İSTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

DATA-DRIVEN AIRCRAFT PERFORMANCE MODELS FOR IMPROVING BASELINE FUEL ESTIMATIONS

M.Sc. THESIS

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Department of Aeronautical and Astronautical Engineering

Aeronautical and Astronautical Engineering Programme

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

KALKIŞ ÖNCESİ YAKIT TAHMİNİNİ İYİLEŞTİRMEK İÇİN VERİ ANALİTİK HAVA TAŞITI PERFORMANS MODELLERİ

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To my family,

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ABBREVIATIONS

ATM	: Air Traffic Management
BADA	: Base of Aircraft Data
TAS	: True Airspeed
CAS	: Calibrated Airspeed
CMB	: Climb Phase
CRZ	: Cruise Phase
DES	: Descent Phase
FL	: Flight Level
LIDL	: Low Idle
APM	: Aircraft Performance Model
TBO	: Trajectory Based Operation
AFM	: Aircraft Fuel Model
QAR	: Quick Access Recorder
FP	: Flight Plan
MSL	: Mean Sea Level
B738	: Boeing 737-800 Aircraft
Aircraft#1	: To Define First B738 Aircraft
Aircraft#2	: To Define Second B738 Aircraft

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DATA-DRIVEN AIRCRAFT PERFORMANCE MODELS FOR IMPROVING BASELINE FUEL ESTIMATIONS

SUMMARY

In this era, modern life in globalized World forces people to live faster compared to previous times. The need which is caused to satisfy this pace incurs some industries a huge responsibility. Aviation industry is one of these main industries. Therefore, there is an enormous cash flow to the industry. As a result of this massive influx of cash even a minor cost reduction in aviation makes a great difference in Global perspective.

This expected growth of aviation industry in Globe, force researchers to design improved Air Traffic Management (ATM) technologies and procedures. In order to increase capacity of the system and its efficiency while reducing environmental impact and maintaining safety regulations. To overcome these challenges, new automation and information systems are being developed and this new global operational concept is called Trajectory Based Operations (TBO).

In aviation, there are some associations such as, EUROCONTROL, IATA, ICAO, ATCA, which focus on Air Traffic Management (ATM). These associations have partnership with operating airlines and aircraft manufacturers such as, Boeing, Airbus, Cessna on projects to reduce fuel consumption.

These partnership relations provide Aircraft Performance Model (APM) documents like BADA to researchers which is an input of TBOs. The BADA APM is designed to simulate and predict the trajectories of aircraft in order to ATM research and operations. The parameters of aircraft performance and trajectories can be calculated using information and data contained in BADA. In order to simulate reality for both operational and research modeling each and every real aircraft needs a corresponding aircraft model and due to experimental study BADA also provides models.

Nowadays in every single moment of 24 hours of a day, there are at least 10000 commercial aircraft cruise in Worldwide. This situation causes to a huge fuel cost in aviation industry and every year there are hundreds of studies to reduce this cost in global. Via new techniques in computer science, aircraft can be modeled better compared to past and as a result of these better models we can get more precise results in our studies. Undoubtfully, Earth does not have infinite sources. Therefore, the motivation of this study focuses to determine fuel consumption of airliners more precisely by using artificial neural network techniques due to reduce the cost which is caused by unnecessary additional fuel.

In trajectory side both deterministic and probabilistic methods are tried but with the improvements in computation science World turn its face to the machine learning algorithms. The motivation of this thesis is improving baseline estimations of aircraft performance models with data-driven methods.

In computer science, python is mostly preferred due to its more understandable nature compared to other coding languages. It is also one of the most effective software language for complicated systems such as aircraft. To be clear, modeling and simulating an aircraft is a very complex interdisciplinary profession. Therefore, python is preferred in this study due to its advantages. In this study Keras, Pandas, Numpy, Scipy, Mxnet, Matplotlib, Bokeh, Glob and Sklearn libraries are used.

Firstly, formulas and technical parameters in BADA document are coded into computer environment. Quick Access Recorder (QAR) is used to store all information for flight in aircraft. It is also known as black box data. Secondly, for this thesis QAR data for the given aircraft which are B738 AC#1 (219 flights), B738 AC#2 (563 flights). QAR data for all flights are modified due to necessity and merged according to their tail number and separated to 3 according to flight phases such as, climb, cruise and descent. After that, these 3 modified and merged csv files are converted to binary to be used in machine learning.

Secondly, artificial neural network algorithms such as Adam algorithm are applied to these binary files. In order to achieve a better learning a lot of method is used in thesis. Black-box model is created in order to control accuracy of data-driven APM. By the results of Black-box model it is easily seen that Black-box model and actual QAR data matches more than %99. After that Throttle/Auto-Throttle model which is the main aim of the thesis study is created. However, standing alone APM model is not sufficient.

Thirdly, to obtain more healthy comparison, these trained models integrated to belonged flight plans and fuel results are compared with each other. In this phase, several data process is applied to the flight plan data. The main reason of data process is originated to the sensor characteristics. On the other hand, it is obvious that, following flight plan completely is impossible due to several reasons such as unexpected weather conditions or high traffic density which is managed by air traffic control (ATC). To overcome these situations an implementation algorithm is used in thesis.

KALKIŞ ÖNCESİ YAKIT TAHMİNİNİ İYİLEŞTİRMEK İÇİN ANALİTİK HAVA TAŞITI PERFORMANS MODELLERİ

ÖZET

İçinde bulunduğumuz globalleşmiş modern hayat, insanoğlunu hayatın her alanında geçmiş zamanlara kıyasla daha hızlı yaşamaya zorlamaktadır. Bu hızlanmayı karşılama ihtiyacı bazı endüstrilere diğerlerine kıyasla daha büyük sorumluluklar yüklemektedir. Havacılık ise bu endüstrilerin en önemlilerinden biridir. Bu ihtiyacın bir neticesi olarak havacılık endüstrisine her yıl inanılmaz büyüklükte para akışı sağlanmaktadır. Bu büyük para akışının neticesinde havacılıkta yapılan görece küçük bir masraf azaltımı bile global perspektiften bakıldığında büyük farklılıklar yaratacaktır.

Havacılık endüstrisinde beklenen bu büyüme, araştırmacıları hava trafiği yönetimi teknolojilerini geliştirmeye zorlamıştır. Bu gelişim sistem kapasitesini ve efektifliğini arttırmak amacındadır ancak bunun yanında çevresel etkileri gözetmeli ve güvenlik regülasyonlarına uymak zorundadır. Bu meydan okumaları aşmak amacıyla otomasyon ve informasyon sistemleri geliştirilmiş ve yeni bir operasyonel konsept olan yörünge bazlı operasyonlar oluşturulmuştur.

Havacılıkta, hava trafiğine yoğunlaşmış EUROCONTROL, IATA, ICAO, ATCA ve benzeri kurumlar mevcuttur. Bu kurumların hava taşıtı üreticileri olan Boeing, Airbus, Cessna gibi şirketler ve bazı hava yolu şirketleriyle yakıt tüketimini azaltmaya yönelik proje ortaklıkları mevcuttur.

Günümüzde 24 saatin her anında, sivil taşımacılık yapan en az 10000 hava taşıtı gökyüzünde seyr-ü sefer etmektedir. Bu durum havacılık endüstrisinde korkunç bir yakıt maliyetine sebep olmaktadır ve Dünya çapında bu maliyeti azaltmak üzere her yıl yüzlerce çalışma yapılmaktadır. Bilgisayar bilimindeki yeni teknikler sayesinde hava taşıtları geçmişe kıyasla daha iyi modellenebilmekte ve bunun sonucu olarak kesinliği daha yüksek sonuçlar çalışmalarda elde edilmektedir. Şüphesiz Dünya sonsuz kaynağa sahip değildir. Bu yüzden bu çalışmanın motivasyonu sivil hava taşımacılığındaki yakıt tüketiminin yapay sinir ağları ile daha kesin olarak belirlemek ve buna bağlı olarak uçuşlarda alınan fazla ek yakıtın sebep olduğu ek maliyeti azaltmaktır.

Havacılıktaki kurumların işbirliği, araştırmacılara BADA gibi hava taşıtı performans modelleri temin eder. BADA performans modeli hava trafiği yönetimi araştırmaları ve operasyonlarında yörünge simülasyonu ve kestirimi yapması amacıyla dizayn edilmiştir. Hava taşıtı performansı parametreleri ve izlenecek yörünge BADA'nın sağladığı data ile hesaplanır. Hem operasyonel hem de simülasyon ve modellemede gerçekliği kopyalamak için her hava taşıtı kendisine tekabül eden bilgisayar ortamında bir modele ihtiyaç duyar ve BADA deneysel çalışmalar sonucu bu modeli bize sağlar. BADA benzeri simülasyon bazlı hava taşıtı performans modellerinin haricinde veri analitik hava taşıtı performans modelleri de mevcuttur. Bu modellerin ortaya çıkması simülasyon bazlı sistemlerin siber-fiziksel sistemlerdeki

yetersizliklerinden kaynaklanır. Hava taşıtlarının da içinde bulunduğu siber-fiziksel sistemler, sensör ve aktüatörler yardımıyla fiziksel dünyaya bağlanan çoğunlukla ekstrem komplikasyona sahip sistemlerin genel adıdır. Bu gibi komplike sistemlerde simülasyon bazlı performans modeli kullanmanın önünde pek çok engel vardır. Bu engellerin doğrultusunda veri analitik modeller, siber-fiziksel sistemlerde simülasyon bazlı modellere kıyasla gözlenen verinin sistem performansına hassasiyetini monitör edebilmek gibi büyük avantajları bünyesinde barındırır.

Havacılığın yörünge tarafında hem deterministik hem de olasılıksal methodlar denenmiş ancak artan işlem gücüyle Dünya yüzünü makine öğrenmesi algoritmalarına dönmüştür. Çalışmanın motivasyonu veri analitik modeller kullanarak hava taşıtı modellerinin referans tahminlerini iyileştirmektir.

Veri analitik modeller isminden de anlaşıldığı gibi informasyon ve bilgisayar bilimleriyle iç içedir. Bilgisayar biliminde, python en çok doğası gereği diğer programlama dillerine kıyasla daha anlaşılabilir olması gereğiyle tercih edilir. Ayrıca hava taşıtları gibi komplike sistemlerde en efektif kodlama dilidir. Daha açık olmak gerekirse, bir hava taşıtını modellemek ve simüle etmek disiplinler arası uzmanlık isteyen çok kompleks bir işlemdir. Bu yüzden python avantajları sebebiyle bu çalışmada tercih edilmiştir. Bu çalışmada Keras, Pandas, Numpy, Scipy, Mxnet, Matplotlib, Bokeh, Glob ve Sklearn kütüphaneleri kullanılmıştır. Bu kütüphanelerden keras ve mxnet, çalışmanın yapay sinir ağları bölümünde, scipy, numpy, glob ve pandas kütüphaneleri veri yönetimi ve işleminde ve son olarak matplotlib ve bokeh kütüphaneleri de veriyi monitör etmek amacıyla kullanılmıştır.

Çalışma kapsamında ilk olarak, BADA dökümanındaki toplam enerji formülü, itki formülleri, sürükleme formülleri, kaldırma formülleri benzeri tüm temel oluşturacak formüller ve teknik parametreler bilgisayar ortamına entegre edildi. Bunun akabinde, uçaklarda uçuş anındaki bilgileri saklamak için kullanılan kara kutu verileri olarak da bilinen QAR verileri veri işlemeden geçirildi. Bu çalışma kapsamında QAR verileri 2 uçaktan alınmış olup bu uçakların ikisi de Boeing 737-800 modelidir. Kullanılan uçuş verileri, 1 numaralı hava taşıtı için 219 uçuş ve 2 numaralı hava taşıtı için B738 563 uçuş olarak sağlanmıştır. Tüm uçuşlar için olan QAR bilgileri kuyruk numaraları baz alınarak ihtiyaç doğrultusunda modifiye edilmiş akabinde birleştirilmiş ve 3 uçuş fazlarına göre (Tırmanma, seyr-ü sefer, alçalma) ayrılmışlardır. Bundan sonra modifiye edilen ve birleştirilen 3 csv (virgul ile ayrılmış değer dosyası) dosyası ikili sisteme çevrilmiş ve makine öğrenmesinde kullanılmıştır.

Makine öğrenmesi işleminde, bu ikili sistem dosyalara adam algoritması gibi yapay sinir ağı algoritmaları uygulanmıştır. Daha iyi bir öğrenme temin edebimek için bu çalışmada pek çok method kullanılmış ve birbirleriyle kıyaslanmış, sonucunda veri veri analitik model için en uygun olanı kullanılmıştır. Kara kutu modeli veri analitik modelin doğruluğunu kontrol etmek amacıyla tasarlanmıştır. Kara kutu modeli sonuçlarına gore bu model gerçek QAR sonuçlarıyla %99 üzeri bir uyum sağlamıştır. Bundan anlaşılacağı gibi giriş bilgisi olarak QAR verilerini kullanan kara kutu modeli çıktı olarak gerçeğe çok yakın değerler vererek uçağın bilgisayar ortamına çok yüksek bir başarı oranıyla aktarılmasını sağlamıştır. Bunun akabinde Gaz kolu/Otomatik Gaz Kolu modeli ki bu tez çalışmasının ana amacı doğrultusunda tasarlanan model yaratılmıştır. Yapısı gereği Gaz Kolu/Otomatik Gaz Kolu modeli ikili sisteme çevrilmiş verileri kullanarak mevcut uçuş için gaz kolu değerlerini çıktı olarak veren bir modeldir. Bu gaz kolu çıktıları daha sonra kara kutu modeline girdi olarak verilip yakıt tüketimi hesaplanır. Ancak sözü edilen modeli tasarlamak kalkış öncesi yakıt tüketimi tahminini iyileştirmek için tek başına yeterli değildir.

Bu sebeple üçüncü olarak daha sağlıklı bir karşılaştırma yapmak amacıyla bu eğitilmiş modeller ilgili uçuş planlarına entegre edilmiş ve yakıt tüketimleri karşılaştırılmıştır. Çalışmanın bu bölümünde uçuş planı verisine pek çok informasyon işlemi uygulanmıştır. Bunun temel sebebi beklenmedik hava koşulları ya da hava trafiği kontrolörleri tarafından yönetilen yüksek hava trafiği yoğunluğu sebebiyle uçuş planını tamamen izlemenin imkansız olmasından kaynaklanır. Bu sorunu aşmak amacıyla uygulama algoritmaları kullanılmıştır.

Modellenen uçuşlar bireysel olarak da incelenmiş ve gaz kolu değerlerinin gerçek uçuşlara kıyası yapılmıştır. Sonuç tatmin edici olup gerçek QAR gaz kolu değerlerine fazlasıyla yakın ve karakteristik olarak benzer yapıdadır. Yapılan bu işlemler sonunda veri analitik modelin, BADA hava taşıtı performans modeli ve saber (uçuş planı yakıt tüketimi) değerlerine göre daha gerçekçi ve iyi sonuçlar verdiği gözlenmiştir.

1. INTRODUCTION

Flying has always been one of the greatest passions of humans in history. There has been more than 100 years after Wright Brothers developed first practical fixed-wing aircraft [1]. These numerous pioneers took the first steps to create modern-days one of the greatest industries. As a result, hundreds of airline companies have been established today in commercial aviation industry. After the Second World War, numerous progressions made by military aviation were actualized in commercial aviation. The USA had a head start on Europe and thusly the more grounded position to rule the market [2]. To illustrate the enormous size of aviation industry, 4,831,576 flight operation has been planned only by US airline companies in 2018 [3]. Industrialization brings some problems with itself. The biggest problem was competition.

Competition between airline companies leads the companies to run research and development projects in order to provide their services much cheaper. Basically, an airline company's costs can be categorized under three main steps which are flight operating costs (FOC), ground operating costs (GOC) and system operating costs (SOC). Most of the total cost is occurred due to FOC and as expected the main cost of FOC is fuel cost. Consequently, fuel cost is the major cost of operating an airliner as expected [4]. There are studies which are focused to reduce the main cost of operating an airliner, fuel cost, on different perspectives. In other words there are different systems to control fuel consumption such as modification on aircraft, execution enhancement retrofits, air traffic management (ATM) rebuilding and refreshed flight operation strategies [5]. Today's and tomorrow's ATM is faced with numerous challenges: capacity increase, safety improvement, diminished environmental impact and cost decrease [6, 7]. This study applies an approach in ATM in order to reduce fuel cost of airliners.

This approach is based on creating a new aircraft performance model (APM) which contains an artificial neural network (ANN) in itself. Basically, ANN is a concept which is inspired by human brain which aims to solve problems in computer environment. During the 1960s, it was demonstrated that systems of such model neurons have properties just like the human brain: these neurons can perform pattern recognition, and they can work regardless of whether a portion of the neurons are extinguished [8]. Nowadays, Python is the most suitable software language for ANN applications. Therefore, python is used in the part of computerize in this study.

The computerized material in this study is constituted the fundamental of base of aircraft (BADA) documentation which is established by EUROCONTROL. This ANN based computerization is performed due to inadequacy of BADA APM in some conditions such as high noise mostly based on wind effect.

The study presented in this thesis is based on the previous work done by Mevlut Uzun et. al [9]. The methodology and architectures of deep neural networks are replicated and the study is extended by applying the same framework on Boeing 737-800 aircraft.

1.1 Motivation

It is an undoubted fact that humanity achieved incogitable technological revolutions since its first ancestors who were appeared 50000 years ago. It is an obvious observation that the technological pulse is advancing in an exponential way. The progressions that industrialization brought were considerably faster than any past period of technological change [10]. To illustrate, technologic improvement which has been improved between the end of Second World War and nowadays is much greater than the previous human history. Surplus value which has created by humans is the reason of this exponential improvement. There are two main parameters which cause to high surplus values of last 70 years compared to previous ages these are, World's population increase and the superposition principle which is valid in technology. For instance, there is a significant product difference between produced wheat which is produced by one farmer who uses traditional harvesting equipment and methods and one hundred farmers with advanced farming machines and modern agriculture methods. To continue this progression, there is a huge responsibility on researchers and scientists. It is an undeniable fact that the resource of Earth is not infinite and reaching its maximum limit is depended on how we use these resources more efficiently.

One of the major costs of the aircraft is fuel cost. Before take-off the amount of fuel which is needed to achieve operation goal is determined by flight crew or flight dispatcher. Main problem of this phase in terms of cost efficiency is caused by additional fuel which aircraft does not need to accomplish its task. To reduce this additional fuel cost aircraft baseline fuel needs to be calculated more accurately. Taking everything into the consideration the motivation of this thesis is making a contribution to the aviation industry. To put a finer point on it, this study focuses to predict fuel consumption of airliners more precisely by using artificial neural network techniques due to reduce the cost which is caused by unnecessary additional fuel.

1.2 Literature Review

In air traffic management (ATM), aircraft is the main component of the system. As a result, in research and development (R&D) studies a realistic computerized aircraft model is needed to control system better. This model is called aircraft performance model (APM). For command and control inputs based on aircrafts position, atmospheric pressure, temperature and airspeed, APM provides response of aircraft [11].

The main purpose of an APM is providing an accurate and full realistic aircraft performance model. Also APM has to contain some specialities. APM must be capable to provide accurate computation on geometric and kinematic subjects. Also APM needs to be applicable for different aircraft types. On the other hand, being applicable for a chosen state of flight is not sufficient standing alone. APM has to be applicable over the entire operation flight envelope and in all flight phases APM has to provide computing requirements [12]. There are numerous approaches to APM in this modern era. However, these approaches can be easily categorized to 2 main subjects such as simulation models and data-driven models.

Simulation models are also known as knowledge-driven are very common to analyze system performance. These kind of models are preferred mostly in aircraft engine modeling by reason of simulation models use a great understanding of system performance in physical point of view. Unfortunately, simulation models can be constitute an impediment where they applied to complex systems such as aircraft [13].

