ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

SENSOR FUSION WITH RELIABILITY RATIOS FOR ALTITUDE ESTIMATION

M.Sc. THESIS

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YÜKSEKLİK KESTİRİMİ İÇİN GÜVENİLİRLİK ORANLARI İLE SENSÖR FÜZYONU

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Nazmi KANKAYA, a M.Sc. student of ITU Graduate School of Science Engineering and Technology student ID 511161136 successfully defended the thesis entitled "SENSOR FUSION WITH RELIABILITY RATIOS FOR ALTITUDE ESTIMATION", which he/she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To Gözde,

FOREWORD

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ABBREVIATIONS

BA	:	Barometric Altimeter
ECEF	:	Earth Centered Earth Fixed
GLONASS	:	Global Navigation Satellite System
GNSS	:	Global Navigation Satellite System
GPS	:	Global Positioning System
IMU	:	Inertial Measurement Unit
LIDAR	:	Light Detection and Ranging
LQR	:	Linear Quadratic Regulator
MEMS	:	Micro Electromechanical Systems
IRNSS	:	Indian Regional Navigational Satellite System
RA	:	Radar Altimeter
RADAR	:	Radio Detection and Ranging
SONAR	:	Sound Navigation and Ranging
VCDL	:	Vertical Channel Damping Loop

SYMBOLS

K	**:** Gain
e	**:** Error
h	**:** Altitude
$\mathbf{e_x}$	**:** Error on x
$\mathbf{e_{x,y}}$	**:** Error on x Caused by y
η	**:** Reliability Ratio

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SENSOR FUSION WITH RELIABILITY RATIOS FOR ALTITUDE ESTIMATION

SUMMARY

Today, many sensors have been designed to measure physical quantities. In addition, different sensors can make measurements using different properties of the relevant physical parameter. During this process, the conversion methods used by the sensors also differ. Additionally, some sensors can be measured by changing the parameter to be measured. All these developments have led to the use of different sensors to measure a parameter. In order to achieve this, algorithm designs have been developed for processing data obtained from different sensors.

One of the working fields for combined sensor structures and data combining algorithms used in almost every field is aviation. These structures, which can also be used in air vehicle sub-systems, are generally preferred for estimating aircraft conditions. In addition to parameters such as orientation, speed and position, the most commonly used parameter of sensor-fusion algorithms is altitude.

In this study, a method for processing the data taken on different sensors will be presented. In order to combine sensor data, it is necessary to select, define and model the sensors to be used. The sensors selected in this study will be GNSS, RA and BA. Besides these sensors, IMU will be added and indirectly included in the calculations in the algorithm. In the first part of the thesis, sensors will be defined, working principles and application areas will be given. After that, error behaviors will be defined and expressed mathematically.

After modeling the sensor data which will be used as input in the algorithm, design will be started. This design consists of different parts. Firstly, the sensor data received will be moved to the appropriate frequency by some recommended methods. In the meantime, the reliability of each sensor will be estimated according to the condition of the system. According to these estimations, the measurement differences between the sensor data will be eliminated. Using the resulting processed data and the reliability ratios, the sensor data were weighted and the combined altitude estimation was obtained. This estimation will be filtered and output using IMU data.

After the design of the algorithm, its accuracy must be tested. For this, an open loop simulation will be created. Test scenarios will be created and harnessed to feed the generated simulation. The results will be examined and the accuracy of the designed algorithm will be examined.

YÜKSEKLİK KESTİRİMİ İÇİN GÜVENİLİRLİK ORANLARI İLE SENSÖR FÜZYONU

ÖZET

Günümüzde fiziksel büyüklüklerin ölçülebilmesi için pek çok sensör tasarımı yapılmıştır. Bunun yanında farklı sensörler, ilgili fiziksel büyüklüğün farklı özelliklerini kullanarak ölçümler yapabilmektedir. Bu işlem sırasında, sensörler tarafından kullanılan çevrim yöntemleri de farklılık göstermektedir. Diğer taraftan bazı sensörler ölçülmek istenen parametrenin değişimi üzerinden de ölçüm yapabilmektedir. Tüm bu gelişmeler bir parametrenin ölçülebilmesi için farklı sensörler kullanılmasının önünü açmıştır. Bunu sağlamak için de farklı sensörler üzerinden elde edilen verilerin işlenmesine yönelik algoritma tasarımları oluşmuştur. Hemen hemen her alanda kullanılan kombine sensör yapıları ve veri birleştirme algoritmaları, için çalışma alanlarından bir tanesi de havacılıktır. Hava aracının alt sistemlerinde de kullanılabilen bu yapılar genellikle hava aracının durumlarının kestirimi için tercih edilmektedir. Diğer taraftan uçuşun sürekliliğinin sağlanabilmesi için, özellikle alçak irtifa uçuşlarında yüksekliği uçuşun en önemli parametrelerinden biri haline getirmiştir. Bu nedenle yönelim, hız ve pozisyon gibi parametrelerin yanında, sensör füzyon algoritmalarının en çok kullanıldığı parametre yükseklik bilgisidir.

Tezin ilk aşamasında böyle bir çalışmanın yapılabilmesi için literatürde bulunan altyapı ve diğer çalışmalar incelenecektir. Bu kapsamda havacılık sektöründe kullanılan Kalman Filtresi, yapay zeka, bulanık mantık gibi farklı yöntemler ve bu algoritmaların kaynak olarak kullandığı bazı sensörler kısaca tanımlanacaktır. Bunun yanında kendilerini kanıtlamış olan bu yöntemlerin çalışma prensipleri algoritma tasarımı yapılırken örnek teşkil edecek şekilde kullanılacaktır. Sonraki aşamada böyle bir çalışmanın yapılma amacı ve hedef noktası verilecektir.

Bu çalışma kapsamında farklı sensörler üzerinden alınan verilerin işlenerek birleştirilmesine yönelik bir yöntem sunulacaktır. Sensör verilerinin birleştirilebilmesi için, öncelikle kullanılacak sensörlerin seçilmesi, tanımlanması ve modellenmesi gerekmektedir. Bu çalışma kapsamında seçilen sensörler GNSS, radar altimetre ve barometrik altimetre olacaktır. Bu kapsamda GNSS uydular üzerinden gönderilen sinyallerin işlenmesi ve her bir uyduya olan mesafenin kestirilerek mevcut pozisyonun elde edilmesi için kullanılmaktadır. Bu pozisyon kesitiriminin bir bileşeni, yapılan ek hesaplamalarla birlikte yükseklik bilgisidir. Yine bu kısımda GPS, GLONASS, Galileo gibi bazı küresel navigasyonel uydu sistemlerinin de tanımlamaları yapılacaktır. Bir diğer sensör olan radar altimetre ise yüzeye gönderilen radyo dalgalarının geri alınması ve gidiş geliş sürelerinin kullanılmasıyla ölçüm yapan bir sensördür. Bu sensör için de kullanım alanlarının ve veri doğruluğunu etkileyen değişkenlerin tanımlaması yapılacaktır. Son olarak barometrik altimetre vasıtasıyla uçuş ortamının statik basıncı ölçülecektir. Bu ölçüm ilgili atmosferik denklemlerin kullanılmasıyla yükseklik bilgisine çevrilecektir. Bu sensörlerin yanına ataletsel ölçüm birimi de eklenecek ve algoritmaya ivme ve açısal hız bilgilerinin girdisi sağlanacaktır. Ataletsel ölçüm birimi

dolaylı olarak algoritma içerisindeki hesaplamalara katılacak ve genellikle filtreleme ve veri türetimi amacıyla kullanılacaktır. Tezin ilk kısmında bu sensörler tanımlanacak, çalışma prensipleri ve kullanım alanları verilecektir. Bunun ardından hata davranışları tanımlanacak ve sensör davranışları matematiksel olarak ifade edilecektir. Özellikle bu hata davranışlarının modelleri hem sensörlerin simülasyonlarının hazırlanmasında hem de ileride güvenilirlik oranlarının hesaplanmasında kullanılacak olmaları nedeniyle önem arz etmektedirler.

