov v metode za izračun trajektorij, ki se uporabljajo v kontrolah zračnega prometa. Te metode za izračun so namreč zelo odvisne od vhodnih parametrov. To so zmogljivosti in karakteristike letal in njihovih procedur ter vremenski pogoji. Z zagotavljanjem boljših vhodnih podatkov lahko pričakujemo, da bodo obstoječe aplikacije za izračun trajektorij delovale bolje z minimalnimi stroški in brez potrebe po velikih spremembah.

Izboljšati želimo sisteme v kontrolah zračnega prometa, ki izračunavajo, kdaj bo kontrolirano letalo preletelo določeno navigacijsko točko. Natančnejše napovedi nam omogočajo boljše načrtovanje in razbremenijo kontrolorje zračnega prometa. Ko so časi točni, se zmanjšajo potrebe po dodatni govorni komunikaciji o pogojih predaje letal med sektorji in poveča se propustnost zračnega prostora. Drugo področje uporabe so simulatorji. Simulatorji, ki so nujno potrebni za šolanje kontrolorjev zračnega

prometa, generirajo trajektorije za simulacijo prometa. Zaželeno je, da prikažejo čim bolj realno okolje. Ko se letala v simulatorjih obnašajo kot prava letala, to doprinese k realnejšemu okolju in bolj kakovostnim vajam.

Veliko aplikacij, ki vključuje funkcije za izračun trajektorij, je odvisnih od pravih vhodnih vrednosti o zmogljivostih letal in vremenskih podatkov. Naša rešitev, ki ponuja vhodne podatke za že obstoječe načine izračunavanja trajektorij lahko z majhnimi stroški izboljša izračune.

A.1.4 Operativne in funkcionalne omejitve sistemov za kontrolo zračnega prometa

Zaradi zagotavljanja varnosti so sistemi za kontrolo zračnega prometa podvrženi strogim postopkom certifikacije. Spremembe, ki jih predlagamo, ne spreminjajo osnovnih funkcionalnosti sistemov. Zagotavljajo le alternativen vir za preverjene in certificirane funkcionalnosti. Na ta način ni potrebno ponovno certificirati celotnega sistema, temveč ponovno ovrednotiti le obstoječe funkcionalnosti. Proces evalvacije in certifikacije je namreč drag in časovno zahteven. Naša rešitev ponuja minimalno spremembo obstoječih sistemov in je zato cenovno učinkovita tudi s tega vidika.

Pomembno je tudi, da sistem deluje zadovoljivo za vse lete. Varnost je enako pomembna za pogoste in redke lete. Ne moremo si privoščiti, da bi bile napovedi bistveno slabše za lete, ki se le redko pojavljajo. Zato moramo upoštevati vse podatke, ki se zbirajo v kontrolah zračnega prometa, in napovedi morajo avtomatsko vključevati tudi sveže podatke.

A.1.5 Cilji doktorske disertacije

Letalske zmogljivosti so lahko podane v različnih oblikah. Najpreprostejša oblika so statične tabele z zmogljivostmi ob različnih pogojih. Bolj napredna predstavitev uporablja fizikalne enačbe, ki opisujejo sile, ki delujejo na letalo.

Najbolj razširjen model za izračun trajektorij je fizikalni model Base of Aircraft Data (BADA), ki ga je razvil eksperimentalni center evropske organizacije za varnost v zračnem prometu (Eurocontrol Experimental Centre (EEC)). V tem modelu so letala razporejena glede na njihove splošne lastnosti, zmogljivosti, konfiguracijo in hitrostne karakteristike.

Kljub temu, da imajo letala lahko vse te lastnosti enake, pa ne letijo enako, saj se posamezna letala istega tipa razlikujejo še po vgrajeni opreми, različni upravljalci letal pa imajo tudi različne metode in prakse, kako učinkovito leteti.

Ne glede na to kako predstavimo zmogljivosti, naletimo na problem, da ista letala ne letijo enako. Na to vpliva še mnogo drugih dejavnikov.

Statične tabele letalskih zmogljivosti lahko izračunamo za določeno težo letala in določeno množico nastavitvev, ki opisujejo, kako letalo leti. Model BADA ponuja take tabele z nominalnimi vrednostmi parametrov. Te nominalne vrednosti so izračunane tako, da minimizirajo napako glede na razpoložljive podatke izdelovalcev modela. Za naš zračni prostor bi morale biti nominalne vrednosti drugačne in za vsako konfiguracijo bi morali imeti drugačne tabele.

Z uporabo fizikalnih enačb lahko uporabimo kot vhodne podatke maso letala in druge parametre za izračun trajektorije, vendar centri za kontrolo zračnega prometa žal nimajo informacij, ki bi jim omogočile prilagoditi vhodne vrednosti za te izračune. Lahko le ugibajo ali pa uporabijo nominalne vrednosti. Z nominalnimi vrednosti lahko izračunamo le enake vrednosti, kot so podane v statičnih tabelah.

Namesto nominalnih vrednosti moramo dobiti vhodne vrednosti, ki nam bodo omogočile izračune zmogljivosti, ki bodo vodile k natančnejšim trajektorijam. Centri za kontrolo zračnega prometa nimajo podatkov, ki bi jim to omogočali, ker jih v preteklosti niso nikoli potrebovali.

Podatki, ki so na voljo kontrolam zračnega prometa, so tisti, ki omogočajo varno in učinkovito vodenje prometa. Kontrole nadzirajo svoje zračne prostore in pridobivajo nadzorne podatke. Nadzorni podatki povedo, kje se letala nahajajo v vsakem trenutku. Za vsak let, ki leti skozi zračni prostor kontrole zračnega prometa, mora kontrola imeti osnovne informacije o letu, kar je razvidno iz načrta leta. Načrt leta mora vsak pilot oddati pred poletom in v njem piše, od kod letalo leti, kam leti, po kateri poti, itd. Zadnji vir podatkov, ki pomagajo napovedovati čase letenja skozi zračni prostor, so vremenski podatki. Vsi podatki so podrobno opisani v poglavju [A.2.2](#). Zbiramo jih v veliko podatkovno bazo, ki vsebuje vse informacije, kako letala letijo skozi naš zračni prostor.