The description data-driven implies that advancement in a movement is constrained by data, instead of by instinct or by personal experience. Considerable majority of modern engineering systems are instrumented with embedded sensors, controllers, actuators, and computational components. General name of this kind of systems are also known as Cyber-Physical Systems (CPS) [14, 15]. A data-driven process in a CPS is basically separated to two main steps. Firstly, in a CPS structure the sensors provide data in order to monitor system performance. In our case, the sensors data which are used in the study is quick access recorder (QAR) data. Secondly due to the development in information and computation sciences the sensor data which obtained in first stage is cooperated with technologies such machine learning algorithms in order to develop a better model compared to current one before data-driven improvement application. It can easily be said that data-driven methods are more capable to provide more realistic estimations of Cyber-Physical systems performance compared to simulation-based models due to two main reasons. First of all, data-driven models are much better at demonstrating sensitivity of observed data in system performance. To be more precise, data-driven methods do not depend on modeling assumptions. Secondly, in complex problems which are need a solid understanding in fundamentals to be solved by simulation-based models can also be analyzed by data-driven models without complete understanding in these fundamentals due to data-driven models characteristics [16]. Briefly, based on its nature the data-driven modeling approach looks promising for applications in near future due to its satisfactoriness about data monitoring [17].

In practice data-driven methods mostly use statistical machine learning techniques to develop its model. Such algorithms like classification and regression process sensor data in order to connect input and output. In machine learning firstly, algorithm creates a mathematical model of sample data which is also known as training data, to perform predictions or decisions without being certainly programmed like simulation-based scenarios to perform the objective [18, 19]. More clearly the advantage of using statistical techniques is the opportunity of predicting the outputs of a new set of inputs. Also it provides the system stochastically instead of deterministically. In the real world most of the systems are stochastic. To illustrate, aircraft is disturbed by random external forces such as wind.

As stated before in this thesis data-driven method is used. The main reason by choosing this methodology is caused by aircraft itself. Since aircraft is a perfect example of a CPS. There are several sensors on an aircraft which provides a significant number of data such as calibrated airspeed, true airspeed, altitude, aircraft mass, fuel flow, heading angle, etc. Before neural network models, working on data-driven models for aircraft is respectably restricted compared to today. In order to achieve the aim of this study artificial neural network algorithms are used in thesis.

As stated, there are several existing approaches to aircraft performance modeling nowadays. Kinetic approach models aircraft forces, while kinematic approach directly models the aircraft flight path characteristics without attempting to model the underlying physics [20].

The result of the thesis is structured as follows. Initially, data-driven aircraft performance model is explained. Then a formal definition is given of the baseline fuel estimation problem. *Aircraft Model* section gives the details about aircraft performance model based on BADA 4. *Data Used In Thesis* section provides an understanding of data used in study which are QAR and FP data. *Data Driven Aircraft Performance Model* section provides information about neural network concepts and preparation of data. The section also introduce Black-Box model and Throttle/Auto-Throttle Estimation model which are designed in order to solve the problem. *Application on Flight Plan* section explains how BADA 4 and Throttle/Auto-Throttle model is implemented to the flight plan. Also this section compares fuel consumption results between them. In A *Brief Example* section throttle values of one of the flights is examined. *Conclusion* section summarizes the method.

2. PROBLEM DEFINITION

In aviation, time is money. To put a finer point on it, each additional second to complete operation or each unnecessary additional fuel causes to cost more for airline companies or military organizations. There are numerous cost types in aviation as stated before. Also as stated, main parameter in cost analysis of an aircraft operation is fuel cost. To keep costs in minimum the efficiency of the operations must be increased. In civil aviation, operation time of an aircraft is depended to the air traffic control (ATC). On the other hand, baseline fuel is estimated by flight crew or flight dispatcher. The main problem which is aimed to be solved in the thesis is finding the answer of the question which is "Can we use data-driven techniques on operational flight data to have a better estimate of fuel flow?". The problem in determination of baseline fuel with simulation based models is that simulation based models depend to the assumptions and out of their assumption envelope they give incorrect outputs. Note that, to overcome envelope overstepping which is caused several reasons during flight such as performance changes during flight artificial neural network (ANN) is used to upgrade baseline performance model and convert it to the data-driven model in this study. The problem of cost caused by unnecessary additional fuel which is caused by inadequate accuracy of baseline fuel estimation is leaded this thesis.

3. AIRCRAFT MODEL

One of the most important fundamental process in this thesis is aircraft modeling. Due to the high expenses in aviation industry most of the time it does not give the opportunity to work experimental to the researchers. To overcome this financial problems researchers use mathematical based aircraft models which are, of course, obeys laws of physics [21]. In this part of the thesis, aircraft motion model and BADA model is explained.

3.1 Aircraft Motion Model

The modeling of aircraft motion is very important for aircraft flight performance analysis. There are two main parameters in aircraft motion model. These are forces and moments which creates equations of motions. Basically, there are four forces which are always applied to an operating aircraft. These are Thrust, Lift Force, Drag Force and aircraft mass. A simplified aircraft motion model is shown in Figure 3.1.

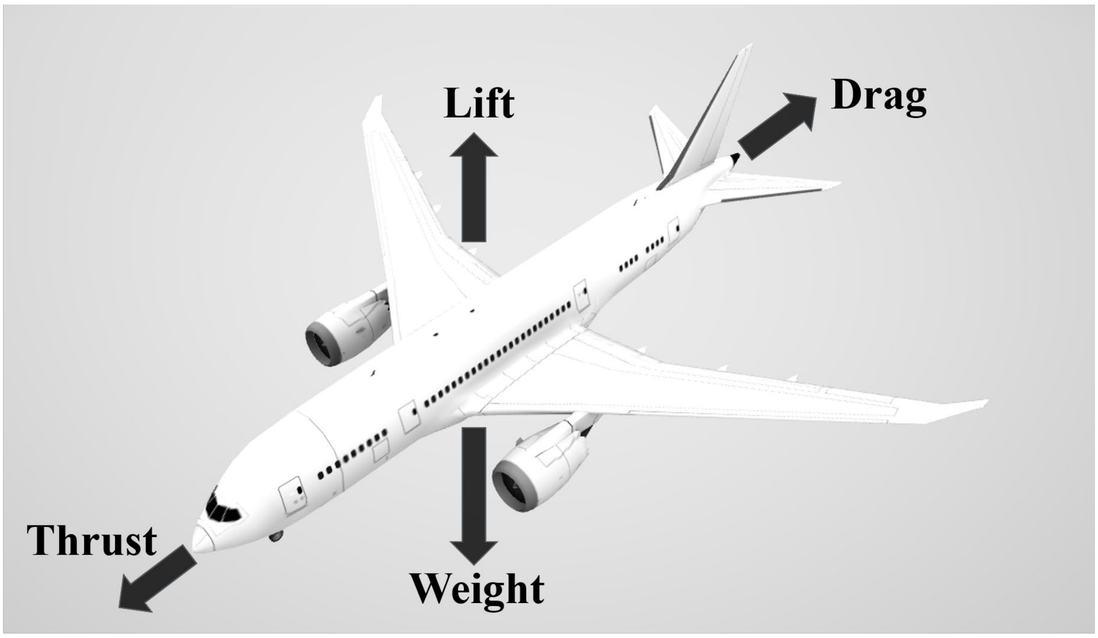


Figure 3.1: Four Forces on an Aircraft.

The interaction between these four forces gives the information about aircraft motion. To illustrate, if the weight is decreased due to burning fuel in a constant lift force the aircraft will climb. Also the interaction of these forces creates moments which are applied to aircraft. Taking forces and moments into the considerations the aircraft equations of motions is showed below,

$$\dot{x}_1 = x_4 \cos(x_5) \cos(u_3) + w_1 \tag{3.1}$$

$$\dot{x}_2 = x_4 \sin(x_5) \cos(u_3) + w_2 \tag{3.2}$$

$$\dot{x}_3 = x_4 \sin(u_3) + w_3 \tag{3.3}$$

$$\dot{x}_4 = -\frac{C_D S \rho {x_4}^2}{2x_6} - g sin(u_3) + \frac{u_1}{x_6} \tag{3.4}$$

$$\dot{x}_5 = \frac{C_L S \rho x_4}{2x_6} \frac{\sin(u_2)}{\cos(u_3)} \tag{3.5}$$

$$\dot{x}_6 = -F \tag{3.6}$$

Where, the state variables of the aircraft are the horizontal position (x_1 and x_2), altitude (x_3), the true airspeed (x_4), the heading angle (x_5) and the mass of the aircraft (x_6). The control inputs of the aircraft are the engine thrust (u_1), the bank angle (u_2) and the flight path angle (u_3). The wind acts as a disturbance on the aircraft dynamics, which is modeled by the wind speed, W= (w_1, w_2, w_3) [22].

3.2 Aircraft Performance Model: BADA

This part of the thesis focuses to explain BADA but before explaining BADA there are some phenomenon have to be introduced such as, dynamic density, air traffic management (ATM) systems and aircraft performance model (APM). Nowadays, aviation industry has a much more rapid growth more than ever. In this era, more and more aircraft cruise everyday due to the operating aircraft needs of the globalized World.

To befittingly satisfy traffic management need in air zones, ATM systems has been developed with the help of APMs. Basically, ATM systems are being used to contain all systems that aid aircraft to depart from its starting point, transit airspace, and land at its point of destination. ATM systems include Air Traffic Services (ATS), Airspace Management (ASM), and Air Traffic Flow and Capacity Management (ATFCM). A productive ATM framework requires arranging of traffic flows that depend on exact estimation of aircraft performance. New operational ideas, that will guarantee consistent administration of the determined development of air traffic and give expanded limit capacity, depend on aircraft trajectory prediction [23]. Of course, ATM systems main aim is provide safety as stated but the output information which are provided by ATM is also open a new door into cost reduction dependent to safety obligations. For instance, ATM gives a chance to compare data from a specific path for different aircraft or same aircraft different flights.

To get more precise results from ATM is strongly depends on the APMs accuracy, in this thesis BADA 4 APM documentation which is a EUROCONTROL project is used since its higher accuracy compared to other APMs like BADA 3. The Aircraft Performance Model embraced by BADA depends on a mass-varying, kinetic methodology. This methodology models an aircraft as a point and requires demonstrating of underlying forces that causes aircraft movement. The BADA APM is organized into three models: Actions, Motion and Operations and Limitations. The action model permits the calculation of the forces following up on the aircraft which cause its movement (aerodynamic, propulsive and gravitational) and related fuel consumption. The Total Energy Model, which identifies with the geometrical, kinematic and kinetic parts of the airplane motion, is utilized to compute aircraft performances and trajectory. The Operations model gives information about the manner in which the aircraft is operated, important to figure related aircraft motion. The Limitations model confines the aircraft conduct with the end goal to keep it between specific breaking points to guarantee the sheltered task of the aircraft. The comparing numerical models are communicated in the type of polynomial articulations [24]. Basically, BADA is an APM which is relevant for airplane trajectory recreation and forecast inside the domain of Air Traffic Management. The BADA 4 APM structure is shown in Figure 3.2.

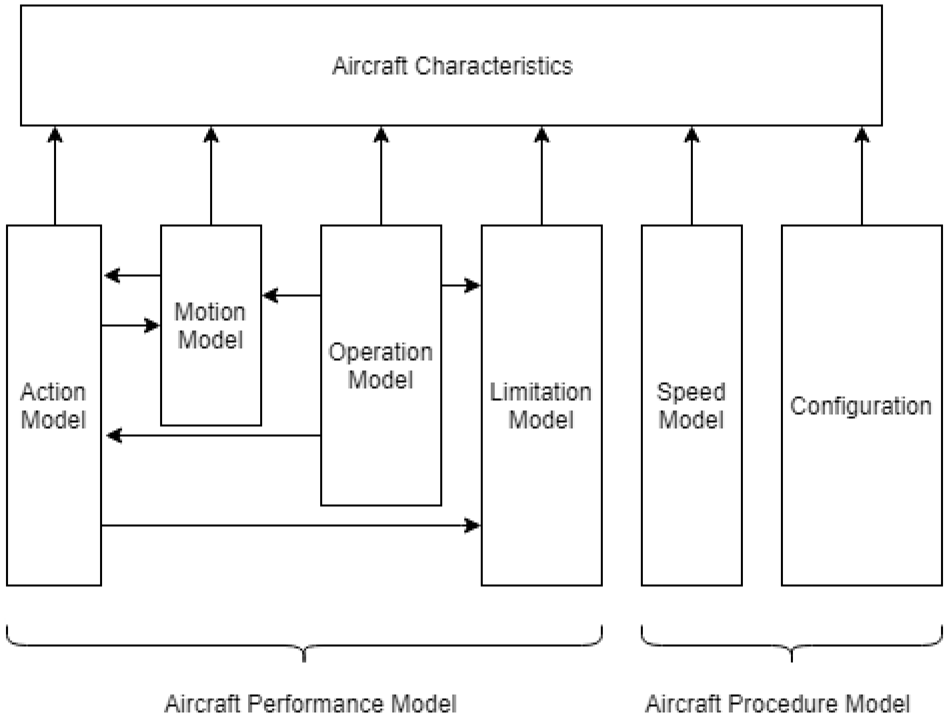


Figure 3.2: BADA 4 APM structure.

3.2.1 Action model

As stated, action model allows the computation of the forces acting on the aircraft which cause its motion such as, aerodynamic, propulsive and gravitational forces and also action model is associated with fuel consumption.

3.2.1.1 Gravitational model

Gravitational model includes weight force. To determine weight force [N], the formula which is shown below is used,

$$W = m\,.\ g_0 \tag{3.7}$$

Where, m is the aircraft mass [kg] and g_0 is the gravitational acceleration $[\frac{m}{s^2}]$ which is equal to 9.80665.

3.2.1.2 Aerodynamic model

The aerodynamic forces are the consequence of the interaction of the aircraft outer surface with the atmosphere during flying through it. These forces are affected by outer surface gadgets such as, high-lift devices, landing gear and speed brakes. It is also affected by the phenomenon such as, the atmospheric properties, and the Mach number. The Aerodynamic Forces and Configurations Model (AFCM) portrays the aerodynamic forces and the conceivable aircraft aerodynamic designs.

In aerodynamic configuration, BADA APM contains the coefficient information to calculate aerodynamic forces depending to the state of the aircraft. For example, Figure 3.3 which is shown below is a basic demonstration of a part of the APM.

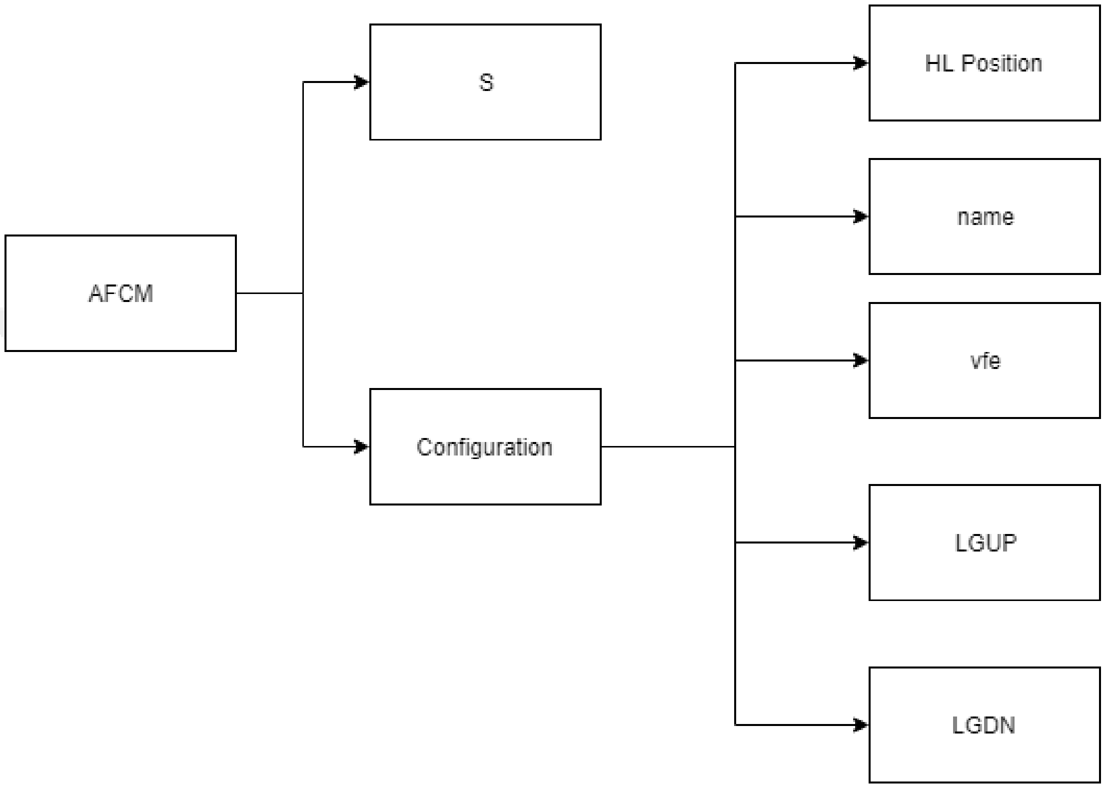


Figure 3.3: BADA 4 APM AFCM scheme.

The lift coefficient, C_L , is determined assuming that the flight path angle is zero. However, a correction for a bank angle is made. Lift coefficient is shown below,

$$C_L = \frac{2 \,.\, m \,.\, g_0}{\delta \,.\, p_0 \,.\, \kappa \,.\, S \,.\, M^2 \,.\, cos\emptyset} \tag{3.8}$$

The lift force, L [N], is then determined from the lift coefficient in the standard manner via,

$$L = \frac{\delta \,.\, p_0 \,.\, \kappa \,.\, S \,.\, M^2 . C_L}{2} \tag{3.9}$$

where, m is the aircraft mass [kg], g_0 is the gravitational acceleration [$\frac{m}{s^2}$], δ is the pressure ratio [-], p_0 is the standard atmospheric pressure at MSL [Pa], κ is the adiabatic index of air, S is the wing reference area [m^2], M is the Mach number [-] and Ø is the bank angle [rad].

The drag coefficient, C_D, is indicated as a component of the lift coefficient C_L and the Mach number M. The type of this relationship relies upon the aircraft aerodynamic configuration. BADA Family 4 proposes two formulas to calculate the drag coefficient: a detailed one for the clean configuration, which takes into record the compressibility of air at high Mach numbers, and a simplified one for non-clean configurations, since those designs can't be utilized at high Mach numbers. In this thesis, due to the data characteristics the clean configuration is used except landing phase. Therefore C_D and Drag force formulas which are used for thesis except landing phase are shown below. On the other hand, non-clean BADA formulas are used for landing phase.

$$C_D = scalar\,.\,[C_0 + \,(C_2 + \,C_L^2) + \,(C_6\,.\,C_L^6) \tag{3.10}$$

with,

$$D = \frac{\delta\,.\,p_0\,.\,\kappa\,.\,S\,.\,M^2.\,C_D}{2} \tag{3.11}$$

where, scalar is a scaling factor [-] from BADA, C_L is the lift coefficient [-], M is the Mach number [-], δ is the pressure ratio [-], p_0 is the standard atmospheric pressure at MSL [Pa], κ is the adiabatic index of air, S is the wing reference area [m^2] and other coefficients are clean drag coefficients [-], from BADA.

3.2.1.3 Engine thrust

There are 3 different thrust model in BADA 4 APMs Propulsive Forces Model (PFM) section. These are TurboFan Model (TFM), TurboProp Model (TPM), Piston Engine Model (PEM). In this thesis TFM is used. The general formulation of thrust is shown below,

$$Th = \,\delta\,.\,W_{mref}\,.\,C_T \tag{3.12}$$

where, δ is the pressure ratio [-],. W_{mref} is the weight force and C_T is the thrust coefficient [-].

A turbofan engine might be worked either by direct control of the throttle, or using predefined settings, called ratings. The accompanying appraisals are demonstrated for turbofan motors: low idle thrust (LIDL), maximum climb thrust (MCMB) and maximum cruise thrust (MCRZ). The MCMB and MCRZ ratings have their own individual arrangement of coefficients yet share same equations, while the LIDL rating is modeled by various formulas.

Non idle rating is used for MCMB and MCRZ and no rating which means direct throttle input. The generalized thrust which is used in this thesis is a function of mach and throttle parameter.