Algoritma bünyesinde girdi olarak kullanılması planlanan sensör verilerinin modellenmesinin ardından algoritma tasarımına geçilecektir. Bu tasarım farklı kısımlardan oluşmaktadır. Sensörlerden gelen verilerin sıklıkları birbirlerinden farklı olabilmektedir. Bu farklılıkların giderilmesi ve sensörlerden alınan verilerin işlenmesiyle frekanslar algoritma çalışma frekansına taşınmalıdır. Bu istenirin sağlanabilmesi için ilerleyen kısımlarda ön filtreleme ve veri türetimi ismi ile iki adet yöntem önerilecektir. Düşük ve yüksek frakanslı veriler için hangi yöntemin tercih edilebileceğine dair yapılan bir çalışma da bu esnada paylaştırılacaktır. Bu esnada sistemin içinde bulunduğu durumlara göre her bir sensörün güvenilirlik derecesi kestirilecektir. Bu kestirimler hava aracının içinde bulunduğu durumlara bağlı, dinamik olarak oluşturulacaktır. Bahsedilen güvenilirlik oranlar 0 ile 1 arasında değer alacaktır. Sensörün etkilendiği her bir parametrenin uçuştaki değerine göre o parametreye ve sensöre özgü bir alt güvenilirlik oranı oluşturulacaktır. Bir sensörün ölçümünü etkileyen her bir parametreye göre hesaplanan alt güvenilirlik oranlarının çarpımı o sensörün dinamik güvenilirlik oranını verecektir. Dinamik güvenilirlik oranının yanında, ortam ve sensör özelliklerine göre bazı sensörler diğerlerine göre daha güvenilir bulunabilmektedir. Bu nedenle dinamik güvenilirlik oranları, statik güvenilirlik oranları olarak adlandırılabilecek, kullanıcı tarafından girilebilen katsayılarla çarpılabilir. Bir sonraki aşamada bu kestirimlere göre uygun durumlarda sensör verileri arasındaki ölçüm farklılıkları giderilecektir. Fark kapatma işlemi her bir sensör için o sensör için kestirilen güvenilirlik oranları ile yapılacaktır. Bahsedilen bu güvenilirlik oranları, referans veri ile sensör verisi arasındaki farkın kapanma hızının belirlenmesinde kullanılacaktır. Elde edilen işlenmiş verilerin ve güvenilirlik oranlarının kullanılmasıyla, sensör verileri ağırlıklandırılacak ve birleştirilmiş yükseklik bilgisi elde edilecektir. Bu noktada güvenilirlik oranı yüksek olan verinin çözümün oluşturulmasında daha büyük pay almasını sağlamaktır. Bunun yanında her bir sensörün düşük güvenilirliğe sahip olması durumunda gene de çözümün ortak ağırlıklandırma ile oluşması amaçlanmıştır. Elde edilen bu yükseklik bilgisi, IMU verisi üzerinden elde edilen yukarı yönlü ivme bilgisi kullanılarak filtrelenecektir. Bu aşamada, düşey eksen sönümleme döngüsü adı altında bir algoritma tanıtılacak ve bu yöntemin kullanılmasıyla elde edilen yükseklik bilgisi çıktı olarak verilecektir.

Algoritma tasarımının yapılmasının ardından, algoritmanın doğruluğunun test edilmesi ihtiyacı ortaya çıkacaktır. Bu ihtiyacın giderilmesi için açık çevrim ile çalışan bir simülasyon ortamı oluşturulacaktır. Bu simülasyon ortamında uçuş mekaniği denklemleri ile referan veriler oluşturulacak ve sensörler için oluşturulan hata modellerinden geçirilerek algoritma girişine beslenecektir. Simülasyon yapısının kurulmasının ardından iki adet senaryo oluşturulacaktır. Bu senaryoların ilkinde, algoritmanın farklı uçuş koşullarına ve manevralara karşı işlevselliğini korunması test edilecektir. Bir sonraki senaryoda ise sensörlerde oluşabilecek hata ya da bağlantı kopukluğu sonrasında kullanımda kalan düzeltilmiş sensör verileri ile uçuşun devamlılığının sağlanabileceği kanıtlanacaktır. Yapılacak bu testler sonrasında elde edilen sonuçlar incelenecek ve tasarlanan algoritmanın doğruluğu irdelenecektir. Son olarak ek olarak yapılabilecek çalışmalardan bahsedilecek ve tezin daha da geliştirilebilmesi için bazı seçenek ve ek çalışmalar önerilecektir.

1. INTRODUCTION

The need for measuring and evaluating physical quantities has led to the formation of sensors. Before modern technology, measurement methods made by comparison over history have entered a different path, especially with the use of electricity in controlled manner. With this new system, the measurement speed, quality and precision have increased. Many sensor designs have been made so far for the physical quantities to be measured. Even though these sensors are sufficient to operate on systems, high performance demands and the need for more advanced systems have increased the need for correctness and accuracy of the sensor data. Although the sensor performance is constantly being improved by the studies, sensor development cannot meet the industrial requirements alone due to physical, economic and technological constraints. At this point, in addition to the development of sensors, one of the solutions to meet the needs is to use different sensor data in a coordinated manner. In other words, correction of measurement errors, increasing the frequency of data, reducing the noise on the data has been the reason for the combined use of data from different sensors.

1.1 Background and Motivation

In order for a physical system to be well analyzed or controlled, it is necessary to accurately measure the state of that system. Given the fact that accurate measurement can never be made, some difficulties will be encountered during the fulfillment of this request. The difference between the actual data and the sensor data will make it difficult to control the process on systems running through closed loop, and in some cases will make the process impossible. In almost all structures designed for system control over the world, closed loop systems are preferred by the feedback of the data obtained from the sensor measurements. For advanced systems, the use of closed-loop systems in almost all designs makes the accurate determination of system states extremely important.

Increasing the quality of a sensor usually leads to an increase in the sensor volume and price or to a reduction in the frequency of data generation. In addition, increasing the quality of data that the sensor will produce after a point will cause the cost to be in other areas according to the system design criteria. Looking at the entire system, the improvement in the quality of the sensor output after this threshold will have a negative impact on the overall system. After a critical point, improvement of the sensor data will not be possible due to physical constraints.

The sensors show different behaviors depending on the physical magnitude and measurement method to be measured. In most cases, the same physical size can be measured using different methods. For example, the measurement of the temperature value can be taken by the processing of the infrared rays reflected on the surface of the object to be measured, or by reading the unit expansion on the mercury. At this point, both measurements will have advantages and disadvantages. While the infrared measuring sensor will make a faster and accurate measurement, the cost of the sensor using mercury will be less, the operating principle is simpler, and the lifetime will generally be longer. It should be noted that there will be differences between the error and measurement behaviors of these two sensors also.

In addition to measuring the physical quantities using different methods, a physical size itself and the rate of change can be measured by different sensors. For example, the liquid flow rate through the flowmeter can be measured during filling of a liquid tank. In addition, a pressure sensor in the tank will give the data according to the shape of the tank and the type of the sensor proportional to the amount of liquid in it. In this case, the value of the amount of liquid to be obtained by processing the pressure sensor is expected to be consistent with the integral value to be obtained over the flowmeter data.

Sensors can make errors in some special cases. This means that, when working with a single sensor, a high level of faulty measurement can be taken instantaneously. This error may cause the wrong command to be generated in the system control, which may cause the system to become undesirable. On the other hand, on the same physical measurement, and numerical data conversion over different physical laws and the ability to obtain information from the change of this physical property have led to the use of sensor data together in the systems. Thus, the accuracy of the measurement will be increased, the noise level on the information will be reduced, and the information obtained on the system will become more reliable.

The combination of sensors is used in many areas such as automotive industry, chemical industry, robotics. One of these areas of use is the aviation industry, which needs low weight, high accuracy and frequency of measurement. In order for an aircraft to function properly, flight conditions should be known as close as possible to the reality with its subsystem functionalities. Flight conditions are usually examined through acceleration, angular velocity, attitude, velocity and position. Although each parameter is important in itself, position information will be particularly important in order to follow the route required by the given task plan. The importance of elevation information, which is a component of this position, is slightly more important than the distances taken in order to ensure flight continuity. In addition to this, there are many sensors such as radar altimeter, barometric altimeter, sonar altimeter, lidar altimeter and GNSS. In this study, by using the sensor data of different characteristics, an approach will be made on the correct estimation of the altitude and the downward velocity information depending on this parameter.