Zračni promet je zelo konzervativna in strogo regulirana dejavnost. Preden bodo podatki pomembni za izračun natančnih trajektorij dostopni kontrolam zračnega prometa, bo preteklo še nekaj vode. Medtem bomo morali najti druge poti za izboljšavo izračunov. Če bi imeli že preproste podatke, kot je na primer vzletna teža letala, bi bili izračuni natančnejši. Vendar niti ti osnovni podatki niso na voljo kontrolam zračnega prometa.

Poleg podatkov iz načrtov letov obstajajo še druge, manj oprijemljive informacije,

kot so na primer upravljavčeve poslovne prakse ali lokalne posebnosti, ki se lahko med seboj razlikujejo.

Naša osnovna predpostavka je, da če je letalo letelo po določenem vzorcu v preteklosti, je precejšnja verjetnost, da bo to počelo tudi v prihodnosti. Isto letalo se lahko vzpenja bistveno drugače, ko leti na ustaljeni relaciji s poslovnimi potniki, kot ob drugi priložnosti, ko pelje turiste v oddaljeno letovišče. Oddaljen cilj zahteva več goriva na krovu in turisti običajno nosijo težjo prtljago. Z modeli, ki modelirajo letalske zmogljivosti, lahko razlikujemo take primere, če imamo nekaj dodatnih informacij o letu. Naša ideja je, da bi napovedovali zmogljivosti s pomočjo informacij o letu, ki na videz z zmogljivostmi nimajo neposredne povezave.

Naša glavna hipoteza je, da lahko z rudarjenjem po podatkih o preteklih letih in z uporabo strojnega učenja dobimo boljše parametre za izračun napovedi trajektorij.

Z radarsko opremo snemamo položaje letal in iz teh podatkov nato izluščimo zmogljivosti in parametre za vsak let posebej. Te podatke obogatimo še s podatki iz načrta leta, ki sicer nimajo neposredne povezave z zmogljivostmi letal. Kljub temu pa posredno dajo informacije o letalskih zmogljivostih. Na primer, odletno in priletno letališče določata dolžino letenja in nakazujeta na potrebno količino goriva. Količina goriva pa neposredno vpliva na vzletno težo letala. Nekateri podatki nam ponujajo dodatne informacije o tem, kako naj bi letalo letelo, drugi ne. Naš cilj je bil razviti algoritem, ki bo našel v množici podatkov tiste posredne kazalnike, ki najbolj vplivajo na letalske karakteristike. Na ta način lahko napovemo letalske zmogljivosti in izračunamo natančnejše trajektorije.

A.1.6 Operativne in funkcionalne omejitve predlagane rešitve

Z opisanimi zbranimi podatki lahko začnemo z napovedmi. Zahteve za napovedi nakazujejo, katere metode učenja so primernejše. Glavne zahteve za zbiranje podatkov in napovedi so:

- algoritem za napovedovanje naj uporablja tudi najbolj sveže podatke;
- podatkovna baza znanja naj se avtomatsko dnevno osvežuje brez potrebe po ročnih posegih;
- strojno učenje naj ne zahteva dodatnih preverb ali ročnih posegov zaradi novega znanja.

Glavno načelo procesa zbiranja znanja, procesiranja in učenja je, da je popolnoma avtomatsko.

Napovedovanje ne sme delovati dobro le za najbolj pogoste lete. Pomembno je, da leti, ki se pojavljajo redko, ne bodo obravnavani kot napake in, da napovedovanje zanje ne bo uporabilo kar napovedi bolj pogostih letov.

Ker se novi poleti pojavljajo vsak dan, lahko kadarkoli dobimo nove attribute o letih v podatkovno bazo. Izbrali smo pristop z učenjem na primerih, ki ščasoma sam izboljšuje napovedi za nove lete, ko ti začnejo redno leteti skozi naš zračni prostor.

Eden od naših zelo pomembnih ciljev je bil razviti tak sistem, ki ga je relativno preprosto replicirati. Potem lahko pričakujemo, da bodo potencialni uporabniki sledili našemu zgledu in si sami vzpostavili svoj sistem, ki jim bo omogočal boljše napovedi. Če bi bilo potrebno veliko finih nastavitvev in bi bila vzpostavitev sistema prekompleksna, bi to odvrnilo večino uporabnikov.

A.1.7 Kako lahko predlagano rešitev uporabimo v praksi

Naš glavni cilj je izboljšati splošno uporabljano in najboljšo metodo izračuna trajektorij.

Napovedi zračne hitrosti so že precej dobre in tu ne moremo pričakovati veliko točnejših časov preletov posameznih točk na poti. Lahko pa pričakujemo znatna izboljšanja pri vzponih in spustih. Navpični manevri niso zaželeni, ker si piloti želijo čim prej priti na potovalno višino in čim dlje ostati na njej. Ko natančneje napovedujemo vzpone in spuste, s tem pilotom dovolimo, da ostanejo dlje časa na potovalni višini. Lažje bi dosegli neprekinjene vzpone in spuste, če bi kontrolorji zračnega prometa vedeli točneje, kje in kdaj bo letalo izvajalo manevre, in koliko časa bo tak manever trajal. Tako bi lahko z večjo gotovostjo ugotovili, če bo neko letalo presekalo pot, kateremu od letal na višinah, ki jih bo preletelo. Vse te izboljšave omogočajo prihranke in povečujejo propustnost prometa.

Priporočamo, da sistemi obdržijo obstoječe metode za izračun trajektorij. Potrebno je spremeniti le vhodne parametre, ki se uporabljajo za izračune, z boljšimi.

Storitev napovedovanja mora ponuditi napovedi v razumnem času, da bodo lahko obstoječe aplikacije delovale enako kot doslej.

Ocenjujemo, da bi bila investicija, ki spreminja le vir vhodnih parametrov, bistveno nižja kot zamenjava in izboljšava obstoječih metod.

Napovedi smo ponudili v obliki spletnih storitev, da so lahko široko dostopne različnim uporabnikom. Ker je napovedovanje relativno preprosto, je vse, kar je potrebno, podatkovna baza s podatki o preteklih letih in spletna storitev, ki uporablja to podatkovno bazo. Obstoječe aplikacije bi tako dobivale vhodne parametre od storitve namesto iz statičnih tabel, kot jih zagotavlja model BADA.