3.2.1.4 Fuel consumption

As stated on previous section BADA APM contains 3 engine thrust model as a result of this, it contains 3 different fuel consumption model depending on engine type. General fuel consumption formula which is shown below,

$$F = \delta \,.\, W_{mref} \,.\, C_F \,.\, a_0 \,.\, L_{HV}^{-1} \,.\, \theta^{1/2} \tag{3.13}$$

where, δ is pressure ratio [-], θ is temperature ratio [-], W_{mref} is the weight force [N], a_0 is the speed of sound at MSL, L_{HV}^{-1} is the fuel lower hearing value $[\frac{m^2}{s^2}]$ from BADA and C_F is the fuel coefficient [-].

3.2.2 Motion and operation model

This part of BADA APM is define the system of equations that describes the aircraft motion, as well as different ways of operating the aircraft. The main tool used in this section is Total energy model which is briefly stated before.

3.2.2.1 Total energy model

In a deeper perspective, The Total Energy Model (TEM) is defined as the rate of work which is done by forces stated in Action section on the aircraft to the rate of increase in potential and kinetic energy. TEM is calculated via formula which is shown below,

$$(Th - D) - V_{TAS} = mg_0 \frac{dh}{dt} + mV_{TAS} \frac{dV_{TAS}}{dt} \tag{3.14}$$

where Th is the thrust acting parallel to the aircraft velocity vector [N], D is the aerodynamic drag [N], m is the aircraft mass [kg], h is the geodetic altitude [m], g0 is the gravitational acceleration [m/s2], V_{TAS} is the true airspeed [m/s] and $\frac{d}{dt}$ is the time derivative [s^{-1}]. Coefficients of total energy model is shown in Figure 3.4.

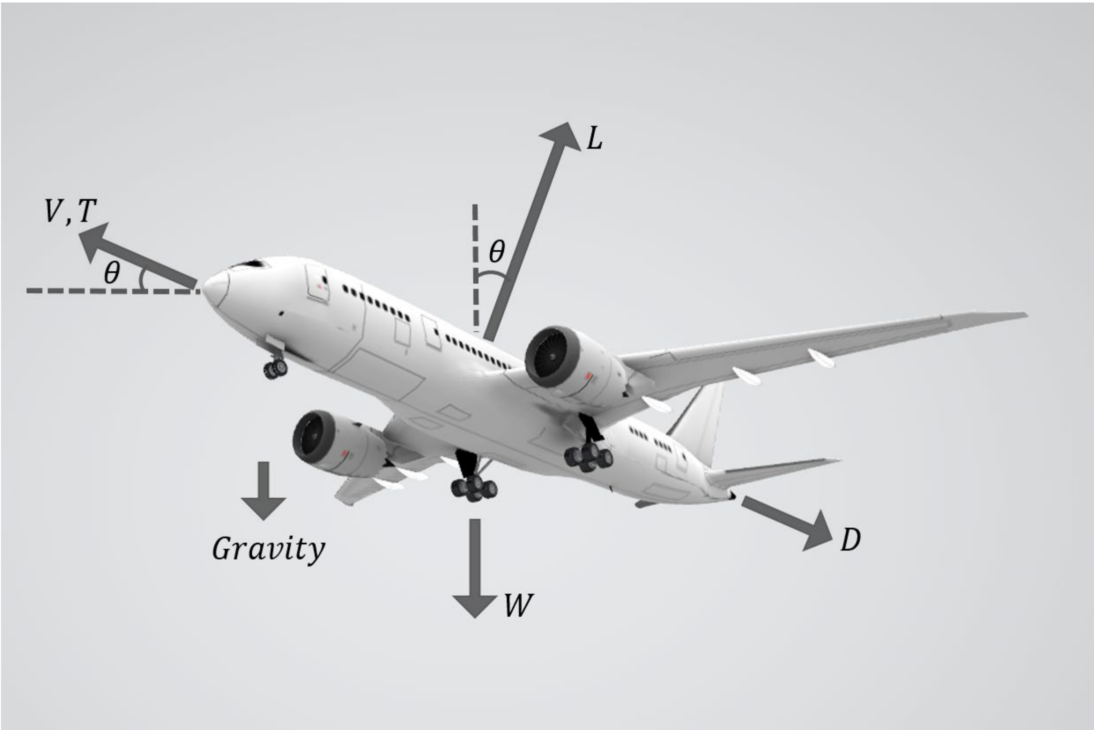


Figure 3.4: Basic demonstration of forces affecting on aircraft.

3.2.2.2 Aircraft control laws

By ignoring the effect of devices such as spoilers, leading-edge slats or trailing-edge flaps, there are 2 main control inputs which effect vertical trajectory of an aircraft. These control inputs are throttle and elevator. Via controlling only 2 of thrust, speed and rate of climb or descent (ROCD) the other one can be calculated due to aircraft control law. These control laws aid us to compare our results. To illustrate, for controlled thrust and speed we can calculate ROCD is shown below,

$$ROCD = \frac{T - \Delta T}{T} \frac{dh}{dt} \tag{3.15}$$

Via isolating $\frac{dh}{dt}$ in TEM formula we get,

$$ROCD = \frac{T - \Delta T}{T} \frac{(Th - D) - V_{TAS}}{mg_0} \left[1 + \left(\frac{V_{TAS}}{g_0}\right)\left(\frac{dV_{TAS}}{dh}\right)\right]^{-1} \quad (3.16)$$

The exponential part which as -1 is called energy share factor as $f\{M\}$.

$$f\{M\} = \left[1 + \left(\frac{V_{TAS}}{g_0}\right)\left(\frac{dV_{TAS}}{dh}\right)\right]^{-1} \quad (3.17)$$

This leads to ROCD equals to,

$$ROCD = \frac{T - \Delta T}{T} \frac{(Th - D) - V_{TAS}}{mg_0} f\{M\} \quad (3.18)$$

Energy share factor (ESF) is an important parameter for our thesis results comparison because there are some specific ESF values for specific phases and values. For instance, in stratosphere for constant Mach in cruise ESF equals to 1.

3.2.3 Limitation model

There is a limitation model in BADA 4 APM which contains geometric, kinematic, buffet, dynamic and environmental limitations. Which avoid go out of boundaries of the real world. For example, for geometric limitations maximum geopotential pressure altitude, for kinematic limitations maximum calibrated airspeed as regards to high-lifting devices and landing gears positions or maximum accessible mach number in safety envelope, for buffet limitations maximum lift coefficients or minimum mach number to avoid stall, for dynamic limitations mass and load factor gaps, for environmental limitations maximum and minimum temperature deviations.

In this thesis, limitations are considered in behalf of conserve physical reality and avoid non-realistic results. Taking everything into the consideration BADA 4 APM is separated as which is shown in Figure 3.5 and the parts of its which are used in thesis are explained in this section.

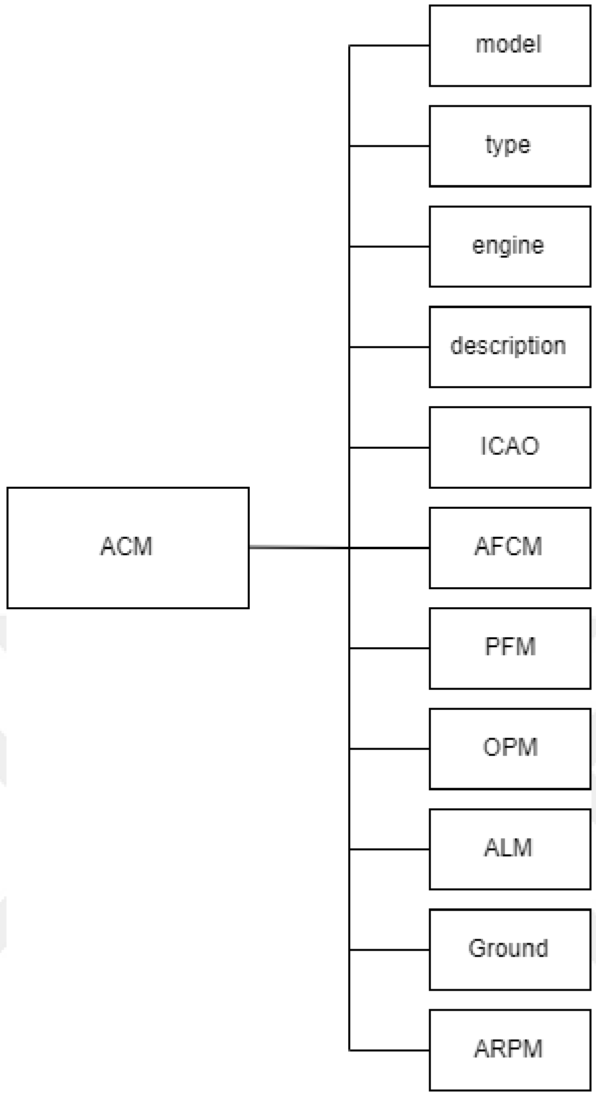


Figure 3.5: BADA 4 APM scheme.

4. DATA USED IN THE THESIS

In this thesis, quick access recorder (QAR) data and flight plan (FP) data is used. The QAR data is used to create aircraft performance in two different ways. Firstly, QAR is used directly in order to create performance model by providing values such as true airspeed, calibrated airspeed, mach number, etc. Secondly it is used indirectly in order to create performance model by providing needed values to calculate BADA equations such as drag, thrust, etc. The FP data is used to complete data-driven model by integration with neural network model.

4.1 Quick Access Recorder

Crashed protected flight recorders which is known as “black box” is a compulsory component of any commercial or private aircraft. It contains 4 main systems: a Flight Data Recorder (FDR), a cockpit voice recorder (CVR), an airborne image recorder (AIR) and a data link recorder (DLR) [25]. With today’s technology, image and data link recording can be recorded on either FDR or CVR. A demonstration of a FDR system is shown in Figure 4.1.

Figure 4.1: Flight Recorder

First FDR is invented in 1956 by Dr. David Warren, an invention which has transformed the amount of information available in air accident investigations [26]. Purpose of the FDR is monitoring and saving information which is provided by aircraft sensors several times per second such as altitude, temperature, speed, etc. At first, FDR is invented for safety and become a safety regulation but after that researchers noticed that they can use FDR data for their studies. It was very useful at the beginning but with advancing technology FDR remained incapable on the basis of providing data for researchers.

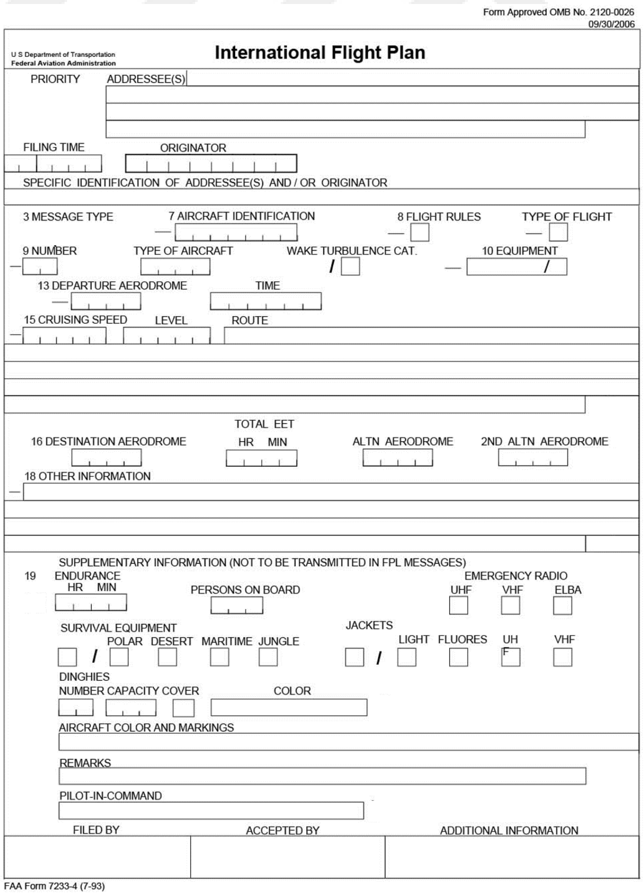
Based on this, Flight Operational Quality Assurance (FOQA) or Flight Data Management (FDM) programs are created. The goal of a FOQA program is to utilize flight information to distinguish specialized defects, risky practices, or conditions outside of desired working techniques early enough to enable convenient mediation to turn away mishaps or incidents. These programs are intentional endeavors via carriers that include preparing aircraft with particular gadgets to persistently record up to several diverse flight data parameters from aircraft systems and sensors, examining the information, recognizing patterns, and making a move to adjust potential issues. The examination of flight information enables aircraft to reproduce whole flights based on the qualities after some time of flight data parameters, for example, heading, altitude, throttle settings, ground speed, and numerous others [27].

Quick Access Recorders (QAR) which is one of the most popular FOQA data recorder gadget becomes popular due to their design it was much more lightweight. To illustrate, L3Aviation has a micro QAR model which has a SD card inside of it and total weight is lighter than 170 grams as seen in Figure 4.2, but that was not the only reason. QAR is designed to provide quick and easy access to raw flight data [28]. Due to its characteristic, QAR monitors avionic sensors and records over 2000 flight parameters which provide bigger and better information compared to FDR.

4.2 Historical Flight Plans

Flight plan (FP) is a document which is filled by pilot or flight dispatcher in order to explain their intentions in flight and send specific data to the aviation authorities. Therefore, a FP represents the basic contract between a pilot and air traffic control. FP arrange is indicated in Document 4444 of ICAO. Most part of the FP contains simple information, for example, departure and arrival points, evaluated time in transit, exchange air terminals if there should arise an occurrence of dangerous climate, type of flight (regardless of whether instrument flight rules [IFR] or visual flight rules [VFR]), the pilot's information, number of passengers on board. International flight plan is shown in Figure 4.3.

Figure 4.2: Micro Quick Access Recorder.



Form Approved OMB No. 2120-0026
09/30/2006

U S Department of Transportation
Federal Aviation Administration

International Flight Plan

PRIORITY ADDRESSEE(S)

FILING TIME ORIGINATOR

SPECIFIC IDENTIFICATION OF ADDRESSEE(S) AND / OR ORIGINATOR

3 MESSAGE TYPE 7 AIRCRAFT IDENTIFICATION 8 FLIGHT RULES TYPE OF FLIGHT

9 NUMBER TYPE OF AIRCRAFT WAKE TURBULENCE CAT. 10 EQUIPMENT

13 DEPARTURE AERODROME TIME

15 CRUISING SPEED LEVEL ROUTE

16 DESTINATION AERODROME TOTAL EET HR MIN ALTN AERODROME 2ND ALTN AERODROME

18 OTHER INFORMATION

SUPPLEMENTARY INFORMATION (NOT TO BE TRANSMITTED IN FPL MESSAGES)

19 ENDURANCE HR MIN PERSONS ON BOARD EMERGENCY RADIO UHF VHF ELBA

SURVIVAL EQUIPMENT POLAR DESERT MARITIME JUNGLE JACKETS LIGHT FLUORES UH VHF

DINGHIES NUMBER CAPACITY COVER COLOR

AIRCRAFT COLOR AND MARKINGS

REMARKS

PILOT-IN-COMMAND

FILED BY ACCEPTED BY ADDITIONAL INFORMATION

FAA Form 7233-4 (7-93)

Figure 4.3: International Flight Plan.

Fundamentally, FP is used to secure that the aircraft can achieve its goal, with satisfying the prerequisites of aviation authority, to avert midair incidents. On the other hand, complying to the regulations converts FP to a useful source to compare fuel cost of the flights routes. To find least costly route to achieve cost reduction, flight planning tools are created by airlines.

4.2.1 Flight planning tools

In order to reduce cost, most of the airlines aim to improve the accuracy of their flight plans. Baseline fuel is one of the major parameters which effects operating cost. To illustrate in some conditions, flight dispatcher can elect to add more fuel which is needed to complete the flight as planned. On the other hand, the heavier aircraft causes to burn due to extra weight and increases operating costs and emissions.

To accomplish cost reduction which is caused by incorrect baseline fuel estimation and non-optimal cruise, airlines use computerized flight planning tools which gives useful output such as optimal speed for current phase in flight, trip fuel, total departure fuel and how it is allocated, what route on ground to follow, and what profile in altitude to cruise. There is an example of output of a computerized flight planning tool in Figure 4.4.