In addition to the mentioned methods, there are many methods for generating a altitude information through different sensors. Particle filter, various artificial intelligence methods, other.

1.2 Literature Survey

Many studies have been done on the co-ordinated operation of sensors on closed loop systems. The estimation of the elevation estimation a significant part of the studies on this subject.

One of the most common methods used to combine different sensor data simultaneously is Kalman Filter. Kalman Filter is used for filtering and combining many data in many areas. One of these areas is the height estimation. The Kalman Filter is often used to combine a sensor that measures a altitude rate or an acceleration on a vertical axis and a sensor that measures altitude. The proportional sensor is usually selected as an IMU (Inertial Measurement Unit). The measurement in altitude channel can be obtained via a camera, RA, BA, LIDAR, SONAR or GNSS. First of all, the system model and the error behavior of the sensors are added to the Kalman Filter structure. The Kalman filter estimates the current status of the system and the next state of the system using the data from the sensors. The known noise characteristic is filtered by using LQR. The difference between estimation and measurement is scaled by a parameter called Kalman gain and added to the system input to improve subsequent estimates. As a result, the difference between the system output and the reference data is multiplied by a gain, then the proportional measurement sensor (usually IMU) is added to the data. This new input is passed through the system model and given as output in the next step and this process is continued throughout the flight [1].

Artificial neural network method is one of the methods of data merging and filtering. In this method, sensor data is considered system input. Usually, the parameters that the sensors change depending on the measurements are added to the system inputs. After that, the system inputs are processed with each other and they create new states on the hidden layer of nodes. Situations that are the outputs of these new nodes are treated again by each other according to the system requirements, creating a new hidden layer. This process series ends with the desired value or values. The weighs to be used in the nodes within the neural network can be done by using the system model or by way of training over the reference test data. This method, which can accept almost any sensor data as input, is generally preferred for complex processing structures.

Another method called vertical channel damping loop can also be used to connect sensors in the altitude channel. In order to use this structure, there is a need for two sensors, one of which is to be measured on the physical parameter and the other one measuring the derivative of this parameter. At this point, it would be appropriate to use a sensor that measures in a height channel such as RA, BA or GNSS, and a sensor which is proportional in the same channel as IMU. According to this method, the value obtained as a model output is compared with the reference data. This difference is then passed over a PI controller structure and added to the vertical acceleration data on the model input. The derivative of the difference between the reference data and the model output is then added back to the obtained velocity after the integral is taken for the velocity. After the final integral process for the elevation information at the model output, the combined elevation data following the reference elevation information is obtained.

1.3 Problem Statement

Ideally, all sensors will produce the same data without error. However, in real systems the sensors will perform different measurements in different situations. However, in some cases this error may be too large to be used. In addition, permanent damage to the sensors may be encountered when the operating conditions are exceeded. In this case, the healthy re-use of the sensor may not be appropriate. Although the filtering and data fusion process provides resistance against incorrect measurements for short periods, it will not be possible to continue the process with incorrect data in the long term. When this time is defined as flight, the severity of the sentence established will increase.

Another problem during the process is that some sensors require an external source. For example, all of the sensors running over GNSS fall into this category. Therefore, errors on satellite signals will affect system behavior. In particular, the use of GNSS in the production of elevation channels requires a critical examination of this issue.

On the other hand, the use of other sensors in the system in closed loop will increase the efficiency of the system. Therefore, increasing the number and type of sensors provided that they do not exceed the mass, volumetric or economic limits will be positive for having more resources related to the process.

Considering all the definitions, it is seen that it is beneficial for the system to identify the situations where the sensors are suitable for use and to include all existing sensors in the process. In addition, the reliability of each sensor should be checked during the process. Most advanced systems have a number and variety of sensors to build such a structure. In addition, it is a great requirement to detect system states in a way that minimizes the error.

In this study, certain sensors will be selected and the sensors will be combined in the altitude source. The sensors selected for operation will be RA, BA, GNSS and IMU. The process of fusion will first begin by matching the frequency between the sensor data. The fixed errors between the sensor data will then be corrected via the selected reference data. During the consolidation process, the reliability of RA, BA and GNSS will be examined. After this examination, a reference is made and a reference data will be obtained by combining these three data. The resulting reference data will be passed through a loop along with the vertical acceleration information received over the IMU and the combined elevation data will be obtained at the output. The difference between the fused data and the data that taken from sensors will be closed dynamically with using a slow filter.

2. SENSOR SPECIFICATION

It is important to recognize the inputs of that algorithm before working on an algorithm. If there is a possibility of unexpected behavior on these inputs, it is becoming more important to recognize the inputs. For this study, it has great importance to define these sensor behaviors and to examine their error characteristics before the step of the sensor data is fusion. Here, the sensor models obtained as a result of this review will be created for use in the fusing algorithm. The sensors selected for this study will be IMU, GNSS, radar altimeter and barometric altimeter. These headings are discussed in the next section.

2.1 Inertial Measurement Unit

2.1.1 Sensor definition

Inertial measurement unit, or simply IMU, is a sensor which using for measure angular velocity and acceleration that are applied to itself. It is used frequently in many areas due to the fact that it does not need any external resources (dead reckoning), it is able to make frequent and high accuracy measurements and it is able to measure proportionally in terms of navigation. IMU consists of two components as accelerometer and gyroscope. Advanced IMU systems can have more than one of these parts.

As the name implies, the accelerometer is the part used for the acceleration measurement in the 'IMU'. According to Newton's second law, the force applied on an object is equal to the momentum of the body and the mass of the body. Using this information, a tiny mass is placed in the accelerometer. In advanced sensors, this is done separately on the axes that form the Cartesian coordinate system. The force acting on this tiny mass can be measured using electromechanical methods. It is also possible to measure the acceleration on the sensor by using mass information.

The gyroscope or gyro for short is the other part of the IMU and is used to measure the angular velocities acting on the sensor. A method similar to the accelerometer is used for this measurement. Newton's second law, which was used during the acceleration measurement, is replaced by the angular momentum equation at this stage. Moment that is applied to a known mass with its inertial properties can be measured using electromechanical or electro-optic methods. This data can be used to measure the angular velocity generated on the sensor. The measurement of angular velocity is multiplied and customized on the axes forming a cartesian coordinate system, as in the accelerometer operation for advanced sensors. [2] [3]

It is an absolute measure of the angular velocity and acceleration information on the IMU. This means that even when the IMU is stationary on a table, a value that is not equal to zero and which is independent of the noise will occur. The gravitational force acting on the sensor is balanced by the reaction force applied by the surface. This force also acts on the mass or masses in the accelerometer and used for measurement. In the structures used to measure these masses (usually mechanical springs), a force is created to meet the gravitational acceleration. This causes the gravitational acceleration to be reflected in the measurement. Similarly, the angular velocity caused by the rotation of the earth is perceived by the IMU. In other words, an IMU, which stands on a surface, will measure the angular velocity resulting from the rotation of the earth. When making navigation calculations, these factors which cannot change the fixed position according to the ECEF coordinate system are calculated and subtracted from the IMU measurements. Although these measurements, which are seen in static form, may affect the integration of the navigation as an error, they can be used to estimate the initial attitude of the sensor.

2.1.2 Usage areas

Although they can be used for impact and swing measurements, the main uses of IMUs are navigation calculations. Due to the high frequency, reliable data characteristics, the knowledge of all three axes and the design of the dead reckoning, for most designs, the IMU was the most necessary sensor. Although it does not measure directly the position and orientation, the parameters related to the calculations of these parameters can be obtained. At this point, it is necessary to share the knowledge that a calculation algorithm will be needed in the navigation works to be carried out via IMU. In addition, one of the most important features of IMU is that it can be combined with different sensors that make measurement in navigation and allows to create more reliable algorithms.

IMU can be used in all areas where navigation calculations are needed. This sensor can be used in combination with GNSS systems for regional or intercontinental seafaring. In cars, speed and position measurement can be used to check the airbags and detect some error conditions. Also, speed and position measurements are combined with various sensors are used in trains. In addition, IMU has managed to become an indispensable sensor in the aviation industry due to its ability to work on three dimensions. In almost all aircraft, the IMU, which is often used in conjunction with other sensors, is often placed on the basis of navigation calculations.