A.1.8 Prednosti predlagane rešitve

Ocenili smo, za koliko lahko izboljšamo naše napovedi. Za primer vzemimo odsek leta, ki traja 100 s. Če z modelom BADA ocenimo čas leta na 120 s in naša napoved da vrednost 110 s, rečemo, da je napoved izboljšana za 10%. Napaka se sicer zmanjša z 20% na 10%, kar je 50% izboljšanje napake. Napoved časa letenja pa je za 10 s boljša, kar predstavlja 10% izboljšanje pri odseku trajajočem 100 s. Torej je napoved izboljšana za 10%.

Z opisano metodologijo lahko pričakujemo za hitrost letenja na potovalni višini izboljšanje napovedi le do 1%. Za hitrosti letenja med vzpenjanjem in spuščanjem so izboljšave že boljše – 1% do 3%. Najboljše rezultate smo dosegli pri napovedih hitrosti vzpenjanja in spuščanja. Za vzpenjanja lahko pričakujemo 2% do 10% izboljšanje, pri spuščanjih pa celo 10% do 20%.

Evropa je že investirala milijarde Eurov v programsko opremo za vodenje zračnega prometa in zaradi tako visokih vložkov je življenjska doba takih sistemov vsaj 20 let. Čakanje na zamenjavo takega sistema lahko traja zelo dolgo in ni nujno, da bodo novejši sistemi imeli boljši izračun trajektorij. Nerealna so tudi pričakovanja, da bo izračun trajektorij izboljššan v obstoječih sistemih.

Eden od ciljev boljših napovedi so tudi prihranki in zmanjšanje onesnaževanja. Letno preleti slovenski zračni prostor približno 300.000 letal. Če naredimo zelo površno oceno in privzamemo, da z našo izboljšavo prihranimo nekaj Eurov na let, ker smo optimizirali zračno pot ali zmanjšali zamudo, lahko pričakujemo milijon Eurov prihranka na leto samo v našem zračnem prostoru. Za tako nizek vložek se zdi prihranek kar velik. Če to razširimo na večji prostor in večji promet, so prihranki lahko še veliko višji.

A.1.9 Znanstveni doprinos

Glavni cilj te disertacije je boljši izračun trajektorij, ki bo združljiv z obstoječimi sistemi kontrol zračnega prometa. Če ne bi upoštevali splošnih omejitev obstoječih sistemov in načina, kako se ti sistemi uporabljajo, praktično ne bi bilo možnosti, da bi bili rezultati te disertacije uporabni v praksi. Najpomembnejši doprinos disertacije je radikalno nov koncept izračuna trajektorij, ki za vsak let posebej prilagodi parametre za napoved trajektorije. V disertaciji pokažemo, da je možno s pomočjo vedenja o preteklih letih bolje napovedati trajektorije kot s trenutno najboljšimi metodami.

Ostali znanstveni prispevki tega dela so:

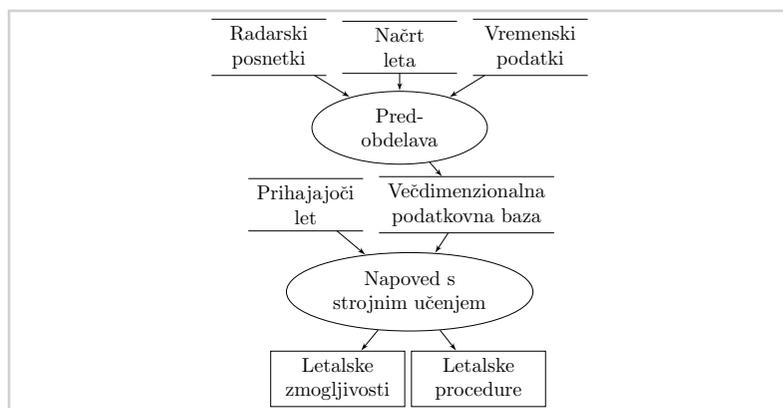
- nova, inovativna pot zajema vremenskih podatkov;
- postopno zbiranje podatkov iz treh ločenih virov v eno bazo znanja, ki jo lahko uporabimo za analizo, učenje in napovedovanje letalskih trajektorij;
- dinamično določanje letalskih zmogljivosti s pomočjo strojnega učenja;
- napovedovanje letalskih zmogljivosti na podlagi posrednih lastnosti brez kompleksnega fizikalnega modela;
- nova, inovativna metoda za določanje vhodnih parametrov statičnega modela BADA in omogočanje izračuna trajektorije, ki je prilagojen vsakemu letu posebej;
- preizkus in primerjava delovanja na realnih podatkih za obdobje petih let iz slovenskega zračnega prostora s približno 1.500.000 poleti.

A.2 Pristopi strojnega učenja in rudarjenja podatkov

Za celoten postopek zajema podatkov in napovedovanja so pomembni trije glavni viri podatkov, ki so na voljo centrom za kontrolo zračnega prometa:

- radarski posnetki,
- načrti letov in
- vremenski podatki.

Podatki se redno zbirajo z vseh treh virov in se pred-procesirajo, da so primerni za uporabo. Po pred-procesiranju podatke hranimo v večdimenzionalni podatkovni bazi, ki je vir znanja za napovedovanje. Ko potrebujemo napoved za nov let, poiščemo podobne lete v večdimenzionalni podatkovni bazi in napovemo zmogljivosti na podlagi znanja, ki se je nabralo do takrat. Celoten proces je prikazan na sliki A.1.



Slika A.1: Proces napovedovanja temelji na zbranih podatkih o letih, njihovih načrtih in vremenskih podatkih.

A.2.1 Pred-procesiranje

Podatke smo začeli zbirati v mesecu februarju leta 2011 in od takrat brez večjih prekinitev podatkovna baza raste vsak dan. Področje zbiranja posnetih trajektorij je razširjen slovenski zračni prostor do meja, kamor seže radarska pokritost Kontrole zračnega prometa Slovenije.