To determine best route of a flight is an independent operation for each flight. These operations include forecast upper air winds and temperature, the payload on the aircraft, and the time-based costs of that day. This situation turns flight planning to a time-based dynamic problem. Wind effect is the major parameter in this process and it cannot be underestimated [29]. There can be a huge of distant between great circle route and planned route. The reason of this difference is that there are two establishments in the world which gives forecast wind data which is used in flight planning tools. These establishments are U.K. Meteorological Office and U.S National Weather Service which updates winds in every six hours. Figure 4.5 is a good illustration of direct route (shortest path) and planned route (least cost path).

```
                              COMPUTER FLIGHT PLAN
SPEED SKD      CLB-250/340/.84      CRZ-CI40      DSC-.84/320/250

                FUEL    TIME
POA ZBAA       224000   10/31
ALT ZBTJ       006100   00/15
RESV           008500   00/30
CONT           011200   00/40
REQ            249800   11/56
XTR            000000   00/00
TOT            249800   11/56

KSEA..YVR J528 TRENA J488 UAB..YYD NCA34 YXY J515 FAI J502 OTZ B244
FRENK G902 ASBAT B337 URABI G212 DABMA W74 SABEM G332 GITUM GIT01A ZBAA

FL  300/YVR   320/YYD   340/FRENK 348/BUMAT 381
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Figure 4.4: Computer Flight Plan.

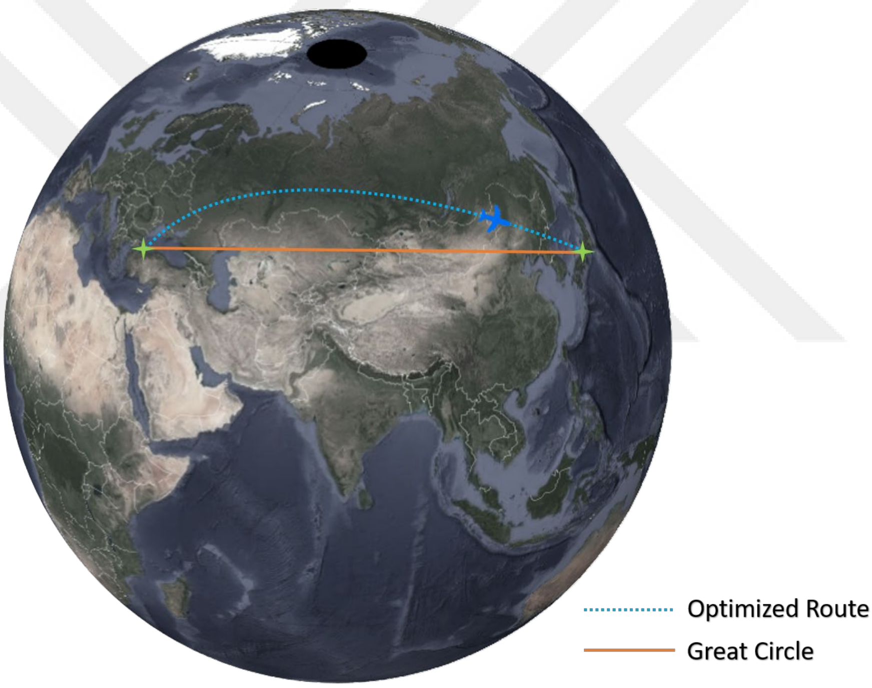


Figure 4.5: Optimized Route vs Great Circle.

5. DATA DRIVEN AIRCRAFT PERFORMANCE MODEL

Main objective of this thesis is determining fuel consumption of a commercial aircraft more accurate compared to today methods. The most famous APM fuel model is BADA 4 which is documented by EUROCONTROL but due to environmental disturbances, for example wind effect, applying BADA APM causes misleading results. To illustrate, comparison of fuel consumptions of BADA fuel model and actual flight of B738 for climb, cruise and descent phases are respectively shown in figure 5.1, Figure 5.2, Figure 5.3.

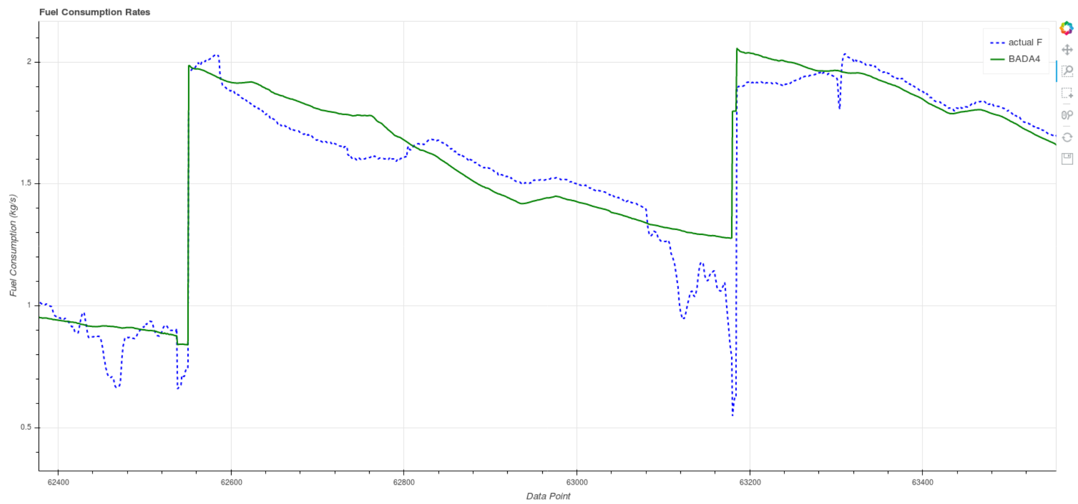


Figure 5.1: B738 AC#1 BADA Fuel Vs Actual Fuel in climb.

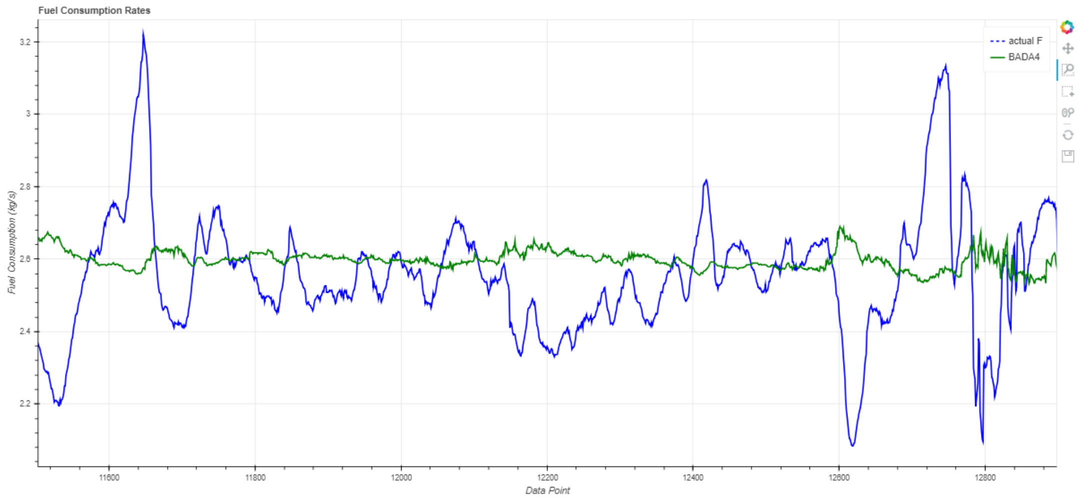


Figure 5.2: B738 AC#1 BADA Fuel Vs Actual Fuel in cruise.

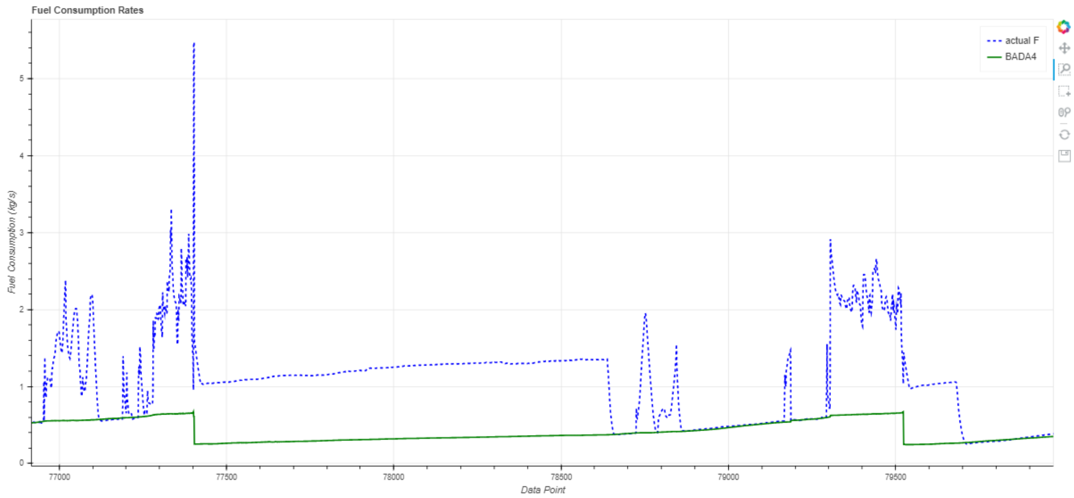


Figure 5.3: B738 AC#1 BADA Fuel Vs actual fuel in descent.

BADA operates significantly satisfied for correct parameters but in reality disturbance which is applied to the aircraft can cause to misleading. To overcome this misleading, in this thesis BADA is updated with operational data.. To achieve this aim, fundamental parts which are briefly explained at previous chapters are used. The scheme which is shown in Figure 5.4 is a brief demonstration of thesis study. In the thesis, 551 B738 Aircraft#1 flights and 817 B738 Aircraft#2 flights are used.

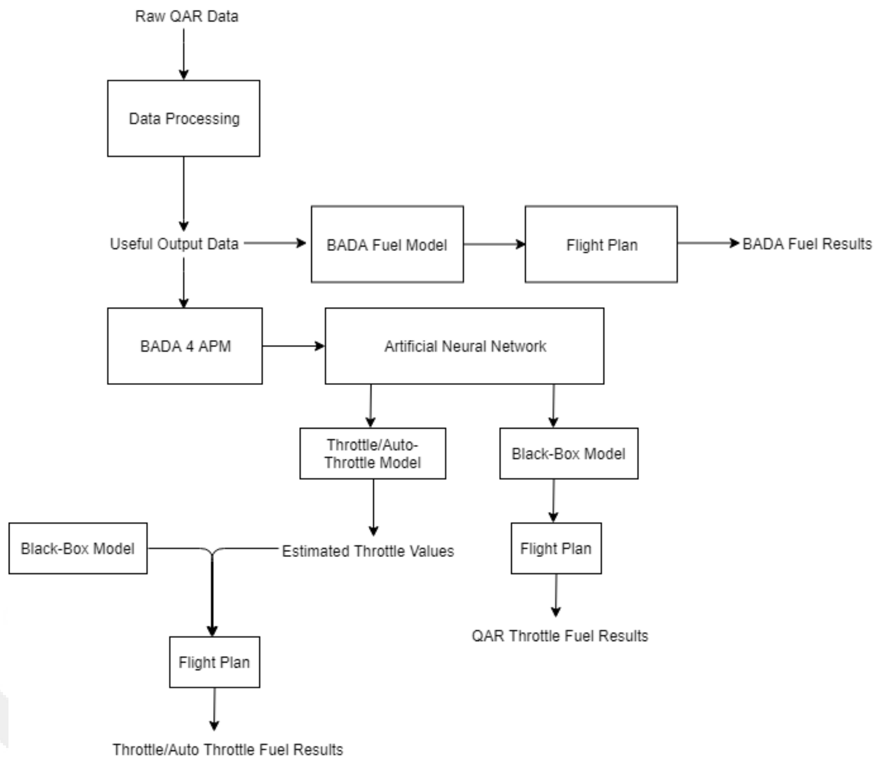


Figure 5.4: Method Scheme.

5.1 Fuel Flow Estimation Through Machine Learning

Artificial Neural Network (ANN) is a data handling phenomenon that is influenced by the biological nerve systems in order to process data. Based upon it operate procedure human brain is a good example to understand ANNs [30]. The key component of this phenomenon is the novel structure of the data preparing framework. It is made out of a high number of exceptionally interconnected handling components, which are named as neurons, working as one in order to take care of particular issues. ANNs, similar to humans, learn by example. In computation science this learning process is called as data training. An ANN is designed for a particular application, for instance, design acknowledgment or information characterization, through a learning procedure. Learning in natural systems includes changes in accordance with the synaptic associations that exist between the neurons. This is also valid for ANNs.

Neural system reenactments give off an impression of being an ongoing advancement. In any case, this field was built up before the appearance of computers, and has made due something like one noteworthy mishap and several eras.

Numerous important propels have been helped by the utilization of reasonable PC emulations. Following an underlying time of eagerness, the field survived a time of dissatisfaction and unsavoriness. Amid this period when subsidizing and proficient help was negligible, critical advances were made by generally few researchers. These pioneers could create persuading innovation which outperformed the constraints recognized by Minsky and Papert. Minsky and Papert, distributed a book (in 1969) in which they summed up a general sentiment of dissatisfaction (against neural systems) among analysts, and was consequently acknowledged by most without further examination. At present, the neural system field appreciates a resurgence of intrigue and a relating increment in financing.

The principal counterfeit neuron was delivered in 1943 by the neurophysiologist Warren McCulloch and the rationalist Walter Pits. In any case, the innovation accessible around then did not enable them to do excessively.

Neural systems, with their astounding capacity to get significance from convoluted or loose information, can be utilized to extricate designs and identify patterns that are too mind boggling to possibly be seen by either people or other PC strategies. A prepared neural system can be thought of as a "specialist" in the class of data it has been given to examine. This situation would then be able to be utilized to give projections given new circumstances of intrigue and reply "imagine a scenario in which" questions. Different points of interest include are shown below,

Adaptive Learning: A capacity to figure out how to do undertakings dependent on the information given for preparing or introductory experience.

Self-Organization: An ANN can make its own association or portrayal of the data it gets amid learning time.

Real Time Operation: ANN calculations might be done in parallel, and exceptional equipment gadgets are being structured and fabricated which exploit this capacity.

Fault Tolerance via Redundant Information Coding: Partial obliteration of a system prompts the comparing corruption of execution. In any case, some system capacities might be held even with real system harm.

In engineering approach, a counterfeit neuron is a gadget with numerous sources of info and one yield. The neuron has two methods of activity; the preparation mode and the utilizing mode. In the preparation mode, the neuron can be prepared to flame (or not), for specific info designs. In the utilizing mode, when a trained info design is identified at the information, its related yield turns into the current yield. In the event that the info design does not have a place in the showed rundown of information designs, the terminating guideline is utilized to decide if to flame or not. A simple neural network neuron is shown in Figure 5.5.

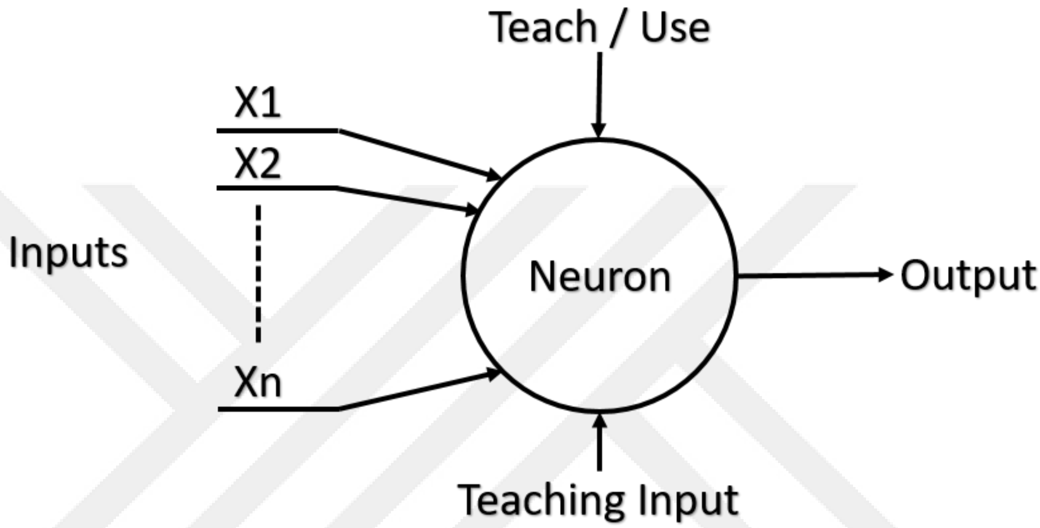


Figure 5.5: A Simple Neuron.