With the development of today's technology, IMUs have reduced to very small dimensions. With these structures called MEMS (Micro Elektromechanical Systems), IMUs have been involved in many structures such as mobile phones and tiny vehicles. For example, IMUs are the most important data sources of mobile phone applications that determine the step counters and location detections. From a more general point of view; these small but effective sensors are preferred in many areas where they are used in small household appliances.

2.1.3 System modelling

Like every sensor, the IMU also has a noise on it. This noise is not affected by flight conditions and environmental impacts, and is usually due to in-sensor design. Errors seen on the accelerometer and the gyroscope, and the process of the formation of these errors may be different. Therefore, as in the definition, it would be appropriate to make error modeling of these two components separately.

The fault behavior for the accelerometer can be examined in two different parts. The first of these error behaviors is the bias between the actual value and the measurement. The majority of this difference is due to the structure of the sensor itself. Another factor that caused it is formed depending on the magnitude of acceleration on the sensor. The second error behavior is due to noise on the sensor measurement. This noise appears as Gaussian. [4]

The main reasons of the errors seen on the gyroscope can be given as errors in the system, instrument reflection errors, random walk coning and sculling errors. When these errors are combined, there are two types of error behavior, as seen on the accelerometer. The first one is the drift, the second is the noise error. Therefore, it is inconvenient to model the errors seen on the gyroscope in this way. It is given in eq. 2.1 mathematically. [3]

$$e_{imu} = e_{imu,bias} + e_{imu,noise} \tag{2.1}$$

where:

$e_{imu,bias}$ = is the bias error on IMU

$e_{imu,noise}$ = is the noise on IMU

Error model was created and the acceleration data received over IMU was integrated into the initial velocity and position information to obtain altitude information. As can be seen in the Figure 2.1, the error model on the IMU was also processed by the actual data, resulting in a velocity and therefore an error in the position based on the actual data.

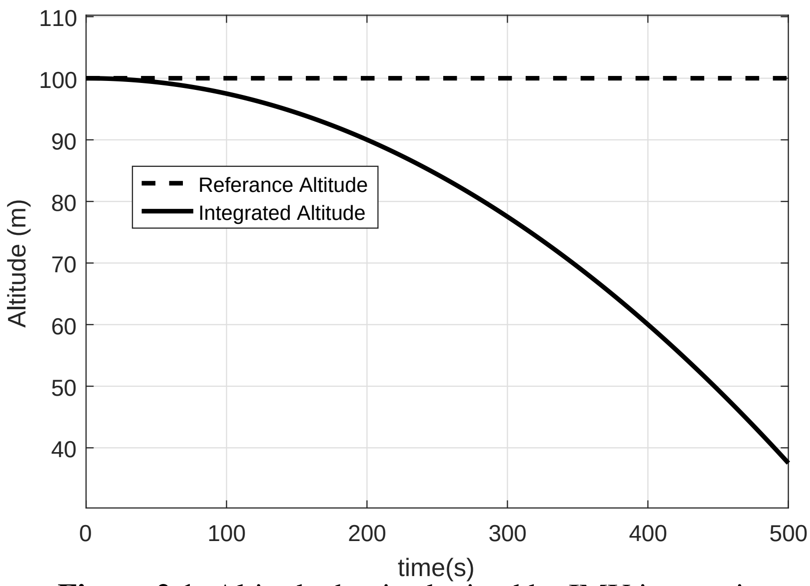

Figure 2.1: Altitude that is obtained by IMU integration.

2.2 Global Navigation Satellite System

2.2.1 Sensor definition

By the 1970s, the accuracy of the navigation calculations was still not fully resolved. Especially with systems driven through the INS, systems with long distance requirements were not easy to implement. The GNSS project was proposed as a solution to solve the navigation problems of the US defense industry in the 70s. The first step in implementing this idea was in 1978 when the first satellite was placed in orbit. In 1995, the system called GPS was introduced. Then, with the addition of a circular trajectory defined by them at a radius of 26560 km, 24 satellites circulating in about 12 hours are used to determine the position. The system is divided into two parts as civilian use and military use. Different signal frequencies are used for both subsystems [4] [5].

Following the GPS system, a system called GLONASS was created by the Soviet Union. Similar to GPS, GLONASS also has 24 satellites. In this satellite system, which is currently being controlled by Russia, satellites move in their orbits of a defined radius of 19100 kilometers. Similar to GPS, it has two different modes of operation: military and civilian.

Galileo; In addition to GPS and GLONASS systems, it is another GNSS system designed by the European Union. Unlike previous GNSS systems, it is designed for civilian use. 22 of the 30 satellites planned as of May 2019 were placed in planned trajectories. This system with an orbit radius of 29600 km will be used in the coming years. In addition to the given examples, there are also GNSS systems which are developed by BeiDou developed by China and the regionally developed IRNSS (Indian Regional Navigation Satellite System). These two examples are still under construction like Galileo.

The working principles for the given GNSS systems are similar. Each satellite in the system transmits a unique message using radio waves. This message contains the position and time of the satellite. A receiver receives these messages via different satellites and gives them to the sensor algorithm. The difference between the time when the radio wave is transmitted over the satellite and the time information received over the clock on the sensor will give the time the radio wave passes over the atmosphere. It is possible to estimate the distance between the sensor and the corresponding satellite by using the information that the radio waves are moving at the speed of light on the medium. In this way, distances from different known satellites are obtained. This distance and position information is solved using the least squares fitting method and the position information of the sensor is calculated.

The accuracy and performance of GNSS systems are constantly checked by ground stations. Continuous data is received from satellites by ground stations located in different regions of the world. The position of ground stations is known correctly. With this information, the compatibility of message information received from different satellites is always checked. When an error is found or if an update is requested, a message is sent to the satellite via the control center.

2.2.2 Usage areas

GNSS systems are often used for location-based services. The use of GNSS receivers in search and rescue operations in large areas allows the solution to be reached much faster than before. In addition, the use of GNSS provides a great convenience for navigation to transportation vehicles in different ways. In addition, the orientation of different vehicles and vehicles has become simpler with this method. Many sports areas, public works and environmental assessments are examples of other areas where GNSS can be used. When the subject is reached, the use of GNSS for the navigation of the aircraft is very often preferred.

2.2.3 System modelling

As with any sensor, there are certain headings that can cause errors in the use of GNSS. These errors are caused by the number of satellites seen, timing errors, atmosphere specifications and environmental impacts. In addition, it is possible to fix some errors for measurement accuracy.

At least three satellites are needed for getting solution from GNSS. In this way, three equations will be obtained over three satellite positions and distance. These equations are sufficient to calculate the position in three-dimensional space consisting of parallel, meridian and elevation unknowns. However, in most cases, these three equations are not sufficient to ensure that the solution is formed in a healthy way. This is because the synchronization between the satellite and sensor clocks cannot be fully achieved. In other words, the difference between the sensor clock and the satellite clock creates a further unknown, called time offset, along with the position information. An additional satellite will be needed to eliminate this shift. Therefore, in addition to the given proposition, at least four satellite information is needed to calculate parameters of parallel, meridian, elevation and time.

The satellites are usually precisely adjusted. However, if no adjustment is made, there may be a shift in the satellite clock over time. On the other hand, an error may be present on the receiver clock. It should be noted that the fact that this error can be calculated in addition to the position information makes the error on the sensor clock relatively unimportant to the error on the satellite clock. On the other hand, an error on the satellite clock is of critical importance to ensure that the solution can be generated correctly, as this will result in incorrect calculation of the distance between the satellite and the receiver [3].

Environment that is radio waves traveling between the satellite and the receiver have critical importance for distance calculation. Ionosphere is a layer that starts at 70 km and ends at 400 km when it referenced to to surface of Earth. The high ion density in this layer creates a break on the radio wave depending on the frequency. This causes the path of the radio wave to be extended and the distance between the receiver and the sensor is estimated incorrectly. Modeling and measurement can be performed on ionospheric delay. The troposphere is part of the atmosphere from the 8th km of the Earth's surface to the 40th km. It consists mostly of nitrogen, oxygen and water vapor and is neutral in contrast to the ionosphere. The main reason is the gas density in its structure. The delay in this section is examined in two parts as wet and dry delay. The wet delay caused by the vast majority of water vapor constitutes 10 percent of the error. The remaining 90 percent is caused by dry gases such as nitrogen and oxygen. Dry delay can easily be modeled, but it is relatively difficult to model wet delay [6].