Za testiranje učinkovitosti in točnosti napovedi smo izbrali obdobje od januarja do decembra 2015. Za približno 265,000 letov iz tega obdobja smo napovedali letalske zmogljivosti in jih primerjali s posnetki, ki so zabeležili dejanske podatke o teh letih. Približno 1,250,000 letov zbranih v letih 2011 do 2014 so bili osnova za napovedovanje. Rezultati so predstavljeni v razdelku A.3.

A.2.2 Viri podatkov

Radarski podatki

Prvi vir podatkov so radarji, ki merijo položaje letal. Posamezen radar ob vsakem obratu zabeleži vsa letala, ki so v njegovem dosegu in javi njihove položaje kontroli zračnega prometa. Ker imamo več radarjev, ki med seboj ne morejo biti sinhronizirani, dobivamo neurejene in neuskklajene podatkovne tokove položajev letal iz več neodvisnih virov. Posamezni radarji tudi niso dovolj natančni, da bi le z njihovo pomočjo dovolj natančno izluščili letalske zmogljivosti. Potrebujemo predvidljivejši in natančnejši vir, ki ob rednih intervalih javlja položaje letal. V ta namen kontrole zračnega prometa uporabljajo napredno programsko opremo, ki združuje vse radarske podatke. Ta programska oprema upošteva natančnost, položaj in druge pomembne lastnosti posameznega radarja, da oceni, koliko je možno v danem trenutku zaupati njegovi meritvi. Z vsem tem in upoštevanjem splošnih lastnosti letalskih zmogljivosti programska oprema učinkovito izniči napake pri meritvah in posreduje izračunane najbolj verjetne položaje letal glede na meritve in vse upoštevane okoliščine. Ta programska oprema se imenuje sledilnik ("tracker"). Izhodni podatki sledilnika so primerni za obdelavo in izračun letalnih lastnosti posameznega leta.

Iz položajev letal izluščimo letalske zmogljivosti in druge parametre letenja. V naši raziskavi smo se osredotočili na dva vidika izračuna trajektorij letal, ki oba izhajata iz modela BADA.

Prvi zanemarja fizikalni model in izlušči gole letalne karakteristike iz trajektorije. Take karakteristike model BADA nudi v obliki tabel, ki jih izračuna iz fizikalnega modela. Tabele vsebujejo podatke o hitrostih letenja, vzpenjanja in spuščanja letala na različnih višinah in pri različnih vremenskih pogojih.

Drugi način je upoštevanje fizikalnega modela in izračun trajektorije s pomočjo vhodnih parametrov o fizikalnih lastnostih letala in podatkih o krmilnih funkcijah. Vhodni parametri za fizikalni model so tudi podani v obliki tabel, a tokrat so to podatki o teži letala in nekaj osnovnih hitrosti letenja. Vse ostale zmogljivosti dobimo z izračunom izbranih fizikalnih enačb za določen tip letala.

Prvi način imenujemo model letalskih zmogljivosti drugega pa model letalskih procedur.

Iz vsake trajektorije torej izluščimo dva tipa letalskih parametrov – gole letalske zmogljivosti in parametre letalskih procedur. Za letalske zmogljivosti izračun ni zahteven.

Potrebno je opredeliti posamezne faze leta (vzpenjanje, spuščanje, letenje na višini). Iz teh faz s pomočjo razlik v času in prostoru med posameznimi položaji letal izračunamo hitrosti vzpenjanja, spuščanja ali letenja.

Za model letalskih procedur je izračun kompleksnejši. Enačbe fizikalnega modela nam pomagajo izračunati letalske zmogljivosti, če imamo vhodne parametre. V našem primeru imamo posnetke trajektorij, iz katerih lahko izluščimo letalske zmogljivosti, dobiti pa moramo vhodne parametre. V ta namen smo fizikalne enačbe obrnili v drugo smer. Iz hitrosti vzpenjanja ali spuščanja letala tako, na primer, lahko izluščimo težo letala. Enačba za hitrost vzpenjanja ali spuščanja letala *ROCD* (Rate Of Climb or Descent) je:

$$\frac{dH_p}{dt} = ROCD = \frac{T - \Delta T}{T} \left(\frac{(Thr - D) \cdot V_{TAS}}{mg_0} \right) f(M) \quad (\text{A.1})$$

kjer so posamezne vrednosti:

<i>ROCD</i>	- hitrost vzpenjanja/spuščanja	[m/s]
H_p	- višina letenja po pritiskovnem višinomeru	[m]
$\frac{d}{dt}$	- sprememba po času	[s ⁻¹]
<i>T</i>	- standardna temperatura	[K]
ΔT	- odklon od standardne temperature	[K]
<i>Thr</i>	- potisk, ki deluje v smeri letenja	[N]
<i>D</i>	- zračni upor	[N]
V_{TAS}	- zračna hitrost	[m/s]
<i>m</i>	- masa letala	[kg]
g_0	- gravitacijski pospešek	[9.8m/s ²]
$f(M)$	- funkcija Machovega števila	[]

Enačbo **A.1** preuredimo in dobimo enačbo za maso letala:

$$m = \frac{T - \Delta T}{T} \left(\frac{(Thr - D) \cdot V_{TAS}}{ROCD \cdot g_0} \right) f(M) \quad (\text{A.2})$$

Žal ni tako preprosto, da bi samo vnesli podatke v enačbo **A.2** in bi izračunali maso. Zračni upor letala je funkcija mase in hitrosti. Torej ne moremo izračunati zračnega upora *D* brez mase. Z iterativno metodo podobno bisekciji kljub temu lahko dobimo oceno mase. Podobno iz drugih enačb izluščimo ostale parametre, ki jih shranjujemo v podatkovno bazo modela letalskih procedur.

Načrti letov

Vsak pilot ali njegova družba mora oddati načrt leta pred poletom. Poskrbeti mora tudi, da načrt leta prejmejo vse kontrole zračnega prometa, ki bodo na poti tega letala imela aktivno kontrolo nad letalom. Načrti letov vsebujejo mnogo pomembnih informacij o letu:

- pozivni znak letala,
- tip letala,
- odletno letališče,
- priletno letališče,
- načrtovano zračno pot z višinami in hitrostmi,
- načrtovan čas odhoda,
- načrtovan čas letenja,
- opremo letala,
- vrsto poleta,
- pravila letenja,
- itd.