As stated, to create a data-driven model in a CPS artificial neural network is a very useful tool. In this thesis, adam algorithm is used due to its advantages compared to other algorithms for aircraft subject. The upcoming chapter 5.1.1 explains what is adam algorithm and why is that chosen in this thesis.

On the other hand neural network structures (inputs, outputs, layer number, dense, kernel initialize and optimize etc.) which are used in the thesis is explained in the usage part in chapter 5.4 and 5.5 due to increase readability and avoid confusion.

5.1.1 Adam algorithm

In this study, ADAM algorithm which is created by Kingma and BA is used. Briefly, ADAM is a algorithm for productive stochastic advancement that just requires first-order gradient with little memory necessity. The technique registers individual adaptive learning rates for distinctive parameters from appraisals of first and second moments of the gradients this is the reason why the algorithm is named as Adam, it is gotten from adaptive moment estimation. The technique is intended to consolidate the points of interest of two as of late prevalent methods which are AdaGrad [31] which functions admirably with meager gradients, what's more, RMSProp [32], which functions admirably in non-stationary and on-line settings [33]. This method is selected due to its advantages in large datasets.

5.2 Preparation of Data

In this thesis, QAR raw data is used in csv format. Due to the purpose, raw data is processed in python with pandas library. This process has a crucial importance for this study. For example, one of these flights (Aircraft type B737-800) which departures from Sabiha Gökçen Airport (SAW) in Istanbul and lands to Fiumicino Airport (FCO) in Rome, contains more than 7.7 million data which is constructed by 9145 rows and 845 columns. Note that, this flight cruises for only two and half hours. Study without processing this raw data causes to enormous complication problems and reduce studies efficiency.

There is a huge size difference between original QAR and processed QAR. As stated, this is a compulsory process since hundreds of flight is used in this study. There is a comparison about size of processed and raw data is shown in Figure 5.6. Also there is a demonstration of processed QAR file in Figure 5.7. In QAR data preparation process, QAR data is updated with only necessary features which are needed in the study. These features are time, latitude, longitude, standard altitude, barometric altitude, heading, calibrated airspeed, ground speed, mach number, total air temperature, weight, auxiliary power unit (APU) fuel consumption, fuel flow engine #1, fuel flow engine #2, throttle #1, throttle #2, wind direction, wind speed, flap angle, landing gear position and speed break angle.

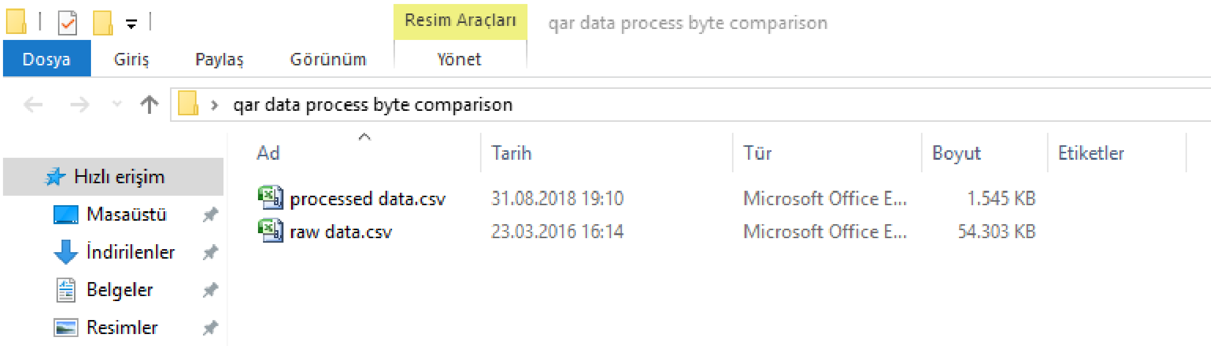


Figure 5.6: Size comparison of Original QAR and Processed QAR File.

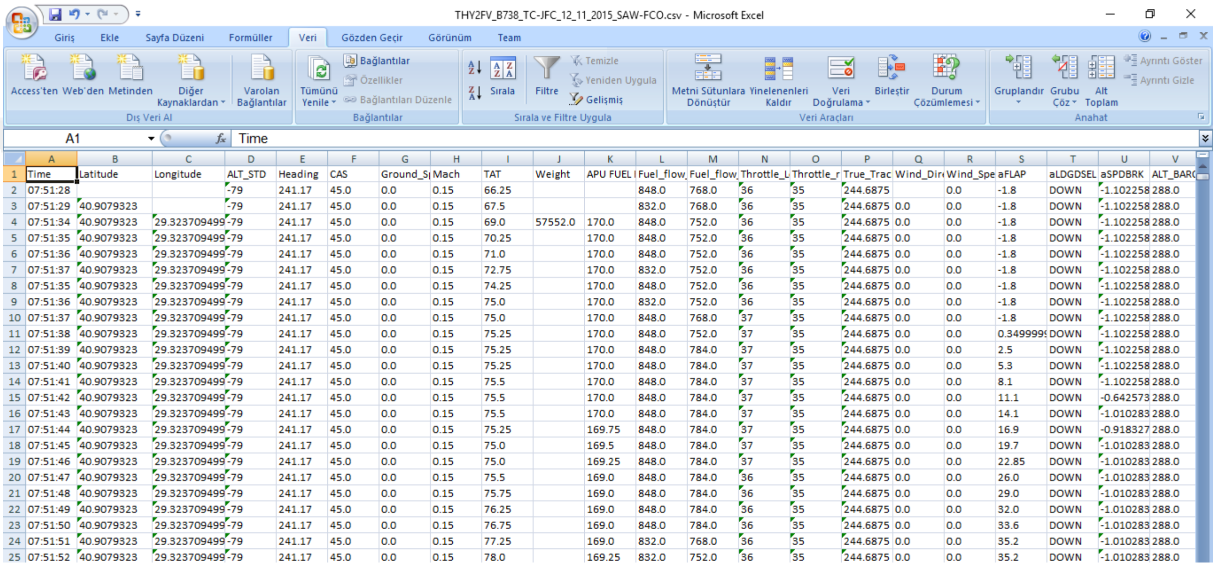


Figure 5.7: An Example of Processed QAR File.

5.2.1 Splitting into flight modes

After processing all QAR files there is another data process is applied in this study. As stated, for two aircraft all QAR files are processed with pandas package in order to use. The QAR files of these two aircraft are separated by each other and divided to 3 in order to their flight phases as climb, cruise and descent. Also this QAR data is processed with BADA equations which are mentioned on previous chapter. Note that in this process numpy package is used. Then these 6 separated data converted to binary code. At the end, 6 binary file which include timestamp, latitude [deg], longitude [deg], altitude [ft], heading [deg], cas [kt], ground speed [kt], mach [-], total air temperature [C], mass [kg], apu fuel [lb/hr], fuel flow 1 [$\frac{lb}{hr}$], fuel flow 2 [$\frac{lb}{hr}$], throttle 1 value, throttle 2 value, course [deg], wind direction [deg], wind speed [kt], flap [deg], landing gear position (up or down), speed break, zero fuel weight [lbs], fuel onboard [kg], air pressure [mb], ground speed derivative [$\frac{kt}{s^2}$], altitude derivative [$\frac{ft}{s}$], heading derivative [$\frac{deg}{s}$], true airspeed [$\frac{m}{s}$], true airspeed derivative [$\frac{m}{s^2}$], gamma [rad], drag [N], thrust [N] are created. So at the end of QAR data processing output is looks like in Figure 5.8.

Ad	Tür	Boyut
Climb_B738AC#1	Dosya	56.059 KB
Climb_B738AC#2	Dosya	147.049 KB
Cruise_B738AC#1	Dosya	190.343 KB
Cruise_B738AC#2	Dosya	415.052 KB
Descent_B738AC#1	Dosya	89.493 KB
Descent_B738AC#2	Dosya	237.263 KB

Figure 5.8: QAR Data Processing Outputs.

5.2.2 Data correction

In the study, a data correction process is needed due to nature of sensor errors. For both QAR and FP, this process is crucial for the sake of study. The data correction process is separated to two main types. First type of data correction is data readjustment which is converting sensor outputs to correct units for calculations. To be more specific for example, in QAR data static air temperature (SAT) is converted to total air temperature (TAT) temperature for calculations with the Equation 5.1. The second type of correction is data fixing. To illustrate, in FP data mach numbers only given when cruise altitude is changed. This means that without state changes FP data gives mach number as zero. To fix this situation sensor caused error CAS to TAS and TAS to Mach or directly TAS to mach conversions are applied and FP data is rewritten. Note that, in this study CAS to TAS and TAS to mach conversion is preferred instead of TAS to mach conversion and the reason of this situation will be explained in chapter 7.

$$TAT = SAT(1 + 0.2Ma^2) \quad (5.1)$$

Flight plans which are used in this study contains cost index, altitude (FL type), ground speed [kt], indicated airspeed [kt], mach [-], true airspeed [kt], wind speed [kt], fix name [-], time [min], Fuel Burned [kg], fuel remaining [kg], aircraft mass

[kg], ground distance [nm], ISA Deviation [C], latitude [deg], Longitude [deg], waypoint type [-]. An example of B738 flight plan is shown in Figure 5.9.

T1

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1		Cost Inde:	Altitude	Ground Sp	Indicated	Mach	True Airsp	Wind Spe	Fix Name	Time (mir	Fuel Burn	Fuel Rema	Aircraft M	Ground Di	ISA Deviat	Latitude (d	Longitude	Waypoint Type	
2	0	40	0.0	452.0	475.0	0.768	426.0	34.0	LEBL	0.0	297.0	13795.0	71847.0	0.0	-2.0	41.2967	2.0783	PA	
3	1	40	17.0	318.0	211.0	0.0	327.0	-9.0	411703N0	2.0	531.0	13561.0	71613.0	4.0	-1.0	41.2833	2.1467	XX	
4	2	40	53.0	318.0	211.0	0.0	327.0	-9.0	SUKOS	3.0	693.0	13399.0	71451.0	9.0	-1.0	41.285	2.2367	EA	
5	3	40	150.0	311.0	211.0	0.0	327.0	-16.0	BL010	7.0	1128.0	12964.0	71016.0	28.0	-1.0	41.195	2.6217	PC	
6	4	40	206.0	303.0	211.0	0.0	327.0	-24.0	TASOS	9.0	1370.0	12722.0	70774.0	44.0	-1.0	40.945	2.65	EA	
7	5	40	269.0	300.0	211.0	0.0	327.0	-27.0	LARPA	13.0	1689.0	12403.0	70455.0	68.0	-3.0	40.6267	2.3483	EA	
8	6	40	282.0	428.0	299.0	0.0	452.0	-24.0	TOLSO	14.0	1773.0	12319.0	70371.0	76.0	-5.0	40.5	2.3933	EA	