Multipath errors are caused by taking different paths between the satellite and the signal. This is usually due to reflections from different objects or obstacles. Usually this error in urban areas can reach up to 10 m.

The locations of the satellites are being updated by ground stations so as not to cause a major fault. However, despite a good follow-up and frequent updates, the position of a satellite may be incorrectly estimated. Therefore, some error is observed in the position calculation of the sensor. There is also a difference in the signal level between the satellite being partially seen by the receiver and the clear view. [7]

Finally, measurement errors on the receiver can be taken as one of the significant error reason. This error can be caused by the overheating of the sensor, the noise on the received signal or the inadequacy of the signal processing algorithm.

In the advanced receiver systems and algorithms, velocity calculation can be made by using Doppler effect. In cases where the number of satellites is sufficient, many of the identified faults are generally analyzed in unified condition and the noise behavior of the systems running over GNSS is usually done over the normal distribution. This value may be as low as 0.7 m for parallel and meridian channels, although the signal strength varies according to the phenomenon such as the length of the radio wave conveyed message and the operating frequency of the receiver. The error for the height channel may be slightly higher. The 3 sigma value of the noise over the velocity values is usually below 0.1 m / s. Mathematical equation is given by eq. 2.2

$$e_{gnss} = e_{gnss,clk} + e_{gnss,atm} + e_{gnss,mp} + e_{gnss,rcv} \tag{2.2}$$

where:

$e_{gnss,clk}$ = is the timing error

$e_{gnss,atm}$ = is the atmospheric error

$e_{gnss,mp}$ = is the multipath error

$e_{gnss,rcv}$ = is collected error that is caused by reveiver

The error model that may occur on GNSS is shown on the Figure 2.2. The graph is divided into 5 regions for this review. Since the number of satellites in the first zone is less than 4, no solution has been produced. Since there is sufficient satellite in the second region, a solution has been produced on GNSS. The number of satellites increased to R5 and the noise level on GNSS decreased.

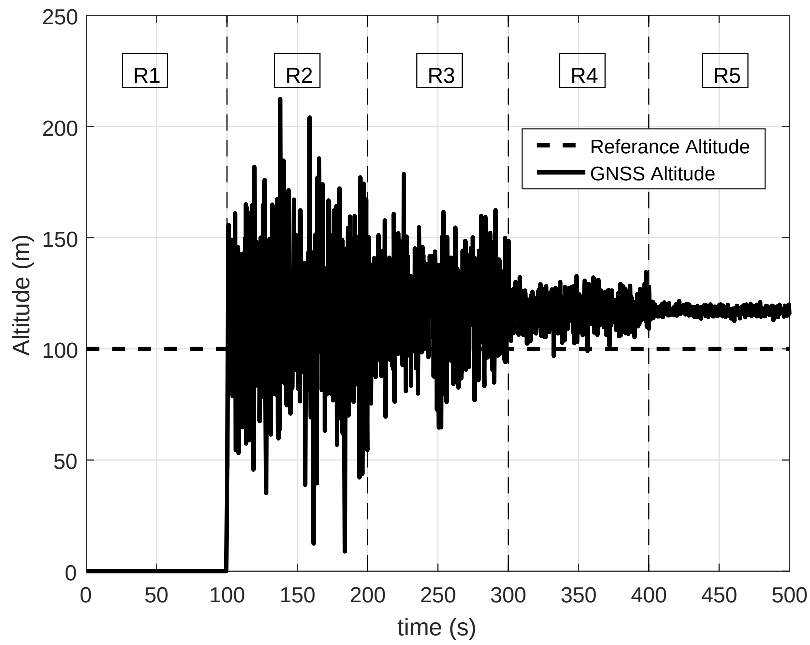

Figure 2.2: Altitude that is obtained by GNSS.

In addition to the noise on GNSS, there is a bias between the reference altitude and the altitude obtained by GNSS. This bias is due to the difference between the ellipsoidal altitude and the mean sea level altitudes, which differ according to the location on the Earth. This difference can be calculated with high accuracy over parallel and meridian information. In order to use the altitude information received via GNSS, this difference is usually added to the data received on the sensor in the algorithm.

2.3 Radar Altimeter

2.3.1 Sensor definition

Radar is a word formed by the abbreviation of Radio Detection and Ranging. For the first time, it was discovered during the communication experiments that the transmitted radio waves were changed after striking an obstacle. The idea that this change on radio waves can be used for distance measurement has laid the foundations of radar altimeter. There are two sub-systems called the receiver and transmitter that transmission the signal on the radar altimeter and collect this broadcast. Two different frequencies are selected to perform the operation. The transmitter transmits at a frequency ranging between these two frequency values. The transmitted signal is emitted in the waveform and turns back after hitting an obstacle. Signal that is coming back is detected by the

RA receiver. It is known that the radio wave will travel with the speed of light. At the same time, the difference between the time at which the signal is sent and when it is detected by the receiver can be read with high resolution using the frequency change. Through this frequency change, the time between sending and retrieving the signal can be obtained. It is possible to know how far a wave travels with the signal speed and the time spent in the environment. The path traveled between the sensor and the obstacle twice as this path first traveled from the sensor to the obstacle and then from the obstacle to the sensor. Therefore, the distance between the sensor and the nearest obstacle can be calculated simply by the following formula [8].

2.3.2 Usage areas

Radar technology has a wide range of uses, such as military areas, air and land traffic guidance and space exploration. Usually the distance and relative velocity measurement are used to measure the area of the radar altimeter is a subject of the measurement of altitude. Unless there is a closer barrier between the sensor and the surface, the fact that the absolute distance can be calculated makes the use of RA essential for the aviation industry. On the other hand, the fact that this altitude can be determined only for limited sizes caused a great limitation. Therefore, radar altimeter can be used for landing and take-off stages of aircraft, low-altitude flights or similar short-range measurements.

2.3.3 System modelling

Radar altimeter is used in many areas in terms of distance measurement. On the other hand, many features of radar altimeter also restrict its use. One of the most important features of this restriction is due to one of the most distinct features of the radar altimeter. Accordingly, the signal coming out of the transmitter in RA structures will bounce back over the nearest obstacle. Therefore, the distance information to be produced by the receiver from the respective algorithm will also represent the distance to this obstacle. Because of that, multipath error that can be seen in GNSS generally is valid here [9]. Although this situation is prevented by making the RA transmission in the form of conical waves, it is not easy to keep the foreign bodies, obstructions or surfaces away from this conical spring.

Another limitation of the radar altimeter is that only a limited distance can be measured. The radar altimeter design is usually made specifically for use. This is because the RA designs are customized for different measurement ranges. Some altimeters can measure up to 6000 m, while others can only measure up to 600 m. Altimeters with smaller upper limits are often more advantageous in terms of resolution or weight. In addition to the upper limit for RA measurements, there is also a lower limit. This value is less than 1 m for high resolution altimeters. The reason for this situation is that there is some distance between RA transmitter and receiver. This distance helps to avoid mixing the receiver and transmitter signals. A time will be needed to cover the mentioned distance. Therefore, a distance information below this distance will not be measured. In addition, the structure of the communication between them also affects this situation.