Ko načrt leta koreliramo z radarsko sledjo, dobimo veliko dodatnih podatkov o letu. Radarska sled sama nam pove le položaj letala, hitrost, višino in identifikacijsko številko sledi.

Za naše napovedi so radarske sledi obogatene s podatki iz načrtov letov najpomembnejši vir znanja za strojno učenje in napovedovanje. Ta proces obogatitve podatkov dodaja pomembne attribute, ki jih pri napovedovanju uporabljamo za iskanje podobnih letov.

Vremenski podatki

Radarji merijo položaje letal glede na zemeljski koordinatni sistem. Ko iz dveh sosednjih položajev in časa preleta izračunamo hitrost letenja, je ta hitrost relativna na zemljo oziroma položaj radarja. Za letenje pa je pomembna zračna hitrost. Če želimo izračunati zračno hitrost, moramo poznati tudi veter, v katerem letalo leti.

Naslednji pomemben dejavnik je temperatura. Gostota zraka se spreminja s temperaturo in ta vpliva na vzgon letala. Pri nižjih temperaturah je zrak gostejši in vzgon je večji, medtem ko je pri višjih temperaturah ravno obratno. Vertikalni manevri letal so zato odvisni tudi od temperature in je pomembno poznati prave vrednosti, da lahko ocenimo točne zmogljivosti.

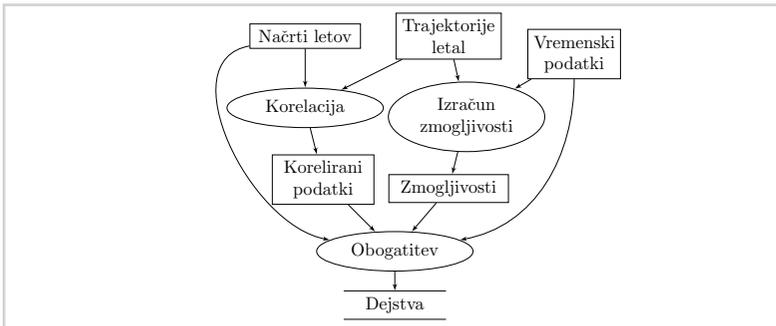
Vremenske podatke uporabljamo dvakrat. Kot smo že omenili, uporabljamo radar-ske posnetke letov, da iz njih izluščimo letalske karakteristike. Ker so radarji pri miru, lahko merijo le hitrost letala relativno na tla – talno hitrost. Za izračun zračne hitrosti moramo torej odšteti hitrost vetra. Od talne hitrosti torej vektorsko odštejemo hitrost vetra, da dobimo zračno hitrost, ki jo shranimo v podatkovno bazo.

Za vertikalne manevre moramo oceniti gostoto zraka oziroma temperaturo, da pravilno ovrednotimo hitrosti vzpenjanja in spuščanja. Ni dovolj, da vemo, kakšna je bila zmogljivost, temveč tudi, ob kateri temperaturi je bila zabeležena.

Vremenske podatke uporabljamo tudi pri izračunu trajektorij. Če želimo izračunati točne trajektorije, moramo prišteti vetrove zračnim hitrostim, da dobimo talne hitrosti in izračunati čase nad izbranimi navigacijskimi točkami. Podobno moramo uporabiti trenutno temperaturo, da čim točneje napovemo vertikalne manevre.

A.2.3 Združevanje, obogatitev in branjenje podatkov

Glavna značilnost predobdelave podatkov je njihovo združevanje v obogateno celoto, kot je ponazorjeno na sliki A.2.



Slika A.2: Po predobdelavi so zmogljivosti iz posnetih trajektorij obogatene s podatki iz načrtov letov.

Končni rezultat predobdelave je večdimenzionalna podatkovna baza, ki je zasnovana na tehnologiji Online Analytical Processing (OLAP). Taka podatkovna baza nam omo-

goča učinkovite poizvedbe po zmogljivostih podobnih letov. Z relacijsko podatkovno bazo bi bile poizvedbe bistveno počasnejše.

Zahteve za napovedi

Želimo, da se napovedovanje uporablja v sistemih za kontrolo zračnega prometa. To pomeni, da morajo biti napovedi podane v dovolj kratkem času, da ne predstavljajo problema pri procesiranju trajektorij v obstoječih sistemih. Algoritmi za izračun trajektorij običajno dobijo vhodne parametre iz vnaprej izračunanih statičnih tabel. Naša napoved mora nuditi podatke v enaki obliki s to razliko, da bodo naše napovedi dinamično določene v času, ko je bila napoved zahtevana. Tako bo lahko vsak let dobil napovedi, ki so prirejene točno zanj in se bodo razlikovale za vsak let. Napovedi so lahko v dveh oblikah: v obliki tabel modela letalskih zmogljivosti in v obliki tabel modela letalskih procedur.

Da bi iz podatkovne baze dobili lete, ki nam bodo pomagali napovedati zmogljivosti, moramo zmanjšati število iskalnih atributov. S primerno množico lastnosti bomo v podatkovni bazi našli lete, ki nam bodo dali dobre napovedi. Večdimenzionalna podatkovna baza hrani preko 30 lastnosti o letih, torej ima ravno toliko dimenzij.

Prvo redukcijo atributov smo opravili ročno tako, da smo odstranili tiste, ki so identični kakšnemu drugemu atributu, so le redko prisotni, ali iz kakšnega drugega razloga niso pomembni. Po tej ročni obravnavi je ostalo dvanajst atributov, ki so uporabljeni v metodah strojnega učenja. Predstavljeni so v tabeli 4.1.

Ročno smo torej prepolovili število atributov s trideset na manj kot petnajst.

A.2.4 Primerjava standardnih metod strojnega učenja

Z množico ročno izbranih atributov, ki jih bomo uporabljali za napovedi, imamo osnovo za primerjavo in ovrednotenje standardnih metod strojnega učenja.

Z manjšo naključno izbrano množico podatkov smo primerjali metode in ugotavljali, katere ponujajo najboljše rezultate.

Primerjave pokažejo, kako uspešno standardne metode strojnega učenja in naše metode napovedujejo parametre BADA, iz katerih izračunamo trajektorije.