9	7	40	290.0	428.0	299.0	0.0	452.0	-24.0	(T/C)	15.0	1821.0	12271.0	70323.0	81.0	-6.0	40.4183	2.42	XX	
10	8	40	290.0	429.0	299.0	0.773	452.0	-23.0	LISAS	17.0	1909.0	12183.0	70235.0	94.0	-6.0	40.2017	2.4967	EA	
11	9	40	320.0	429.0	283.0	0.0	452.0	-23.0	(T/C)	19.0	2062.0	12030.0	70082.0	109.0	-5.0	39.9583	2.5783	XX	
12	10	40	320.0	431.0	283.0	0.782	452.0	-21.0	MJV	23.0	2272.0	11820.0	69872.0	142.0	-5.0	39.435	2.7583	D	
13	11	40	330.0	414.0	278.0	0.0	455.0	-41.0	(T/C)	24.0	2325.0	11767.0	69819.0	149.0	-2.0	39.32	2.7267	XX	
14	12	40	330.0	414.0	278.0	0.785	455.0	-41.0	ASMOT	25.0	2345.0	11747.0	69799.0	152.0	-2.0	39.2767	2.715	EA	
15	13	40	330.0	414.0	278.0	0.785	455.0	-41.0	OLMIR	31.0	2647.0	11445.0	69497.0	198.0	-2.0	38.5317	2.5183	EA	
16	14	40	330.0	414.0	278.0	0.785	455.0	-41.0	SADAF	38.0	2942.0	11150.0	69202.0	243.0	-2.0	37.8033	2.3283	EA	
17	15	40	330.0	412.0	277.0	0.782	453.0	-41.0	(***)	38.0	2948.0	11144.0	69196.0	244.0	-2.0	37.785	2.3433	XX	
18	16	40	330.0	448.0	277.0	0.782	453.0	-5.0	ALR	48.0	3414.0	10678.0	68730.0	322.0	-2.0	36.6917	3.215	D	
19	17	40	330.0	510.0	274.0	0.775	450.0	60.0	BNA	51.0	3508.0	10584.0	68636.0	340.0	-1.0	36.6517	3.5917	DB	
20	18	40	330.0	517.0	273.0	0.771	448.0	69.0	BJA	59.0	3873.0	10219.0	68271.0	412.0	-1.0	36.715	5.0767	DB	
21	19	40	330.0	520.0	273.0	0.771	449.0	71.0	JIL	63.0	4070.0	10022.0	68074.0	451.0	0.0	36.7983	5.875	D	
22	20	40	330.0	517.0	272.0	0.77	448.0	69.0	(IA1)	72.0	4425.0	9667.0	67719.0	521.0	0.0	36.8267	7.3433	XX	
23	21	40	330.0	516.0	272.0	0.77	448.0	68.0	ANB	74.0	4541.0	9551.0	67603.0	544.0	0.0	36.8317	7.815	D	
24	22	40	330.0	518.0	272.0	0.77	448.0	70.0	MORJA	79.0	4742.0	9350.0	67402.0	584.0	0.0	36.835	8.65	EA	
25	23	40	330.0	518.0	272.0	0.77	448.0	70.0	(***)	79.0	4747.0	9345.0	67397.0	585.0	0.0	36.835	8.675	XX	

Figure 5.9: Sample Flight Plan of B738.

There are two crucial data processes in flight plans due to accomplish accuracy. First one as stated before is mach number generation due to flight plans' data characteristic. As seen via Figure 5.8 which is shown above most of the mach values in column F are zero. In flight plans, due to hardware which is used in aircraft mach number values only shows their real value in fixed position. Therefore Mach numbers are processed and used their real values instead of 0 via TAS/Mach transition formula in Equation 5.2

$$V_{TAS} = M \,.\sqrt{kRT} \quad (5.2)$$

Where V_{TAS} is true airspeed [m], M is mach number [-], k is the adiabatic index approximately 1.4, R is the real gas constant for air [$\frac{m^2}{(K.s^2)}$] and total air temperature [K]. Second one, again because of the hardware misleading, first row of the flight plan which shows a wrong mach number. To avoid this misleading, in all flight plans first row is skipped.

Another significant point for this part is that after these two corrections of FP, the data is interpolated to become a second by second state. In this study, used FP data has sparse characteristics. To calculate fuel consumption for each second of flight, FP must be expanded. To achieve this expansion, FP data is separated to the 3 phases of flight such as climb, cruise and descent with numpy.gradient command. After that, FP time values which are stored in minute unit is converted to the seconds by multiplying with 60. By using numpy.linspace command FP data is upgraded with interpolation. As a result of this process, time, TAS, CAS, mach, altitude, ground speed, wind speed, fuel burned, mass, thrust, derivative of TAS, gamma which is flight path angle, latitude, longitude, temperature and ground distance values are converted from minute to minute to the second to second.

Applying interpolation to the FP data brings some problems with it. The most important problem is time error. As stated FP data gives time in minutes but this can cause to misunderstandings. To illustrate, in a scenario of coordinated turn which last shorter than 1 minute gives 2 consecutive rows which have same time value. To overcome this error, time is rewritten as ground distance difference divided to ground speed and this process is applied to the all FP data row by row.

5.2.3 Data generation

In this part of the thesis drag and thrust generations are explained.

5.2.3.1 Drag generation

Drag is generated by BADA formulas in chapter 3.2.1.2. For climb and cruise clean configuration is used. On the other hand for descent non clean drag configuration is used. On the other hand, FP data does not contain landing profiles. This problem is solved stochastically by investigating landing profiles. System is coded to switch to non clean drag from clean drag at a given time at the end of final descent phase before landing. Clean drag is calculated as a function of aircraft mass, pressure coefficient and mach number. On the other hand non clean drag is calculated due to aircraft mass, pressure coefficient, mach number, flap angle, speed breakers and landing gear position.

5.2.3.2 Thrust generation

Thrust is generated by aircraft motion model as a function of derivative of true airspeed, gamma, mass and drag force as stated in Chapter 3.1.

5.3 Data Monitoring

A lot of methods and input combinations are tried and compiled in this study. And only most effective methods and combinations are used in the thesis. All tests are implemented for three flight phases which are climb, cruise and descent. To achieve more successful big data management and better results for applications, it is necessary to select appropriate programming models, tools and technologies [34]. Naturally, studying with big data makes difficult to show results properly. To avoid misdirection the plots which are shown in tests are randomly picked from main plots. To illustrate that Figure 5.10 demonstrates the big data compared to randomly picked part of the plot is shown below.

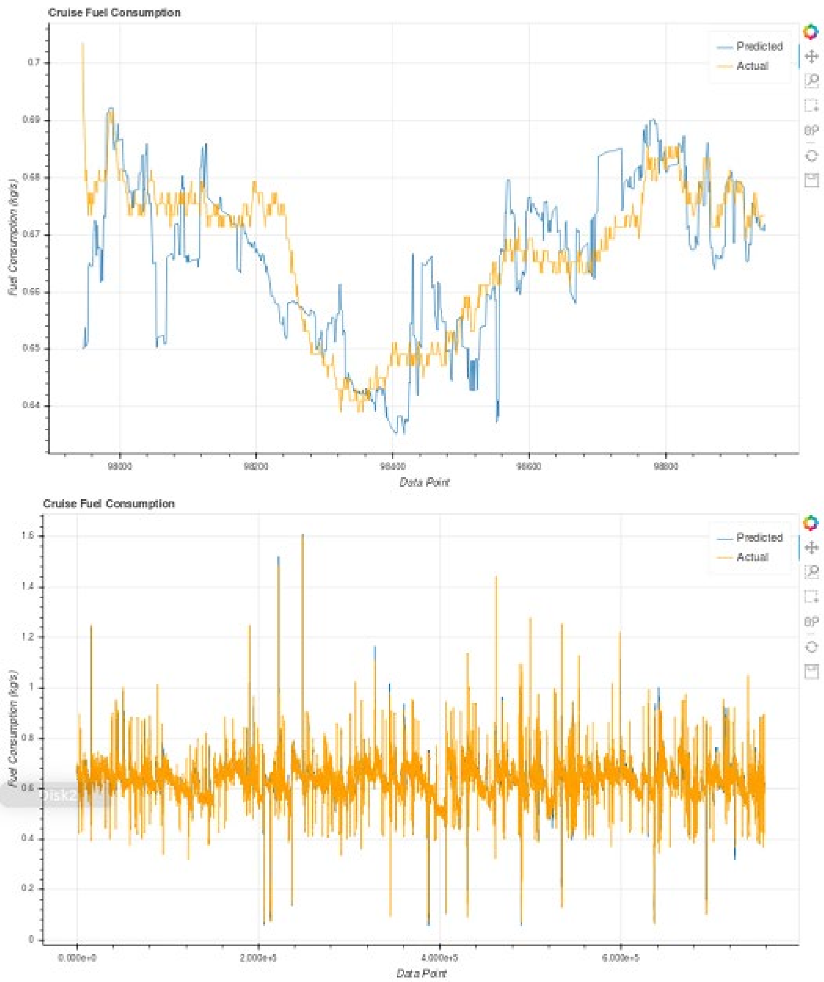


Figure 5.10: An Example of Specified Plot vs Big Data Plot.

5.4 Fuel Flow Estimation: Black-Box Model (QAR Throttle)

In this chapter, processed QAR data is given the system as input. For black-box model inputs and output are given in Table 5.1 for climb phase, Table 5.2 for cruise phase and Table 5.3 for descent phase.

Table 5.1: Inputs and output for Black-Box model climb phase.

Inputs	Unit	Output	Unit
Altitude	ft	Fuel Consumption	kg/s
Mass	kg		
Throttle 1	-		
Throttle 2	-		
Mach	-		
SAT	C		

Table 5.2: Inputs and output for Black-Box model cruise phase.

Inputs	Unit	Output	Unit
Altitude	ft	Fuel Consumption	kg/s
Mass	kg		
TAS	m/s		
CAS	kt		
Throttle 1	-		
Throttle 2	-		
Mach	-		
SAT	C		

Table 5.3: Inputs and output for Black-Box model descent phase.

Inputs	Unit	Output	Unit
Altitude	ft	Fuel Consumption	kg/s
Mass	kg		
TAS	m/s		
Throttle 1	-		
Throttle 2	-		
Mach	-		
SAT	C		

In Neural Network structure 5 layer is used with Dense from 32 to 512 by multiplying 2 (32-64-128-256-512). Activation for layers is ‘relu’ and kernel initalizer is ‘glorot_uniform’. For the model, ‘adam’ is used as optimizer. For loss, ‘mae’ (Mean Absolute Error) is used and for metrics ‘mse’ is used. All Black-box model values are run with 2000 epoch and 512 batch size and ANN structure is briefly shown in Figure 5.11.