Another aspect that may cause an error on the radar altimeter measurement is the navigation features of the vehicle to which the sensor is connected. The forward speed on the sensor, the roll and pitch angles in the attitude of the sensor will affect the measurement of the radar altimeter. The forward speed will cause an error in the measurement of the radar altimeter due to the Doppler effect. In addition, the rolling and pitching angles of an aircraft for high values may prevent RA to stay in the source cone. Errors may occur in the measurements made in this case. [10]

Receiver errors or incorrect evaluation on the system may cause serious errors. A true altitude-specific error will occur in this error model. This error can be added to the RA measurement as a function of the actual height during modeling. Also a noise is expected to be seen over the next measurement. This noise behavior can be modeled by a Gaussian noise. The noise sizing can also be achieved with a sigma to be selected. There is also a possibility of movement on the surface. This situation is an important factor in the movement on the sea. Therefore, the noise to be caused because of given reason must be included in the system. This effect is often modeled using frequent sin waves [11].

$$e_{ra} = e_{ra,bias} + e_{ra,noise} \tag{2.3}$$

where:

$e_{ra,bias}$ = is the bias error on RA

$e_{ra,noise}$ = is the noise on RA

Following the modeling, a graph that is given by Figure 2.3 showing the error behavior of the radar altimeter was created. In this graph, 3 different regions are formed with 3 different features. Measurement is made on a flat surface in the first zone. As can be seen from the figure, there is noise and some bias on the measurement. In the second region the altitude was increased and the radar altimeter was not able to measure after a limited altitude. In the third region, surface fluctuation is modeled according to sea and ocean environments. It is clear that the noise seen in this region is more than the first region.

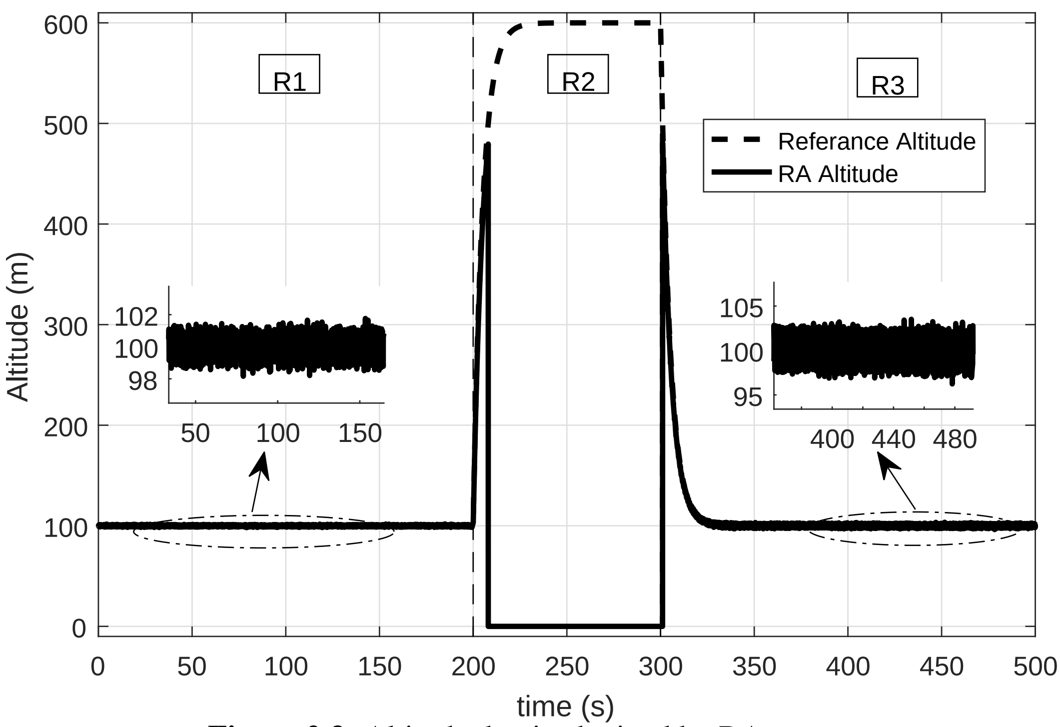

Figure 2.3: Altitude that is obtained by RA.

2.4 Barometric Altimeter

2.4.1 Sensor definition

Many physical properties in the atmosphere vary around certain rules that can be easily described. One of these is the change in atmospheric pressure due to altitude with a specific formula. It should also be shared that there may be errors between real behavior and the formula. It is possible to estimate the altitude over the measured pressure using this rate of change. The barometric altimeter is a sensor used to obtain altitude after the corresponding transformations using the ambient pressure value.

The barometric altimeter has a much simpler structure than INS, GNSS and IMU. For this reason, according to the shared use of other sensors of this sensor even older, it is based on the year 1700. In addition, the barometric altimeter is not an externally dependent system similar to the IMU. This simplicity and operation in its use and design have made Barometric Altimeter one of the most preferred sensors in its field. Generally it can be preferred to use with GNSS [12] [13].

The operating principle of the barometric altimeter is quite simple as mentioned before. Firstly, there is a mechanical part in the sensor that varies in size according to the pressure in the environment. This piece may be in the form of a empty balloon or as a membrane. The amount of change on this mechanical part is usually obtained by electromechanical transformations. In other words, how much the resistance of this part changes under pressure is calculated. This calculation is continued by reading the value of the current passing through the part and digitized at the last stage.

For use on air vehicles, BA is generally used within the pitot tube. In addition to static pressure, dynamic pressure measurement can be made with Pitot tube logic. The speed of an aircraft can be estimated using the difference between these measurements. In addition, advanced pitot tubes allow for estimation of angle of attack and angle of shear. This demonstrates that BA and the pressure processing methods underlying the altitude calculation can be used extensively to estimate the flight dynamics.

2.4.2 Usage areas

In addition to activities such as parachute jumping, hiking and climbing, the most common area for BA has been in aviation. The barometric altimeter, unlike RA, can operate at any height within the troposphere Compared to GNSS, it is advantageous in that it does not require an external source. In the calculations made on the GNSS, the distance to the satellites is calculated and the distance to the earth's surface is calculated relative. At this point, the advantages of the barometric altimeter are that the calculations on the BA are made at reference height and cannot be mixed from the outside.

All aircraft used today have a barometric altimeter. In relation to the size of the aircraft, the number of BA is usually increased and placed in different parts of the aircraft. Due to its high reliability, one of the first points to look at is an unexpected change during the flight. On the other hand, barometric altimeter is also used frequently in missiles, drones and some other air vehicles.

2.4.3 System modelling

The barometric altimeter is a highly critical sensor. This is due to sudden changes in pressure. The main reason for a significant part of the measurement errors seen on the BA is due to the incorrect estimation of the pressure. Low or high pressure may occur at some points in the atmosphere. In these regions it is quite possible to see the difference between the actual altitude and the calculated altitude.

In addition, continuous or sudden air flows can occur at almost every point of the atmosphere. This flow sensor to influence the recipient regardless of the changes in the actual altitude fluctuations in the altitude measurement, that will cause noise at low frequencies. It is also possible to see differences with a low rate of change between the actual altitude and the measured altitude.

The effects of pressure change on the sensor receiver are not experienced only due to atmospheric effects. Generally, pressure measured by BA during maneuvering or acceleration will not stable. This difference can lead to larger errors than atmospheric effects. In order to avoid this situation, the sensor receiver is usually placed at its front end according to the direction of movement of the aircraft. This placement point is intended to minimize the effect of irregular flows that will occur during maneuver on the measurement.

In the barometric altimeter, like other sensors, operations are also performed during the measurement. Some losses or reactions may occur on the elements used to perform these processes, or on the cycle operations. Therefore some losses may occur. These losses are small enough to be neglected in advanced designs. However, there is also a noise affected by pressure changes. This noise usually occurs with normal distribution around pure measurement. Therefore, Gaussian noise can be added to the data obtained by creating a sigma value that can be obtained from the relevant sensor calculations or test data. [14]

$$e_{ba} = e_{ba,bias} + e_{ba,\alpha} + e_{ba,\beta} + e_{ba,M} + e_{ba,noise} \tag{2.4}$$

where:

$e_{ba,bias}$	= is the calibration error seen in equilibrium
$e_{ba,\alpha}$	= is the error caused by the angle of attack
$e_{ba,\beta}$	= is the error caused by the sideslip
$e_{ba,M}$	= is the error caused by the Mach number
$e_{ba,noise}$	= is the Gaussian noise on measurement