Tabeli 4.2 in 4.3 prikazujeta povprečno napako napovedi za parametre BADA, ki so izračunani s standardnimi metodami strojnega učenja in z našimi metodami.

Tabeli 4.4 in 4.5 prikazujeta napako RRSE, ki pove, kako se napovedi obnašajo v primerjavi s povprečnimi vrednostmi. Izračun koeficientov je narejen po enačbah

4.2 in 4.3. Vrednosti manjše od 1,0 pomenijo boljše napovedi od povprečne vrednosti. Večje vrednosti od 1,0 povedo, da je napovedovanje slabo in, da nam, da boljše rezultate povprečna vrednost iz učne množice.

A.2.5 Opis našega algoritma za napovedovanje

Algoritem je podoben algoritmom z izbiro k najbližjih sosedov. Narava podatkov nam otežuje merilo za določitev razdalje med sosedi. Bližnjih sosedov namreč ne iščemo po podobnih zmogljivostih temveč po podobnih atributih. Ali imajo leti istega tipa letala bolj podobne attribute kot leti z isto destinacijo? V nekaterih primerih da, v drugih ne. Kot merilo za oddaljenost med sosedi smo izbrali število enakih atributov:

$$d_{x,y} = \sum_{i=1}^n [x_i \neq y_i] \quad (\text{A.3})$$

kjer so:

- $d_{x,y}$ - razdalja med dvema letoma x in y
- n - število atributov
- x_i, y_i - i -ti atribut

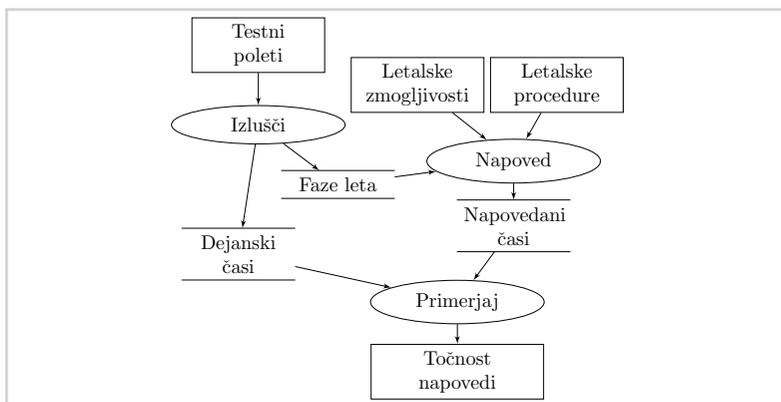
Več, kot imata dva leta enakih atributov, bolj sta si podobna in blizu. Vendar niso vsi atributi enako pomembni. Ni pomembno samo število podobnih atributov temveč tudi, kateri so. Naloga algoritma je tudi, da pri odstranjevanju lastnosti najprej odstrani najmanj pomembne. Tako lahko pričakujemo boljše napovedi.

Algoritem 1 najprej razporedi attribute in potem išče lete z izbranimi atributi. Če v podatkovni bazi ni dovolj letov z izbranimi atributi, algoritem odvzame najmanj pomemben atribut in ponovi iskanje. Vse to ponavlja, dokler ne dobi napovedi za vse zahtevane zmogljivosti.

Za razporejanje atributov lahko uporabimo različne pristope in s tem spreminjamo lastnosti in kakovost napovedi. Kot prvo smo uporabili urejanje po razpršenosti. Za attribute, ki imajo večji vpliv na zmogljivost, lahko sklepamo, da bodo imele vrednosti skoncentrirane bolj blizu. V tem primeru bo standardni odklon manjši. Pri atributih, ki nimajo vpliva na zmogljivost, pričakujemo večjo razpršenost. Eden od kriterijev, ki smo jih preizkusili je bil torej standardni odklon. Atributi so bili v algoritmu razporejeni po standardnem odklonu za vsako zmogljivost posebej. Algoritem je najprej odstranil attribute z najbolj razpršenimi vrednostmi.

A.3 Rezultati

Za testno obdobje od januarja do decembra 2015 smo za vse lete napovedali trajektorije enkrat z uporabo modela letalskih zmogljivosti in drugič z uporabo modela letalskih procedur. Napovedane čase letenja smo primerjali z dejanskimi časi in tako ovrednotili točnost napovedi. Celoten postopek je prikazan na sliki A.3.



Slika A.3: Postopek ocenjevanja točnosti napovedi

Za merilo točnosti napovedi smo izbrali povprečno absolutno napako, ker iz nje lahko hitro razberemo velikost napake. Implementirali smo veliko metod za napovedovanje, ki jih lahko razvrstimo v:

- napovedi z uporabo nominalnih vrednosti,
- standardne regresijske metode,
- napovedi z uporabo hevristične globalne izbire atributov pri iskanju k najbližjih sosedov,
- napovedi z dinamičnim izbiro atributov pri iskanju k najbližjih sosedov.

Prva skupina je referenca, ki ponazarja trenutne metode za izračun trajektorij. Druga predstavlja standardne metode za regresijo. Tretja in četrta skupina sta naši izvedenki algoritma k najbližjih sosedov, ki na različni način iščeta podobne lete.

A.3.1 Model letalskih zmogljivosti

Za model letalskih zmogljivosti smo primerjali pet predstavnikov različnih metod.

1. Prva metoda uporablja vrednosti iz tabel modela BADA. Uporabili smo zadnjo verzijo modela BADA in rezultate v grafih označili z *BADA 3.13*.
2. Druga metoda je neke vrste nadomestek za model BADA z razliko, da uporablja povprečne vrednosti za tipe letal iz naše podatkovne baze. V grafih je označena kot *AC Type Average*.
3. Tretja metoda je linearna regresija kot najboljši predstavnik standardnih metod strojnega učenja na naših podatkih. Označena je z *LR*.
4. Naslednja metoda prikazuje, kako se odrežejo napovedi, če ročno izberemo nekaj atributov, za katere menimo, da so pomembni. Seznam atributov je v razdelku 6.4. Ta metoda je označena kot *FA With Relaxation*.
5. Zadnja predstavljena metoda uporablja dinamično razvrščanje in izbiro atributov. Izbrali smo metodo, ki razvršča attribute po podobnosti. Označena je kot *DA - Similarity*.