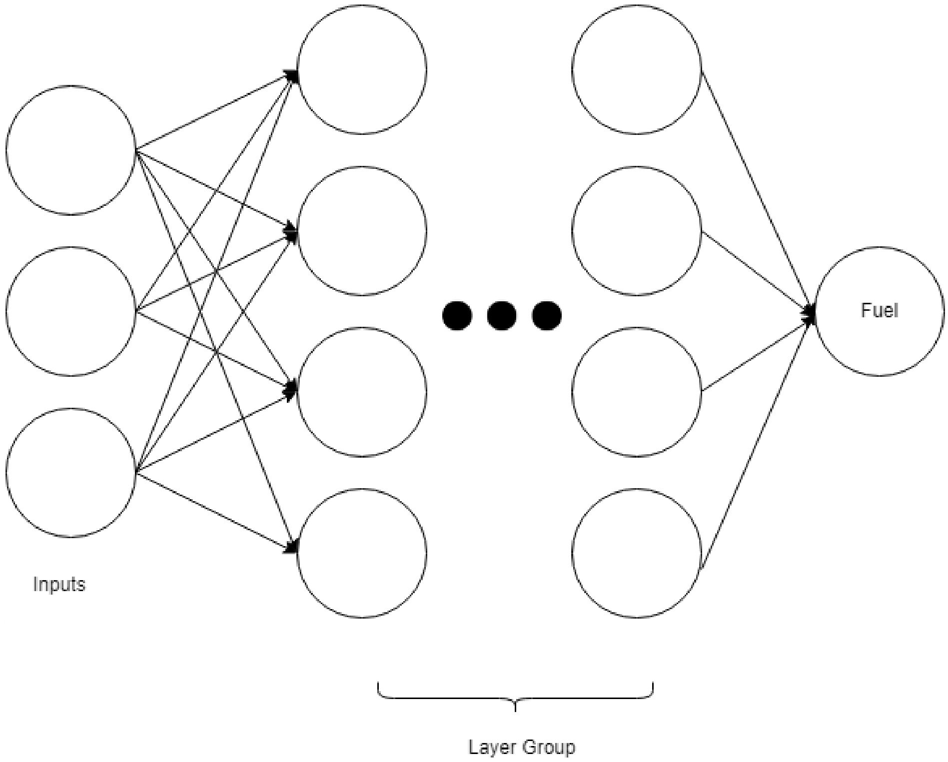


Figure 5.11: Neural Structure of Black-Box Model.

As a result of that structure Mean Absolute Error for phases are shown below,

For B737-800 Aircraft #1 Climb Mean absolute error is 0,0071 (kg/s) and the fuel consumption of AC#1 climb phase is shown in Figure 5.12.

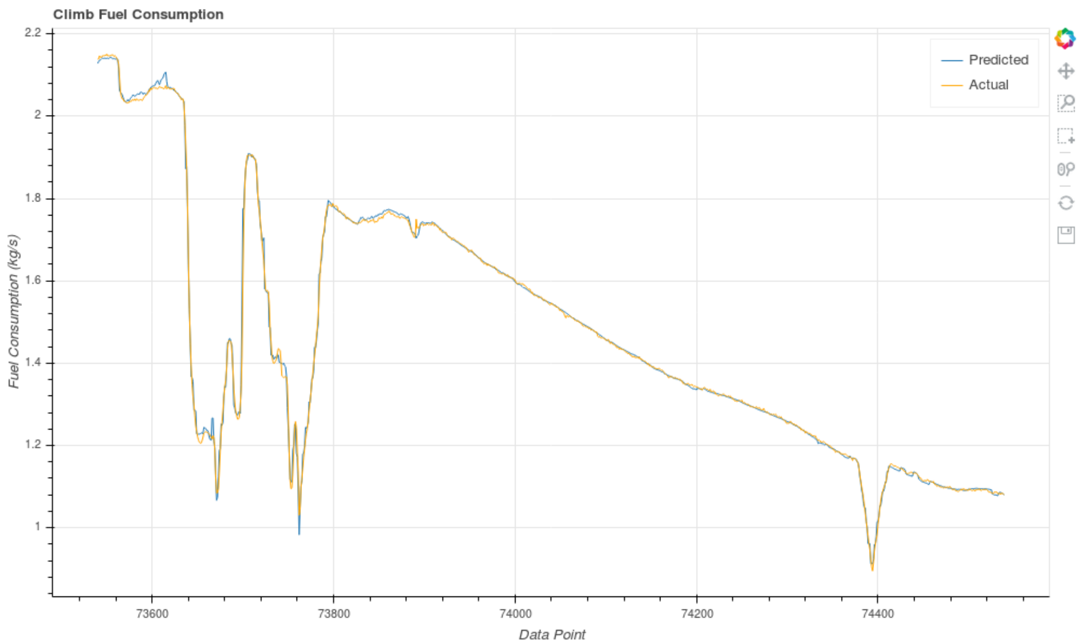


Figure 5.12: Black-Box Model Climb Fuel Consumption for B738 Aircraft #1.

For B737-800 Aircraft #1 Cruise Mean absolute error is 0,0052 (kg/s) and the fuel consumption of AC#1 cruise phase is shown in Figure 5.13.

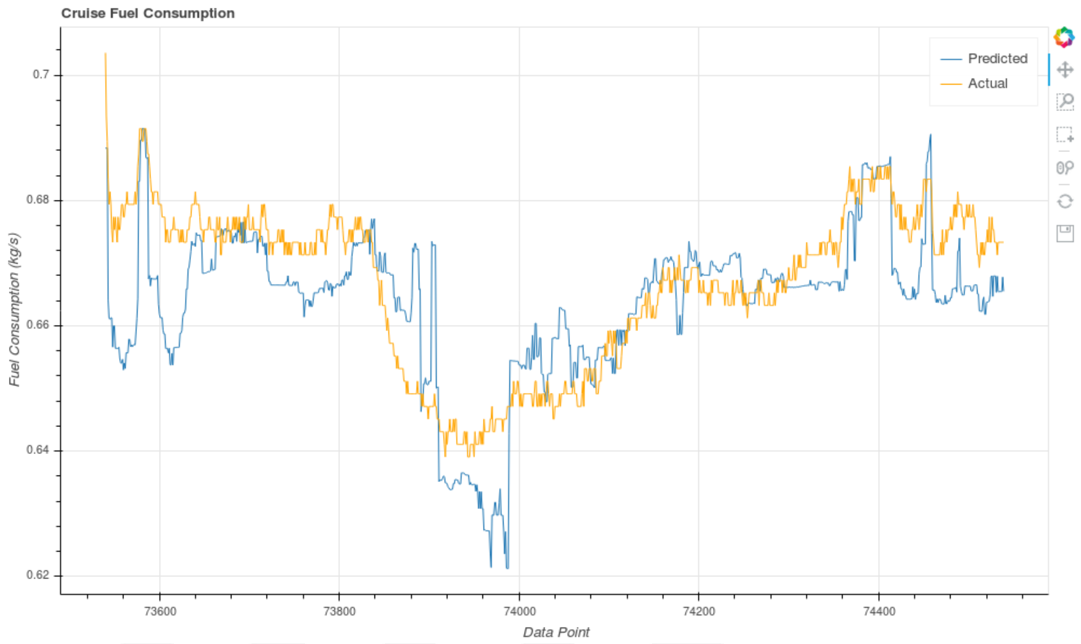


Figure 5.13: Black-Box Model Cruise Fuel Consumption for B738 Aircraft #1.

For B737-800 Aircraft #1 Descent Mean absolute error is 0,0085 (kg/s) and the fuel consumption of AC#1 descent phase is shown in Figure 5.14.

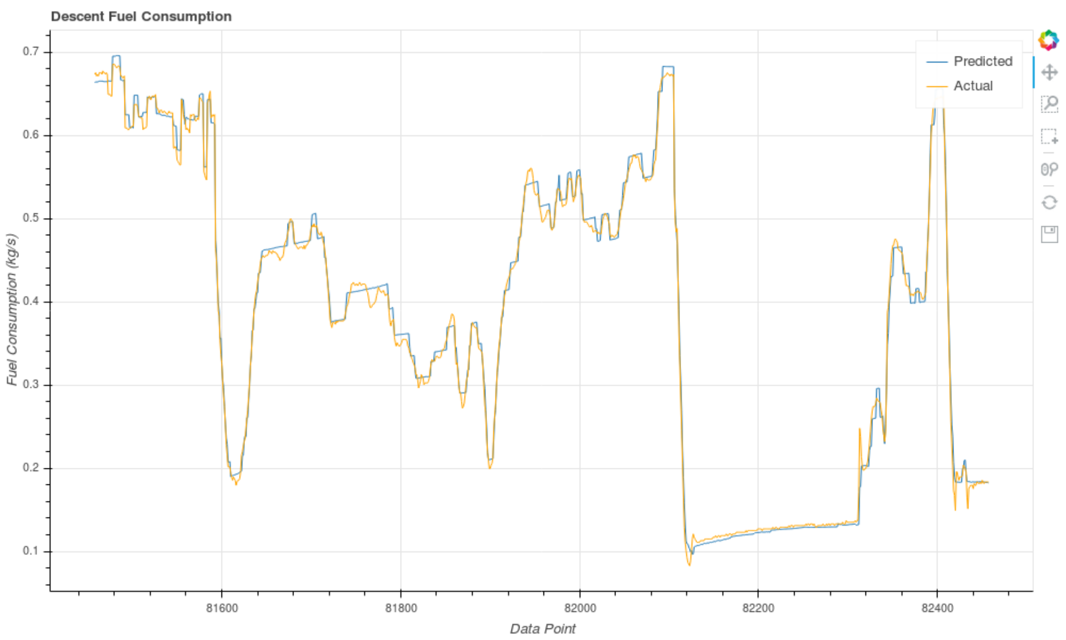


Figure 5.14: Black-Box Model Descent Fuel Consumption for B738 Aircraft #1.

For B737-800 Aircraft #2 Climb Mean absolute error is 0,0091 (kg/s) and the fuel consumption of AC#2 climb phase is shown in Figure 5.15.

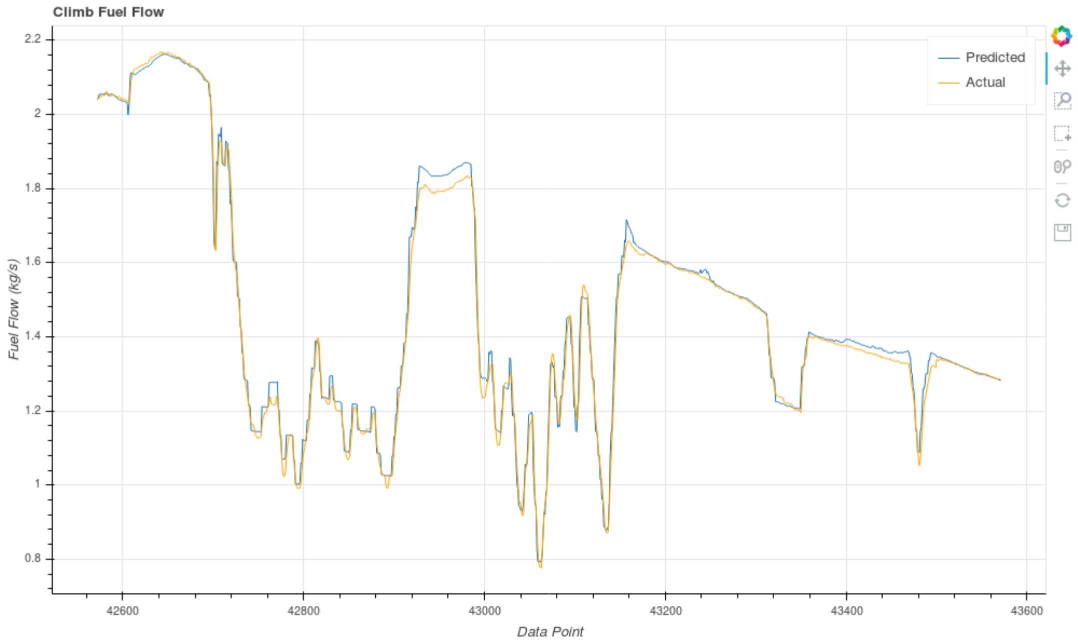


Figure 5.15: Black-Box Model Climb Fuel Consumption for B738 Aircraft #2.

For B737-800 Aircraft #2 Cruise Mean absolute error is 0,0062 (kg/s) and the fuel consumption of AC#2 cruise phase is shown in Figure 5.16.

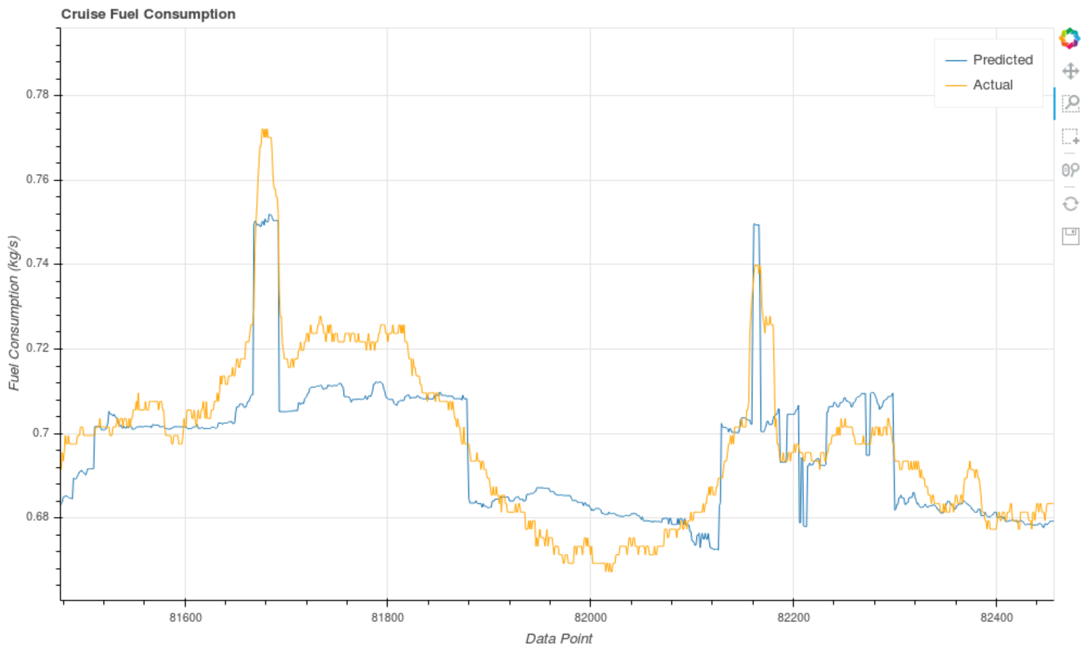


Figure 5.16: Black-Box Model Cruise Fuel Consumption for B738 Aircraft #2.

For B737-800 Aircraft #2 Descent Mean absolute error is 0,098 (kg/s) and the fuel consumption of AC#2 descent phase is shown in Figure 5.17.

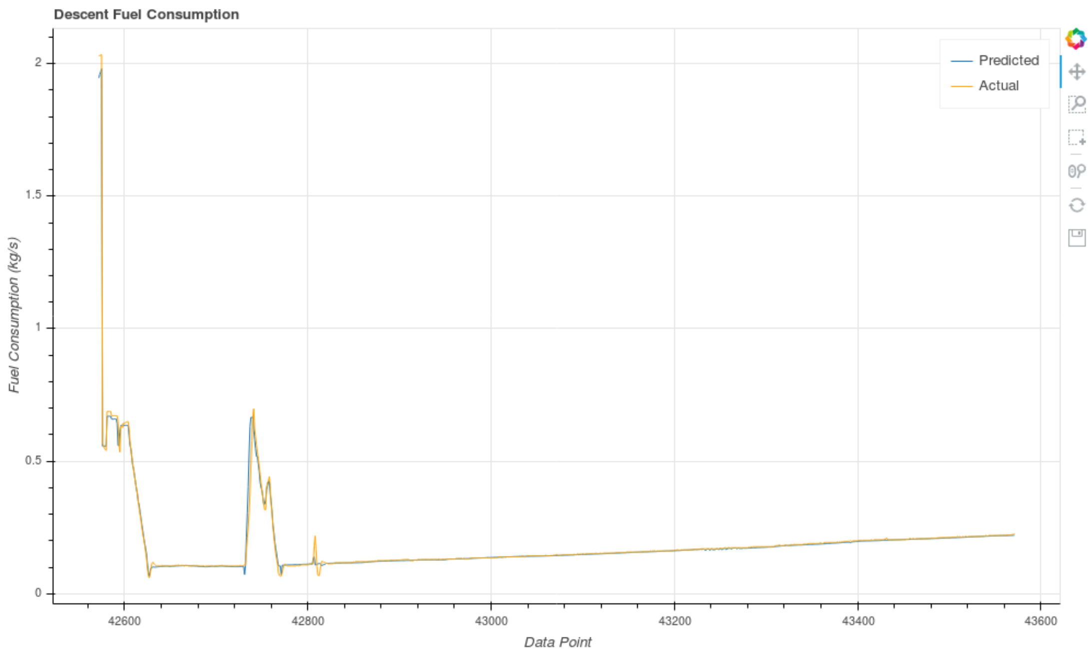


Figure 5.17: Black-Box Model Descent Fuel Consumption for B738 Aircraft #2.

By looking mean absolute error (MAE) values of both aircraft it is easily seen that black-box model is highly satisfying to calculate fuel consumption.

5.5 Throttle/Auto-Throttle Estimation

The main aim of throttle/auto-throttle estimation is define the throttle values from QAR data with neural network. Therefore, rather calculating fuel consumption the aim of throttle/auto-throttle estimation is calculating throttle values with artificial neural network. A brief demonstration of process in throttle/auto-throttle estimation is shown in Figure 5.18.

In Neural Network 2 main structures is used from first to fifth layer is constructs first part which is common for throttle 1 and throttle 2. Dense of the first part is 128-128-256-256-256. Then from fifth to eighth first main structure separates due to throttles. Dense of the second part is 8-16-32. Activation for layers is ‘relu’ and kernel initalizer is ‘glorot_uniform’. For the model, ‘adam’ is used as optimizer. For loss, ‘mae’ (Mean Absolute Error) is used and for metrics ‘mse’ is used. All test 3 values are ran with 2000 epoch and 512 batch size.

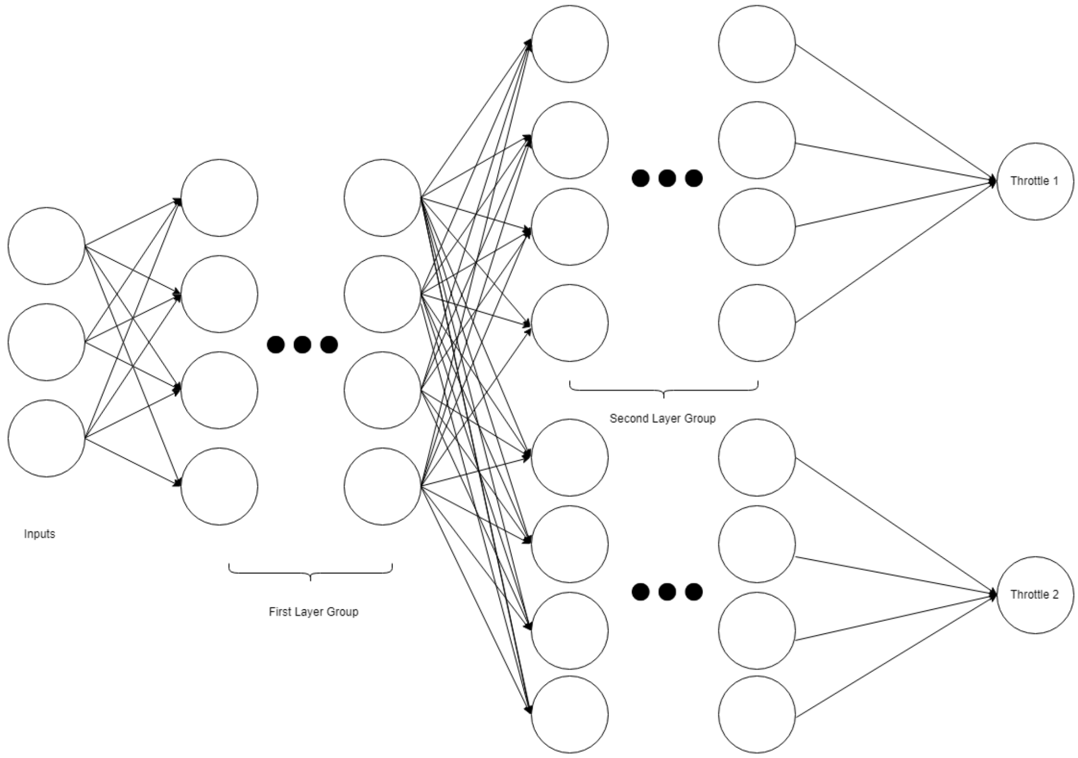


Figure 5.18: Neural Structure of Throttle/Auto-Throttle Estimation.

For Throttle/Auto-Throttle model inputs and outputs are given in Table 5.4 for climb, cruise and descent phases.

Table 5.4: Inputs and outputs for Throttle/Auto-Throttle model for all phases.

Inputs	Unit	Output	Unit
TAS	m/s	Throttle 1	-
Mass	Kg	Throttle 2	-
Mach	-		
Pressure Ratio	-		
$Thrust\ x\ Mach$	-		
Thrust	N		
Wind Speed	kt		
CAS	kt		

Ground Speed	kt
Gamma	rad
SAT	C
Altitude	ft

As a result of these structure Mean Absolute Error for phases are shown below,

For B737-800 Aircraft #1 Climb Mean absolute error is 0,424 (kg/s) and throttle values of AC#1 climb phase is shown in Figure 5.19.

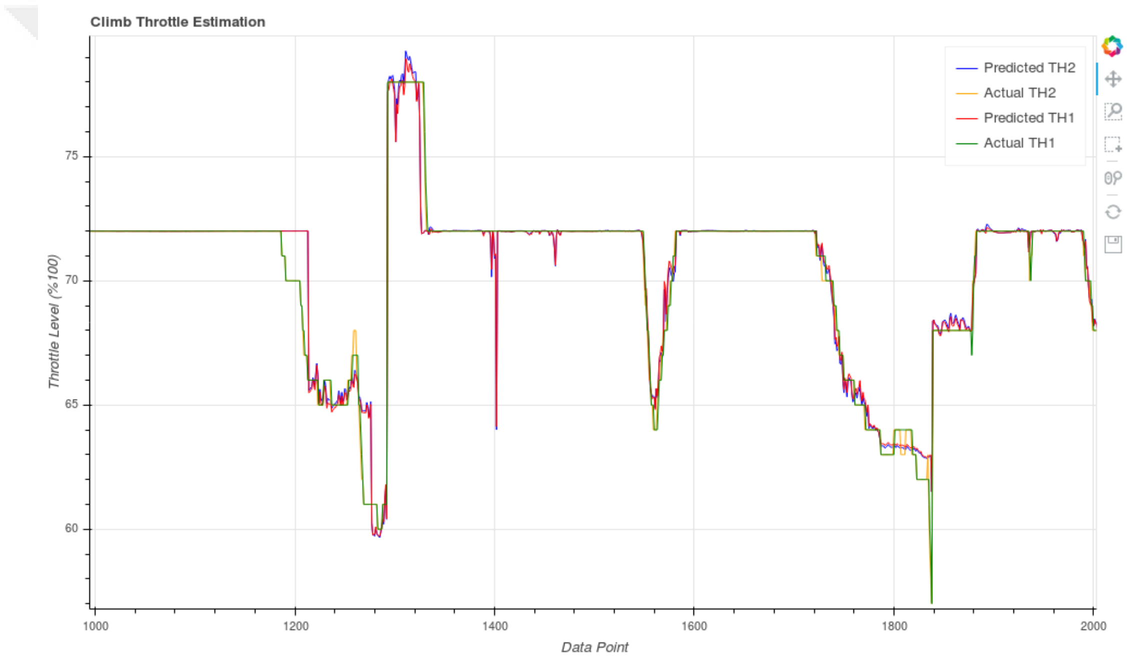


Figure 5.19: Throttle/Auto-Throttle Estimation Climb Throttle Values for B738 Aircraft #1.

For B737-800 Aircraft #1 Cruise Mean absolute error is 0,493 (kg/s) and throttle values of AC#1 cruise phase is shown in Figure 5.20..

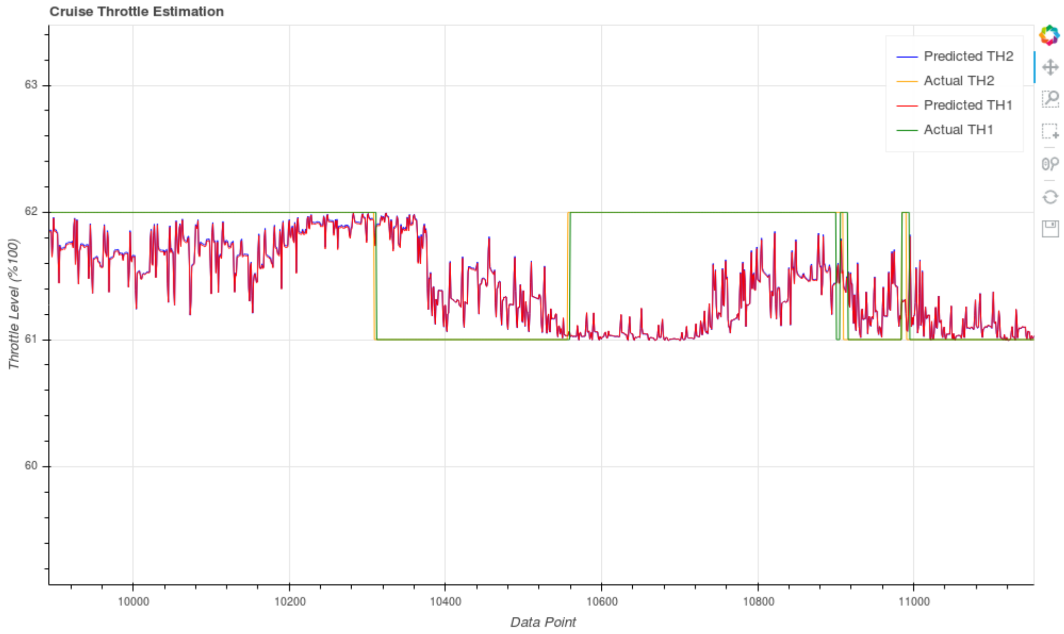


Figure 5.20: Throttle/Auto-Throttle Estimation Cruise Throttle Values for B738 Aircraft #1.

For B737-800 Aircraft #1 Descent Mean absolute error is 0,78 (kg/s) and throttle values of AC#1 descent phase is shown in Figure 5.21.

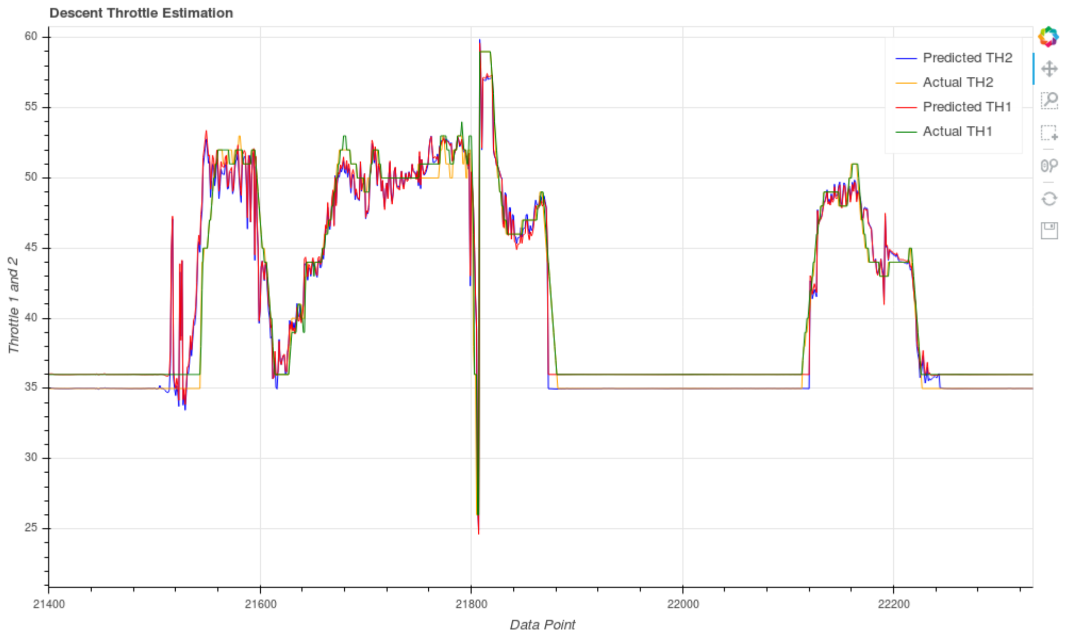


Figure 5.21: Throttle/Auto-Throttle Estimation Descent Throttle Values for B738 Aircraft #1.

For B737-800 Aircraft #2 Climb Mean absolute error is 0,923 (kg/s) and throttle values of AC#2 climb phase is shown in Figure 5.22.

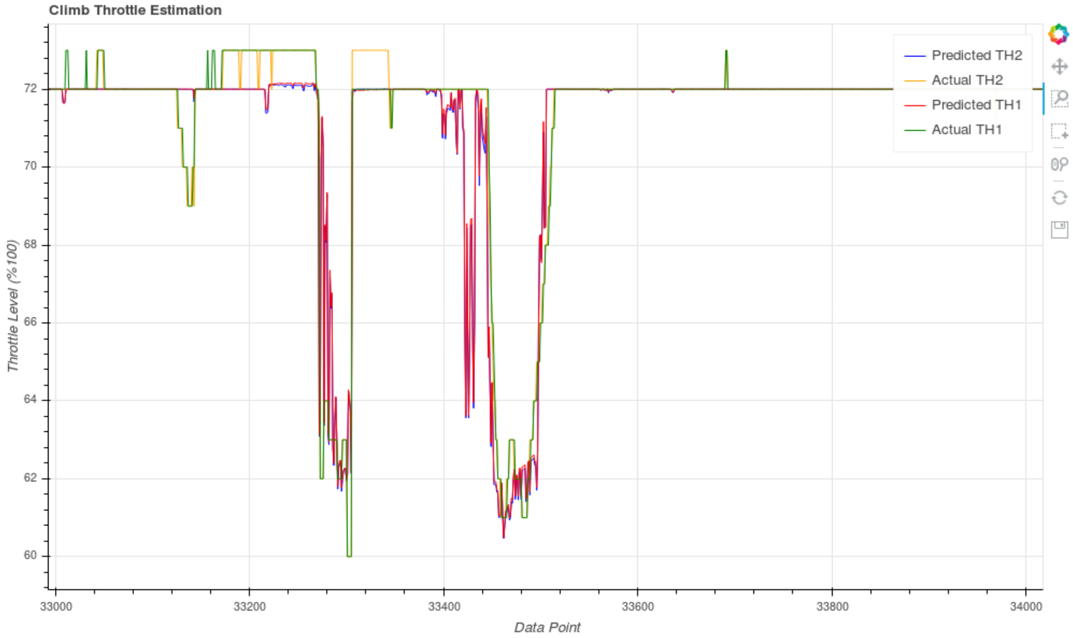


Figure 5.22: Throttle/Auto-Throttle Estimation Climb Throttle Values for B738 Aircraft #2.

For B737-800 Aircraft #2 Cruise Mean absolute error is 0,421 (kg/s) and throttle values of AC#2 cruise phase is shown in Figure 5.23.

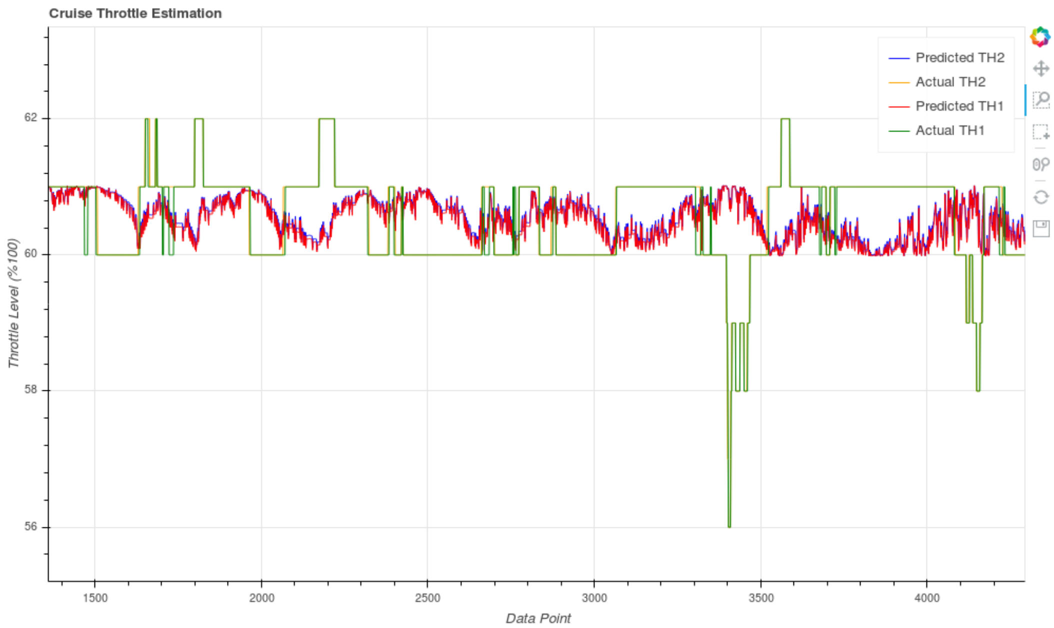


Figure 5.23: Throttle/Auto-Throttle Estimation Cruise Fuel Consumption for B738 Aircraft #2.

For B737-800 Aircraft #2 Descent Mean absolute error is 1,28 (kg/s) and throttle values of AC#2 descent phase is shown in Figure 5.24.

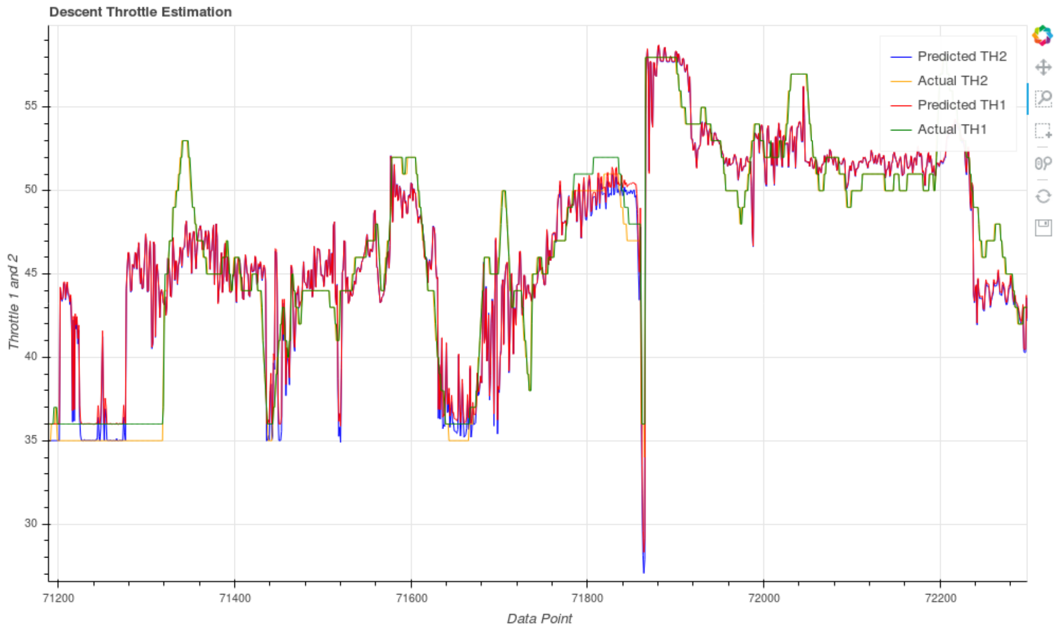


Figure 5.24: Throttle/Auto-Throttle Estimation Descent Throttle Values for B738 Aircraft #2.

Estimated throttle values which are obtained in this part of the study are satisfying especially in climb and cruise phases. Even though not quite good as climb and cruise phase, descent phase is also adequate. The accuracy difference compared to climb and cruise the main reason relatively inadequacy of descent phase is caused by lack of landing profile data.

The motivation of this process is estimating throttle values which are computed and feeding these values to Black-Box Model as input and compared with other outputs. So basically, to calculate fuel consumption of estimated throttle, Throttle/Auto-Throttle Estimation outputs will given to Black-Box Model as inputs instead of QAR throttle values.

6. APPLICATION ON FLIGHT PLANS

In this chapter of thesis data-driven model which is created by using artificial neural network is integrated to flight plans in order to obtain fuel estimation results. To get accurate and correct results first of all, there must be performed a data process to flight plans to avoid misdirection which can be leaded by sensor characteristics. Secondly as stated in previous chapters Throttle/Auto-Throttle Estimation

6.1 Implementation Algorithm

Implementation algorithm is mainly categorized as two steps. First step is giving Estimated Throttle results to the black box model as stated. However an additional second step is needed, due to the air traffic characteristics. It is nearly impossible to follow planned flight plan as %100 by aircraft due to high air density or weather conditions. In these kinds of situations flight dispatcher leads aircraft out of its flight plan. Figure 6.1 and Figure 6.2 are good demonstrations of comparison of two different flights with regards to loyalty to the flight plan.

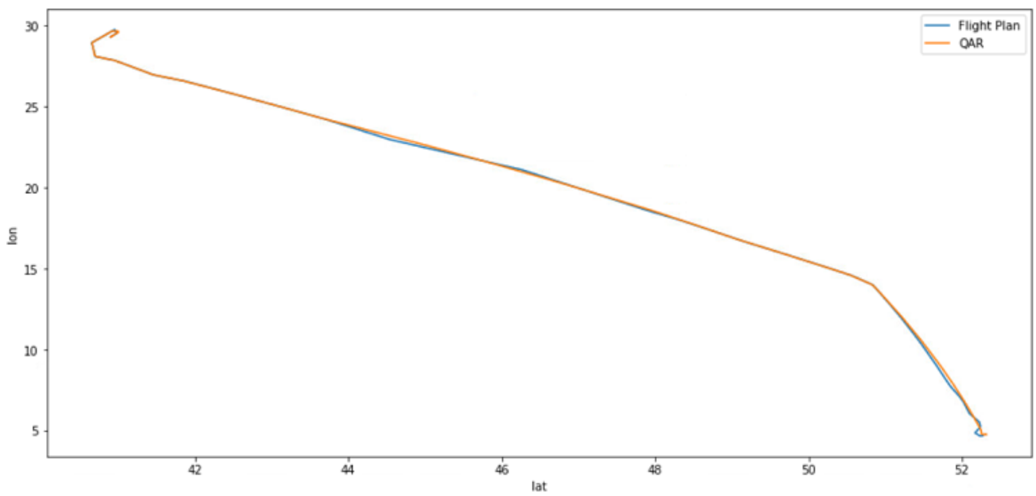
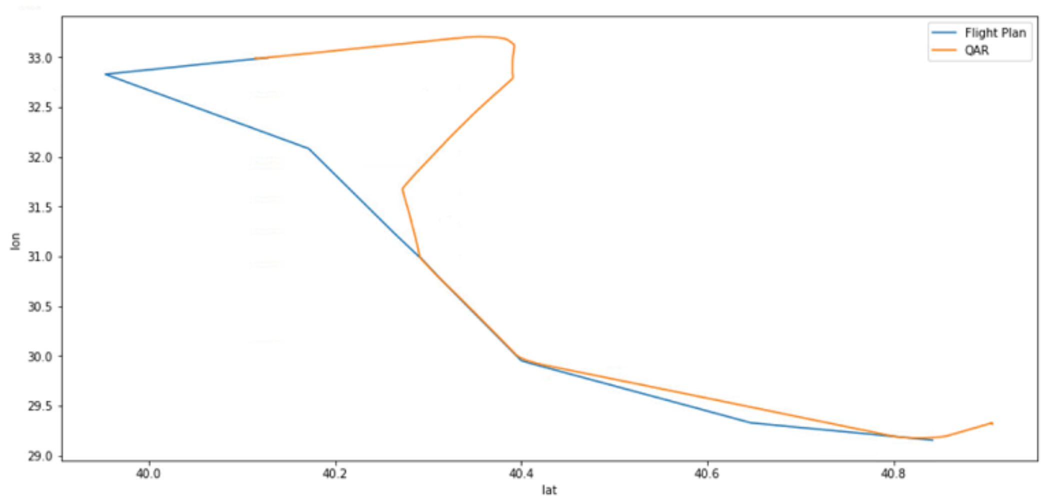


Figure 6.1: Example of FP filter output non eliminated result.