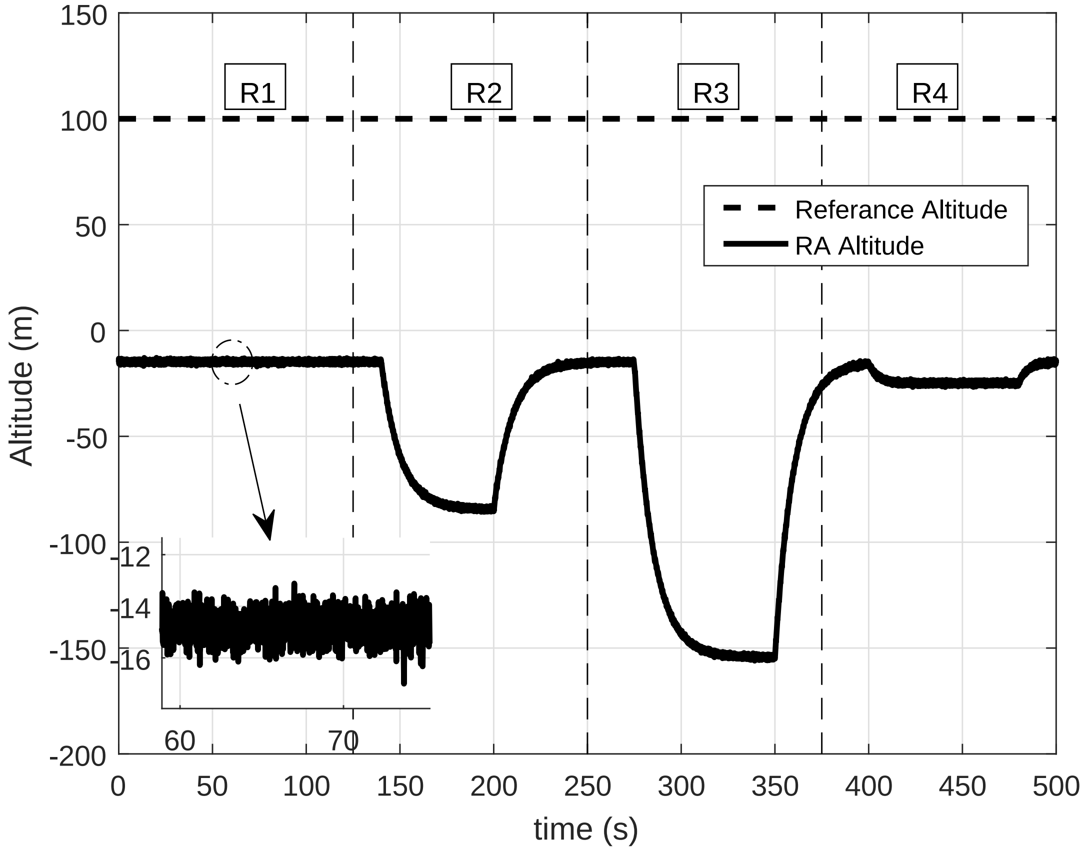

Figure 2.4: Altitude that is obtained by BA.

The barometric altimeter has been previously informed that it will be affected by variables such as angle of attack, sideslip angle and Mach number. Figure 2.4 is divided into 4 regions so that these effects can be displayed on the model. Barometric altimeter measurement information is shown for the static state in the first zone. There is a constant difference between the altitude and the measured altitude. In addition, a decrease in pressure was observed by increasing the attack angle with a reference speed in the second region. This drop caused an error on the height measurement. Similarly, an error occurred in altitude measurement by changing sideslip angle in the third zone. Finally, the effect of the change in Mach number on the altitude measurement in the fourth region can be seen.

3. FUSING ALGORITHM

The fact that each sensor has a operating range has already been given. Furthermore, the fact that the sensor is capable of generating data does not imply that this data is accurate and usable. In order to perform data fusion in the altitude channel, previously sensors named IMU, GNSS, RA and BA have been defined. At the same time, the error behaviors of the specified sensors are defined both as verbal and as formula.

Considering the conditions of an aircraft, these sensors with different operating principles differ in the regions where they operate with a low error. This difference can lead to an idea of the reliability of the sensors by controlling the system states during a flight over a set of pre-defined rules. This idea is digitized to provide a basis for calculating the reliability ratio of each sensor according to the current situation. Therefore, it is possible to obtain information about the reliability of the sensor in which case it can be trusted.

In this section, a fused altitude information for an air vehicle will be tried to be obtained in the vertical axis using the reliability ratios of the sensors. In doing so, the frequency mismatches within the sensors will be eliminated. It will then be predicted how reliable each sensor will be for known states. After this estimation, the biases between the sensor data and the reference data will be eliminated. These processed data obtained by the elimination of the biases and pairing the frequencies will be combined using the reliability ratios and a single reference altitude will be obtained. With this merged altitude obtained, a filter structure will be created by using the acceleration information obtained from IMU and final altitude can be calculated.

3.1 Sensor Frequency Pairing

The different sensors on an air vehicle have different data production frequencies. Therefore, some sensor data can be kept for several time steps according to the algorithm time until the current data arrives. At this point, the actual data is changing, but this change cannot be measured because the sensor cannot receive current data. Therefore, the data generated by the different sensors may not be available continuously for an algorithm time step. In this case it will not always be accurate to combine sensor information for a specific step.

The convenient integration of sensor data will only be possible if each sensor generates current data. If only pure data from the sensors are used, the evaluation of the data will depend on the sensor that measures the lowest frequency. It should also be noted that a scenario is possible, such that each of the selected sensors cannot generate data at the same time. Therefore, it is necessary to change or match the frequencies in order to process the sensor data.

Algorithm operating frequency selection is essential for the correct operation of an air vehicle. This operating frequency is usually not greater than the frequency of the sensor (usually IMU) that gives the highest frequency of measurement. On the other hand, due to hardware constraints, there are limitations in the algorithm operating frequencies. It is correct to choose a working frequency that is high enough to ensure that the incoming data can be properly integrated, provided that these upper limits are not exceeded. Under these conditions, it would be appropriate to convert sensor frequencies to algorithm frequency. It should be noted that the common frequency algorithm to which the sensors are to be combined may be lower than the operating frequency. In this case, however, the system update frequency will be compromised.

Two methods may be proposed to transport low frequency sensor data to a higher frequency. The first of these methods is to preserve the original sensor data at the point where the data is generated, to estimate the data at the points where data is not generated by using current system states or by using different sensors. Another method is to establish a pre-filter structure using the sensor data selected by the IMU data.

When the sensors do not update data, the current status of the system must be well known for data estimation. With the knowledge of the velocity and acceleration on the vertical axis, data can be obtained about what the altitude will be at the next stage. As soon as the data is received on the sensor, the altitude information is assigned to this information and the integration process is continued via the current data. It should be noted that although the noise behavior is maintained during the data update, the error behavior of the data obtained by the integration process will not show the error behavior of the sensor. Therefore, it is not appropriate to use this algorithm in sensors that measure with very low frequency compared to the algorithm frequency. An algorithm that can be used for data generation for frequency pairing is shared with Figure 3.1.

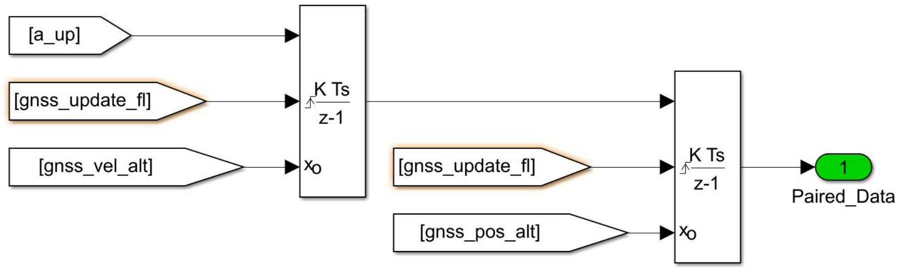

Figure 3.1: Data frequency pairing algorithm with integration.

The acceleration information on the vertical axis can be obtained by using the acceleration data that can be provided by IMU and aircraft attitude information. The data frequency can be increased by pre-filtering with the use of this acceleration information and the sensor information obtained in the height axis. If the ratio of the effect of the reference data to the effect of the IMU data is kept high in this filter to be created, the losses on the characteristic of the sensor data will be minimized. Compared to the method given in the previous section, this method will be more effective in increasing the data frequencies of the low frequency sensors. However, for sensors close to the frequency of the algorithm, the preservation of the raw data characteristics will not be better than the previous method. An algorithm that can be used for pre-filtering for frequaency pairing is shared with Figure 3.2.