Grafi so prikazani v razdelku 6.5.1. Rezultati kažejo, da so za hitrost letenja vse metode zelo enakovredne z manjšo prednostjo preprostih metod *AC Type Average* in *FA With Relaxation*. Pri vzpenjanju in spuščanju se slika spremeni. V vseh primerih so metode, ki napovedujejo iz podatkovne baze bistveno boljše od modela BADA z uporabo nominalnih vrednosti. Pri hitrosti spuščanja opazimo zanimivo lastnost modela BADA. Model namreč uporablja različne enačbe za troposfero in stratosfero. Tropopavzo, mejo med troposfero in stratosfero, je očitno težko točno določiti. Zato model BADA kaže velike odklone za napoved hitrosti spuščanja, ker na slepo preklopi model za ta del ozračja. Naše metode pri uporabi modela letalskih zmogljivosti ignorirajo fizikalni model, zato je ta napaka veliko manj očitna, čeprav je tudi vidna.

A.3.2 Model letalskih procedur

Pri napovedih z modelom letalskih procedur smo uporabili fizikalni model in iz njega izračunali zmogljivosti letal. Te zmogljivosti smo uporabili pri izračunu trajektorij. Predstavljene so naslednje izbrane metode.

1. Prva metoda uporablja vhodne vrednosti za privzetega upravljavca iz modela BADA. Uporabili smo zadnjo verzijo modela BADA. V grafih je označena kot *BADA 3.13*.
2. Podobno kot za model letalskih zmogljivosti smo za drugo metodo izbrali naše nadomestilo za model BADA, ki uporablja tip letala iz naše podatkovne baze za določitev vhodnih parametrov za fizikalni model. Metoda je označena kot *AC Type Average*.
3. Tretja metoda je tudi tokrat najboljši predstavnik standardnih metod strojnega učenja – linearna regresija. V grafih je označena kot *LR*.
4. Četrta metoda spet prikazuje, kakšne so napovedi, če ročno izberemo nekaj atributov. Tokrat smo izbrali metodo, ki uporablja utežena povprečja. Metoda je označena kot *FA With Relaxation W*.
5. Metoda z dinamičnimi lastnostmi, ki se najbolj izkaže za napovedi hitrosti, uporablja razvrščanje po razpršenosti. Označena je kot *DA - Dispersion*.
6. Metoda z dinamičnimi atributi, ki se je najbolj odrezala za vzpone in spuste je malo drugačna. Še vedno uporablja razpršenost, le za vrednosti uporablja utežena povprečja. Označena je z *DAW - Dispersion*.

Grafi so prikazani v razdelku 6.5.2. Tokrat imajo vse metode za tip letala vedno določen atribut, ki se ga ne da odstraniti. Naš model lahko vrne vrednosti vhodnih parametrov za fizikalni model, a brez tipa letala namreč ni mogoče ugotoviti, nekaterih vhodnih parametrov fizikalnega modela.

Rezultati kažejo, da je napovedovanje z dinamičnimi lastnostmi tokrat slabše kot pri napovedih za model letalskih zmogljivosti. Kljub temu so napovedi s statičnim razvrščanjem lastnosti še vedno boljše kot model BADA s privzetimi vrednostmi. Ker se za napovedovanje z modelom letalskih procedur uporablja fizikalni model BADA, imajo tokrat vse metode težave z napovedmi hitrosti spuščanja na tropopavzi.

A.4 Zaključek

Naša pričakovanja po izboljšanju napovedi smo dosegli. Pokazali smo, da lahko dinamično določimo vhodne parametre za vsak let posebej, ki so boljši od nominalnih. Na ta način dobimo boljše rezultate kot najboljše metode, ki so trenutno v uporabi.

Uporaba prilagojenih vhodnih parametrov je največja težava za uporabnike, saj nimajo sredstev ali znanja, da bi ugotovili, kakšne vrednosti imajo parametri za njihov zračni prostor.

Sistem, ki smo ga vzpostavili je relativno preprost in cenovno učinkovit. Ne zahteva, da uporabniki razumejo parametre oziroma, da jih poiščejo sami. Algoritem naredi to za vsak let posebej.

Pričakovali smo, da bodo metode strojnega učenja dale še boljše rezultate, a ta pričakovanja niso bila realna. Če strokovnjaki naredijo oceno in izberejo pomembne lastnosti, ki naj bi dale dobre rezultate, ne moremo pričakovati čarobnega recepta, ki bo drastično izboljšal njihove napovedi. Po našem mnenju je v tem primeru glavna prednost strojnega učenja in napovedovanja ta, da napoved dobimo hitreje in ceneje na podlagi velike količine zbranih podatkov in, da razbremeni ljudi.

Ob pregledu rezultatov ugotovimo, da z dobro izbrano strategijo lahko dobimo opazno boljše rezultate a ne drastičnega napredka. Večina metod strojnega učenja se je izkazala za boljšo izbiro kot nominalne vrednosti iz modela BADA.

A.4.1 Pričakovane izboljšave

Rezultati kažejo, da je uporaba snemanja zmogljivosti in njihova uporaba za napovedovanje prava smer za naprej. Pričakujemo lahko kar velike izboljšave napovedi. Napovedi hitrosti letenja so že sedaj zelo točne in pri njih lahko pričakujemo le 1% do 3% izboljšanje v primerjavi s statičnim modelom BADA. Pri hitrostih vzpenjanja in spuščanja so pričakovane izboljšave veliko večje. Za vzpone do 10%, za spuste pa celo do 25%.

Model BADA se ne izkaže tudi zato, ker je prirejen za širšo uporabo in ne vsebuje lokalnih posebnosti, ki smo jih mi zajeli s snemanjem prometa. V ta namen je bil razvit model letalskih procedur, ki ga lahko iz naše baze zgradimo za naš zračni prostor.

A.4.2 Možne uporabe predstavljenih rešitev

Čeprav naše metode vseskozi primerjamo z modelom BADA, ne predlagamo njegove zamenjave. Naš predlog je, da ponudimo vhodne parametre za model BADA na lažji in preprostejši način. Predlagamo tudi, da strojno učenje ponudi vhodne parametre prilagojene za vsak let posebej. Isti parametri za vsa letala niso prava rešitev. S podatki o letu lahko sklepamo o njem marsikaj in na podlagi tega lahko ponudimo boljše vhodne parametre.