```
QAR and FP of this flight is incompatible due to lat lon
flight number: 11
THY9NA_B738_TC-JFC_01_06_2016_ECN-SAW.csv
['THY9NA_2016-01-06Z_TCJFC_LCEN_LTFJ.csv']
```

Figure 6.2: Example of FP filter output eliminated result.

To avoid misleading results which is explained, a filter is used. The filter consists a classification of QAR and FP data in order to their latitude, longitude and altitude values in a determined gap. The gap which is used in thesis is 0,01 latitude and 0,01 longitude difference and 100 ft altitude difference. This means that if one of the latitude, longitude or altitude differences in FP and QAR for that exact moment of flight is much more than defined gap these FP and QAR data are filtered as eliminated result.

6.2.1 Implementation of fuel with estimated throttle

As stated, BADA 4 APM is inadequate to compute baseline fuel estimations for disturbed short period situations. On the other hand, estimated throttle values by artificial neural network which is trained with QAR data and are taken as input to calculate fuel consumption. In this process, Throttle/Auto-Throttle Estimation results are given to Black-Box Model as input. As a result of, fuel consumptions compared with each other in order to compare results.

For B738 AC#1 Climb fuel consumption rates are shown in Figure 6.3. As it is shown in the Figure 6.3 BADA characteristically follows actual fuel consumption but it fails in short term disturbances. On the other hand, both Black-Box model and Throttle/Auto-Throttle model are both as characteristically and as under short term disturbances follow actual fuel consumption better compared to BADA.

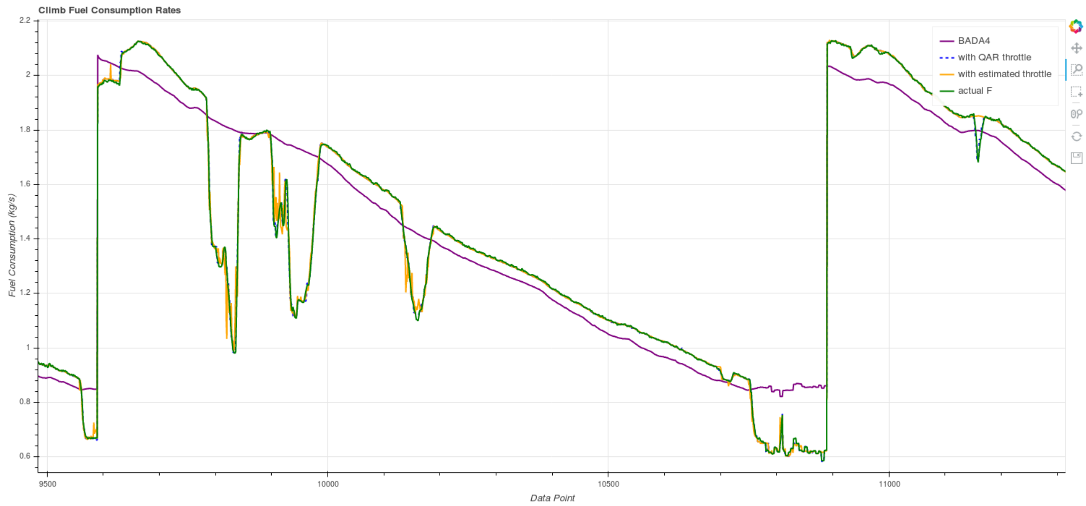


Figure 6.3: Estimated Throttle Implemented Fuel Consumption Comparison for Climb of B738 AC#1.

For B738 AC#1 Cruise fuel consumption rates are shown in Figure 6.4. As it is shown in the Figure 6.4 most part of this specific flight phase Throttle/Auto-Throttle model gives more accurate fuel consumption values than BADA except data points between 40580 and 40680. This kind of misevaluation can be occurred in ANNs but it is an undoubtfully fact that even in this small gap where BADA gives more accurate results, the deviation of Throttle/Auto-Throttle is extremely minor compared to deviation of BADA where BADA is inaccurate. Note that, major part of this fuel consumption data sample plot BADA is less accurate compared to Throttle/Auto-Throttle Estimation model.

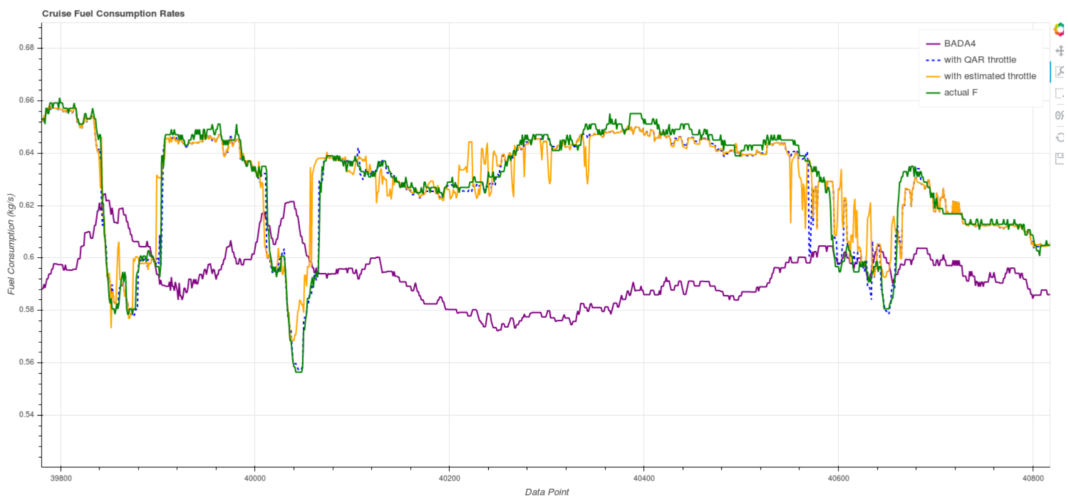


Figure 6.4: Estimated Throttle Implemented Fuel Consumption Comparison for Cruise of B738 AC#1.

For B738 AC#1 Descent fuel consumption rates are shown in Figure 6.5. As it is shown in the Figure 6.5 Throttle/Auto-Throttle model gives accurate fuel consumption results in both characteristically and short period. On the other hand, BADA remains unresponsive to the short period. Due to the disturbed tendency, this plot does not provide enough information to comment BADA characteristically.

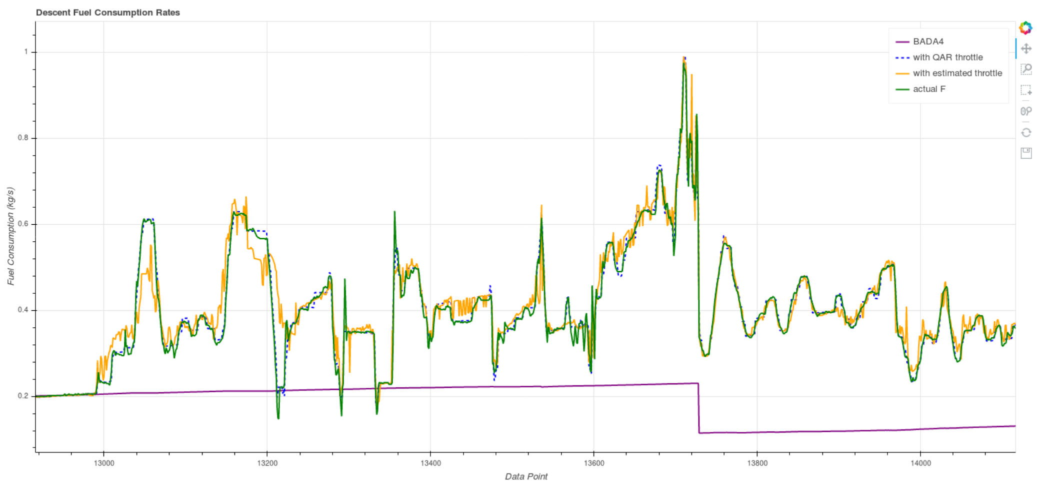


Figure 6.5: Estimated Throttle Implemented Fuel Consumption Comparison for Descent of B738 AC#1.

For B738 AC#2 Climb fuel consumption rates are shown in Figure 6.6. As it is shown in the Figure 6.6 fuel consumption values of climb phase of AC#2 are similar to the AC#1 and it is unnecessary to make a comment again.

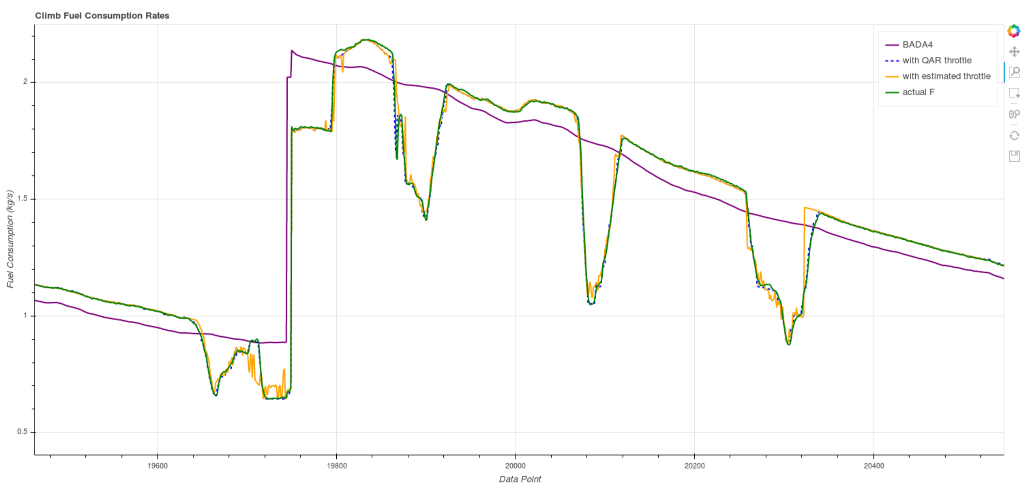


Figure 6.6: Estimated Throttle Implemented Fuel Consumption Comparison for Climb of B738 AC#2.

For B738 AC#2 Cruise fuel consumption rates are shown in Figure 6.7. As it is shown in the Figure 6.7 there is not a single sample point which BADA is more accurate compared to Throttle/Auto-Throttle model. Also in this plot it is obviously seen that Throttle/Auto-Throttle model is quite satisfying even though some misevaluations where it occurs in between sample point 7300 and 7500. Even in the most inaccurate part of the plot note that the accuracy of Throttle/Auto-Throttle Model of this part is more than %95.

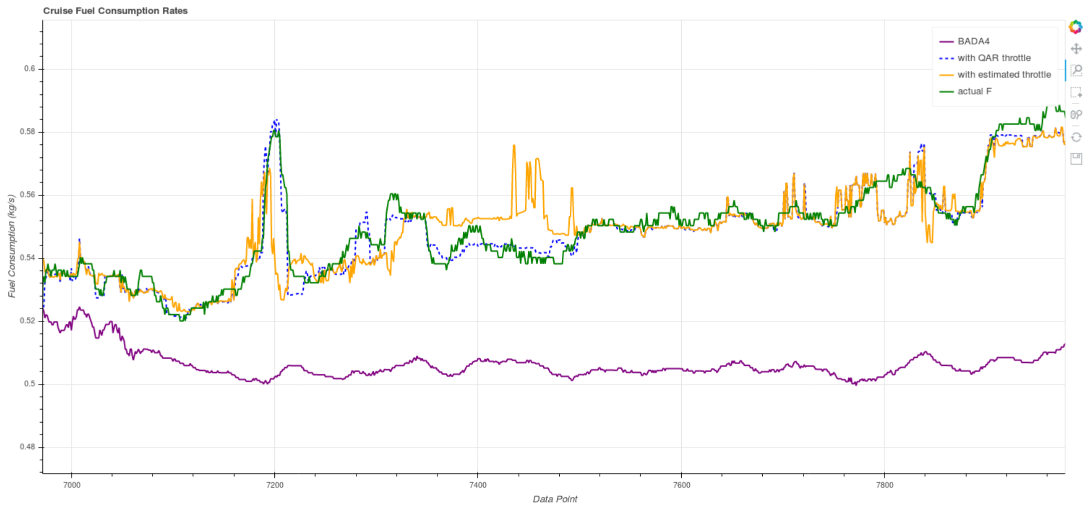


Figure 6.7: Estimated Throttle Implemented Fuel Consumption Comparison for Cruise of B738 AC#2.

For B738 AC#2 Descent fuel consumption rates are shown in Figure 6.8. As it is shown in the Figure 6.8 Throttle/Auto-Throttle model gives accurate fuel consumption results in both characteristically and short period. On the other hand, BADA remains unresponsive to the short period. Plot consists both disturbed and non disturbed territories. This situation provides make a comment of characteristic of BADA. It is easily seen that BADA provides healthy results in non disturbed situations but note that in most part of the descent especially in landing it is a hardly seen scenario due to high disturbance rates in descent.

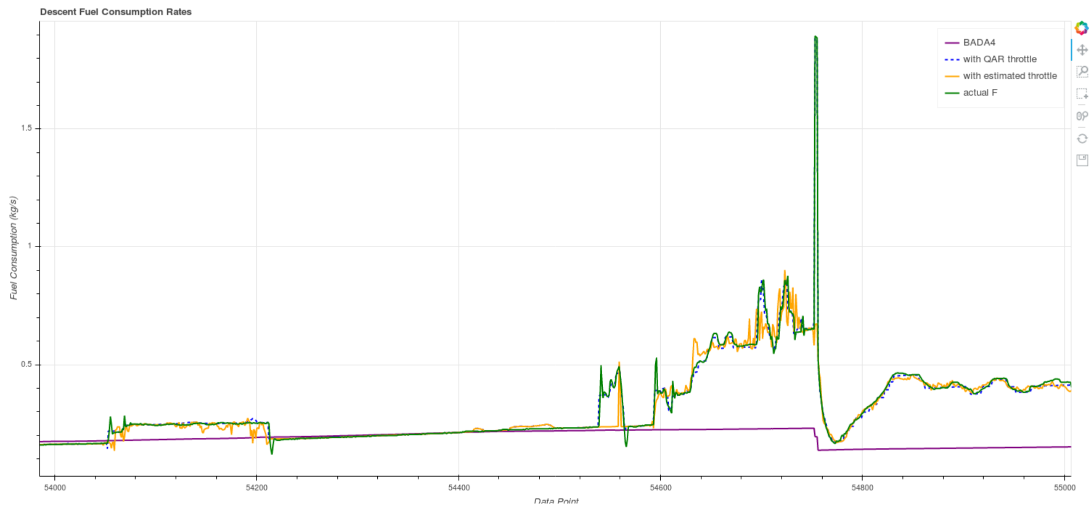


Figure 6.8: Estimated Throttle Implemented Fuel Consumption Comparison for Descent of B738 AC#2.

6.2.2 Implementation of bada

BADA model which is stated in chapter 1 is coded in computer environment. In this part of the study numpy is the main python package which is used. Calculating BADA fuel results contains 3 main phases. First of all, drag and lift coefficients should be determined. This values are calculated due to formulas which are explained in chapter 3.2.1.1, chapter 3.2.1.2, chapter 3.2.1.2.2 and chapter 3.2.1.2.3, as stated. Secondly, thrust value should be determined. Thrust is calculated due to formulas which is showed in chapter 3.2.1.3.1 and chapter 3.2.1.3.2, as stated. Finally, fuel consumption should be calculated. Fuel consumption is calculated due to formulas which are shown in chapter 3.2.1.4 and 3.2.1.4.1 and in this processes turbofan thrust model is taken into the consideration such as MCMB or MCMZ as stated in chapter 3.2.1.3.1.

6.3 Comparison with Baseline Fuel Burn Estimation

In this part of thesis, two APMs which are mentioned in chapter 3.3.7 are given flight plans as inputs to understand their nature better. This process is compiled for all flight plans which are mentioned before. An example of output of flight plan analysis is shown in Figure 6.9. Where, total fuel burned with sabre is the fuel burned according to flight plan, total fuel burned with throttle model is fuel consumption result of chapter 6.2.1, Total fuel burned with BADA model is BADA fuel consumption, SABRE – THR is difference of actual fuel consumption and estimated throttle model, SABRE – BADA is difference of actual flight and BADA fuel consumption, THR EFF and BADA EFF are the definition of cumulative perspective due to sabre fuel consumption. To put a finer point, THR EFF is percentage of difference in actual fuel and estimated throttle divided to actual fuel and BADA EFF is percentage of difference in actual fuel and BADA fuel consumption divided to actual fuel. This analysis is applied for both full flight and flight divided to flight phases. The main reason of this phase is originated by the nature of BADA. As stated, BADA is a simulation based model and cumulative approach gives chance to observe fuel consumption more instantaneously. Because Throttle/Auto Throttle gives better output in glimpses. The average efficiency values are shown in the Table 6.1. Note that these cumulative approach results should not be evaluated alone. The reason of that is these results are average and average value of 2 equally distanced value to zero which is one positive and one negative is near zero. To avoid this misleading it is strongly suggested Table 6.1 needs to be evaluated with Figure 6.9.

Table 6.1: Fuel Consumption Results.

Flight Phase	THR EFF	BADA EFF
B738 AC#1 Full Flight	-0.71	6.75
B738 AC#1 only climb	-0.94	4.64
B738 AC#1 only cruise	1.46	5.18
B738 AC#1 only descent	15.11	29.37
B738 AC#2 Full Flight	0.85	7.55
B738 AC#2 only climb	3.82	4.51
B738 AC#2 only cruise	-0.83	4.52
B738 AC#2 only descent	-6.04	31.33

Note that, for both BADA and Throttle/Auto-Throttle model the average of descent phase is different from full flight or other phases. The main reason of this situation is caused by lack of descent algorithm information in FP data.

	A	B	C	D	E	F	G
1	Total fuel burned with sabre	Total fuel burned with throttle model	Total fuel burned with BADA model	SABRE – EST.THR	SABRE – BADA	EST.THR. EFF	BADA EFF
2	2208	2174.7138671875	2152.4876172237	33.2861328125	55.5123827763	1.507524131	2.5141477707
3	2123	2112.9670410156	2062.6905349597	10.0329589844	60.3094650403	0.4725840313	2.8407661347
4	2119	2154.2487792969	2028.7180597145	-35.2487792969	90.2819402855	-1.663462921	4.2605918021
5	4223	4321.5673828125	3721.0421013858	-98.5673828125	501.9578986142	-2.334060687	11.8862869669
6	1949	2016.384765625	1793.8672690172	-67.384765625	155.1327309828	-3.4574020331	7.9596065153
7	4497	4386.4111328125	4055.5550257309	110.5888671875	441.4449742691	2.4591698285	9.8164326055
8	8079	8124.6430664063	7310.5945943165	-45.6430664063	768.4054056835	-0.5649593564	9.511145014
9	2236	2253.5419921875	1998.5150543122	-17.5419921875	237.4849456878	-0.7845255898	10.6209725263
10	2130	2078.1787109375	2028.3287443832	51.8212890625	101.6712556168	2.4329243691	4.7732983858
11	2116	2189.357421875	2028.4501000385	-73.357421875	87.5498999615	-3.466796875	4.1375189018
12	2305	2366.3139648438	2140.7861206093	-61.3139648438	164.2138793907	-2.6600418587	7.1242463944
13	5640	5743.2475585938	5186.4550225761	-103.2475585938	453.5449774239	-1.8306304715	8.0415776139
14	2139	2029.3742675781	2054.3039496274	109.6257324219	84.6960503726	5.1250926798	3.9596096481
15	7858	7879.7041015625	7233.0073514515	-21.7041015625	624.9926485485	-0.2762038886	7.9535842269
16	2119	2154.2487792969	2028.7180597145	-35.2487792969	90.2819402855	-1.663462921	4.2605918021
17	6172	6087.7065429688	5789.2265773924	84.2934570313	382.7734226076	1.3657397445	6.2017728874
18	2207	2195.4140625	2108.7809458101	11.5859375	98.2190541899	0.5249631853	4.4503422832
19	2358	2453.6713867188	2294.7574085209	-95.6713867188	63.2425914791	-4.0573107175	2.6820437438
20	4897	4924.6782226563	4427.3935357891	-27.6782226563	469.6064642109	-0.5652077324	9.5896766226
21	1781	1855.1157226563	1667.5759006875	-74.1157226563	113.4240993125	-4.1614667409	6.3685625667
22	2265	2315.3239746094	2061.1167620194	-50.3239746094	203.8832379806	-2.2218090335	9.0014674605
23	6968	6964.6474609375	6229.9305386886	3.3525390625	738.0694613115	0.048113362	10.5922712588

Figure 6.9: Full Flight Plan Analysis of B738 AC#1.

7. AN EXAMPLE CASE

The motivation by showing example case is comparing implemented Throttle/Auto-Throttle model with actual flight QAR data and prove validation of the model. As seen in chapter 6.1 the flight plan data have a sparse characteristic. To be more precise, in an absolute FP followed flight scenario the elapsed time between 2 consecutive FP position can be more than 10 minutes. In the same scenario QAR data collects nearly 6000 data points for same consecutive FP position. As a part of study, all acceptable flights which followed FP in an adequate way are filtered in chapter 6.2. The example case which will be examined is randomly selected one of those flights. The main aim in this section is proving throttle values of Throttle/Auto-Throttle model is quite acceptable when throttle values are compared with real flight QAR throttle values. Because as stated in chapter 5.4 Black-Box model can predict fuel flow with high sensitivity when throttle values are known. On the other hand, in Throttle/Auto-Throttle estimation thrust is derived kinematically. This examination also tests the trueness of this approach.

Therefore, a lot of methods are used in the thesis to make our model more accurate. After FP integration it is easily seen that obtaining mach number via CAS/Mach conversion is more accurate compared to TAS/Mach conversion. TAS/CAS conversion is applied with Equation 7.1. The Figure 7.1 shows throttle values of TAS/Mach conversion as Flight Plan, CAS/Mach conversion as Flight Plan CAS main and QAR throttle values.. As seen in the Figure 7.1, basing on CAS gives more accurate throttle values compared to TAS based scenario especially in climb and descent phases. On the other hand both based methods are quite satisfying in cruise phase.

$$V_{CAS} = \left[\frac{2}{\mu}\frac{p_0}{\rho_0}\left\{\left(1 + \frac{p}{p_0}\left[\left(1 + \frac{\mu}{2}\frac{\rho}{p}{V_{TAS}}^2\right)^{\frac{1}{\mu}} - 1\right]\right)^{\mu} - 1\right\}\right]^{\frac{1}{2}} \quad (7.1)$$

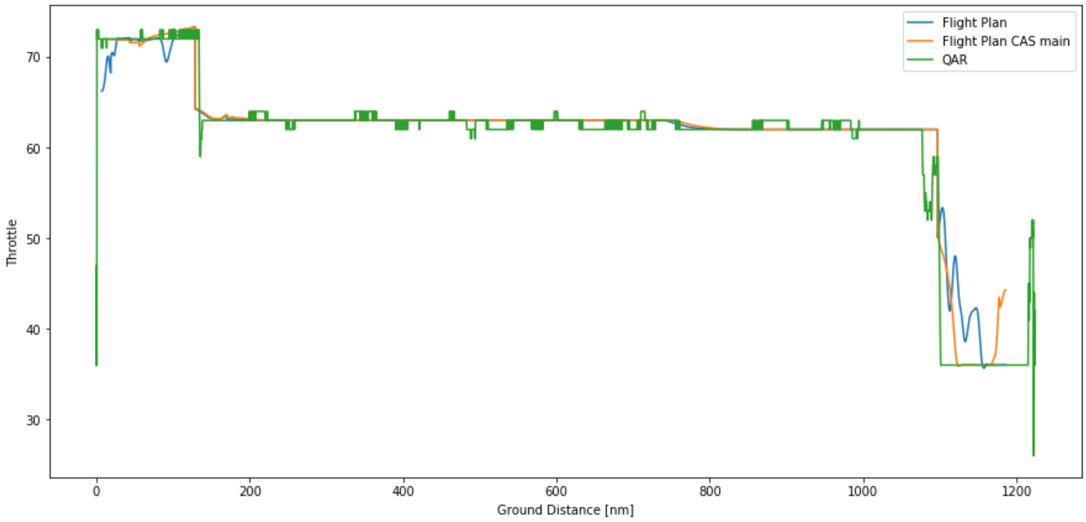


Figure 7.1: Throttle QAR vs Throttle FP TAS vs Throttle FP CAS.

8. CONCLUSİONS

As stated, the main purpose of this thesis is constructing a more precise fuel determination model for commercial aircraft by artificial network. All models have advantages and disadvantages in flights different phases compared to others. Black-Box model has a great consistency with QAR but this model is not acceptable as a prediction model due to its nature. Because there is no throttle data while the implementation of the FP. This situation makes Black-box model is a great control mechanism and keystone of the study but nothing more. BADA model operates sufficient for correct parameters. Because BADA model depends to the manufacturer data but due to the disturbances it makes BADA model weak in a minor perspective. To be clear, BADA model can cause misleading for short period examinations due to the changes of aircraft performance during flight. These changes contravene some assumptions in BADA model and cause overflowing BADA envelope. As a result of this overflowing, BADA deviate out of its envelope especially in climb and descent phases as seen in chapter 6.3. On the other hand there are some obvious observations such as Throttle/Auto-Throttle fuel consumption results are more accurate compared to BADA APM. This is expected because with the improvements with artificial neural network Throttle/Auto-Throttle model overcome this short period contravenes which BADA cannot avoid.

Also as seen in chapter 7 Throttle results of data-driven model is significantly close to the actual throttle values which are obtained in QAR data. Chapter 7 shows that as a result of FP data characteristics putting calibrated airspeed to the work center instead of true airspeed gives more healthy results when throttle results are examined.

Taking everything into the consideration, data-driven aircraft performance models are more accurate compared to simulation based aircraft performance models. As a result of, by using data-driven methods baseline fuel estimation can be predicted more precisely. Consequently, unnecessary cost which is caused by additional fuel can be reduced due to data-driven APM.

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