Drugi način uporabe je izvoz letalskih zmogljivosti in napovedovanje brez uporabe fizikalnega modela.

V mnogih primerih, kjer računalniki pomagajo pri vsakdanjih opravilih, vidimo pristope podobne našemu. En pristop je z razumevanjem in modeliranjem opazovanega sistema. Na podlagi tega zgradimo algoritem zasnovan na pravilih. V algoritmu zasnovan na pravilih vstavimo vhodne podatke in po uporabi vnesenih pravil dobimo rezultate. Druga pot ignorira model in beleži veliko količino vhodnih in izhodnih podatkov. Potem z različnimi statističnimi metodami analizira podatke in ponuja rezultate na podlagi vnesenih vhodnih podatkov. S kombinacijo obeh pristopov običajno dobimo boljše rezultate kot samo z enim.

V takojšnji uporabi naše podatkovne baze vidimo dve potencialni smeri. Za model letalskih procedur lahko iz podatkovne baze izvozimo podatke o posameznih upravljavcih letal in jih ponudimo za izračune trajektorij v obliki tabel. Druga smer je uporaba strojnega učenja namesto uporabe statičnih tabel. Napovedovanje je dovolj hitro, da ga lahko uporabljamo v realnem času med vsakodnevnimi operacijami.

Vsi algoritmi za napovedovanje so ponujeni v obliki spletnih storitev. Obstoječe aplikacije, ki uporabljajo model BADA, lahko zamenjajo vir podatkov in uporabljajo spletni servis namesto statičnih tabel. Tako dobijo možnost boljših napovedi z majhnimi spremembami in minimalnimi vložki.

Podatkovna baza s podatki o velikem delu zračnega prostora pa postane dober kandidat za storitev, ki bi bila na voljo širši množici uporabnikov. V Evropi imamo dobre izkušnje s centraliziranimi storitvami. Eurocontrolov Network Manager Operations Centre (NMOC), nudi storitve na več področjih. Eurocontrol vpeljuje nove centralizirane storitve [51], ki bodo zagotavljale zanesljivo, enotno in cenejšo storitev za celo Evropo. Predlog za storitev izračuna 4D trajektorij ("CS2: 4D Trajectory Flight Profile Calculation for Planning Purposes Service (4DPP)" [52]) naj bi prinesla poenoten

izračun za vse. Taka storitev naj bi uporabljala model BADA. Prepričani smo, da bi z našimi dognanji lahko nastavili model, da bi nudil boljšo in cenejšo storitev za celo Evropo. Ne bi bilo več potrebe, da bi vsak uporabnik investiral sredstva in po svoje izračunaval vsak drugačne trajektorije.

A.4.3 Izboljšave in razvoj v bodoče

Metode in rešitve, ki smo jih prikazali odpirajo mnogo možnosti za izboljšave in prihodnji razvoj. Sami smo jih zaznali precej in predstavljamo jih le nekaj.

Kot smo pričakovali, so napovedi hitrosti precej natančne. Največ problemov povzročajo napovedi vzponov in spustov in na teh bo moral biti večji poudarek.

Rezultate raziskave bi lahko uporabili pri načrtovanju in uporabi procedur, ki temeljijo na zmogljivostih (performance based navigation (PBN)). V zadnjem času se veliko uporabljajo za optimizacijo zračnih poti, ki so prilagojene letalskim zmogljivostim in nudijo prihranke pri času ter gorivu. Po našem mnenju je to eden od prvih korakov proti končnemu cilju – konceptu vodenja prometa s trajektorijami.

Pokazali smo, da se nekatere metode izkažejo bolje na posameznih delih poti, druge pa na drugih. Priporočamo uporabo kombiniranih napovedi, kjer bi uporabili posamezne metode, za tiste dele, kjer so najboljše.

Natančnost napovedi bi lahko izboljšali s temeljito analizo uporabe parametrov. Analiza lahko pokaže, pri katerih uporabljenih atributih so bile napovedi najboljše. S temi podatki lahko prilagodimo napovedi in izboljšamo napovedi.

Za našo raziskavo smo vzeli podatke, ki so nam bili na voljo. Letališča imajo več podrobnosti o tovoru na letalih, vzletni teži, potnikih, itd. S temi informacijami bi lahko imeli celo boljše napovedi. Pridobivanje teh podatkov pa je izven področja te raziskave. Tudi, če bi mogoče dobili nekaj podatkov s katerega od bližnjih letališč, bi bilo to manj kot deset odstotkov letov. Letalo, ki vzleti v Londonu ali New Yorku, leti preko nas v Azijo. Pridobivanje podatkov od oddaljenih letališč je praktično nemogoče in presega okvirje te raziskave. Aktivnosti v tej smeri bi zahtevale leta ali desetletja. Zato smo se odločili, da vzamemo le podatke, ki jih imamo na voljo. Celo zbiranje podatkov za predlagani sistem je težko izvesti v večjih kontrolah zračnega prometa, kjer so podatki razpršeni po različnih oddelkih.

V naših napovedih smo računali le čase posameznih odsekov poti, ki so vidne našim radarjem. Te smo lahko testirali z izmerjenimi podatki. Naslednji korak bi lahko bil nadgradnja s sestavljanjem vseh odsekov v celoto. To zahteva računanje poti glede

na izpolnjen načrt leta in primerjavo z dejansko potjo. To zajema dodatni zajem in obdelavo podatkov navodil kontrolorjev zračnega prometa. Praktično nikoli dejanska pot letenja ni tista, ki je vnesena v načrt leta, ker kontrolorji nudijo letalom bližnjice, jih vodijo po varnih poteh na varnih razdaljah, jim omogočajo letenje okrog neviht, turbulenc in podobno. Podatkov o navodilih kontrolorjev še nimamo. Poleg tega so načrti letov daljši kot le let skozi nekaj sektorjev v naši okolici. Zato bi bila primerjava z načrti letov bolj ali manj zaenkrat še neuporabna.

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