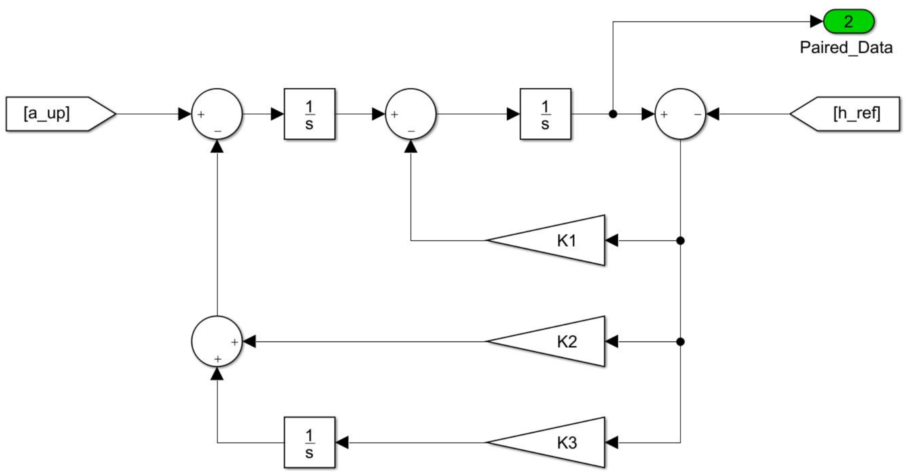

Figure 3.2: Data frequency pairing algorithm with pre-filtering.

The combination of different sensor data received at a low frequency with respect to the frequency of the algorithm can be reduced to this value by reference to the data at the lowest frequency. This would mean eliminating the asynchronous data of the sensors that generate the solution at higher frequency. Elimination of measurements that can be used on the system is one of the methods that can be used although it is not an effective method.

To convert the data at low frequency to the desired frequency, the sample graph obtained by using the data generation method is with Figure 3.3. As can be seen from the graph, using the data generation method for low frequencies distorts the raw data characteristic. Therefore, the use of this method for low frequency data will not be accurate.

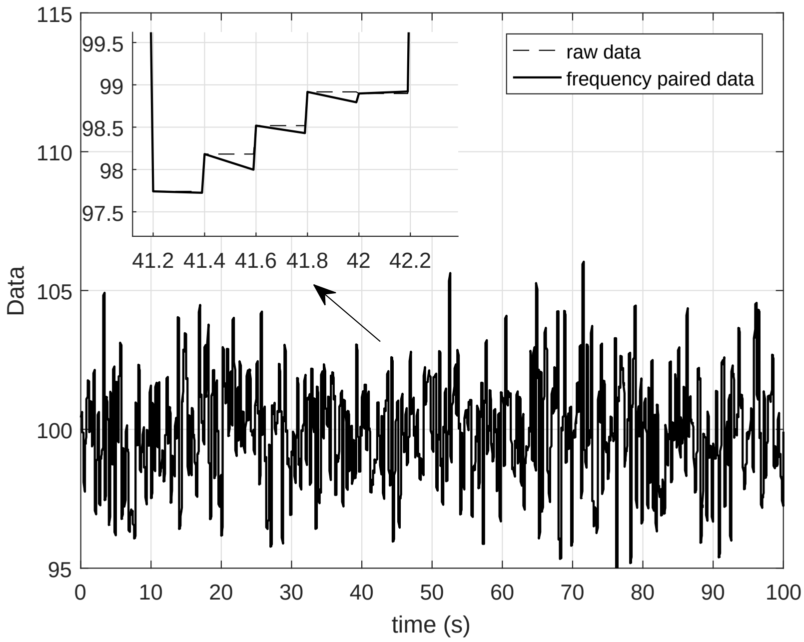

Figure 3.3: Data pairing algorithm for low frequency with data derivation.

Here, the raw data is given at 5 Hz and the derived data at 100 Hz. Using the pre-filtering method, data obtained by filtering a low frequency data by using IMU is given in the Figure 3.4. Compared to the previous option, this method is more positive than the other method. In this way, as long as the sensor behavior is maintained in the long term, the interstices are filled in with the raw data.

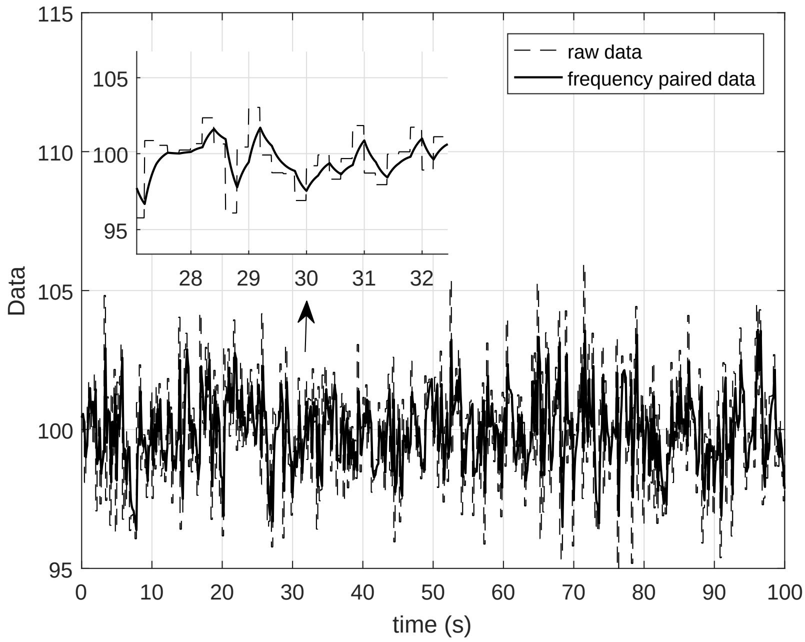

Figure 3.4: Data pairing algorithm for low frequency with pre-filtering.

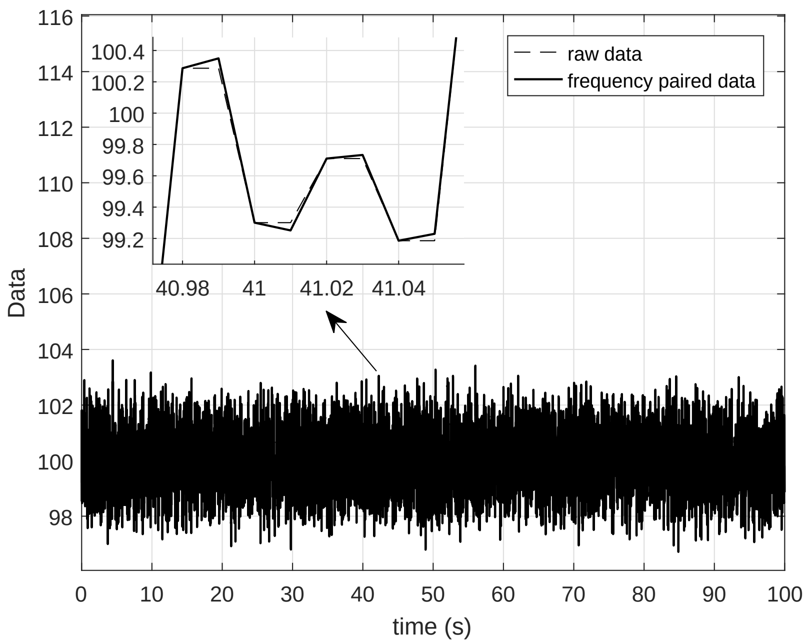

Figure 3.5: Data pairing algorithm for high frequency with data derivation.

Similar to the generation example, the frequency of the raw data was 5 Hz, while the frequency of the filtered data was 100 Hz. The graph of a sensor output whose frequency is close to the desired frequency is obtained in Figure 3.5 by using the data generation method. By selecting such a frequency level data generation method, it is observed that protection of the noise behavior on the raw data is very high. Therefore, it is appropriate to use the data derivation algorithm in cases close to the frequency of the algorithm.

In this example, the raw data given at 50 Hz was moved to 100 Hz. By the pre-filtering method, the data obtained by filtering the data close to the frequency of the frequency of the algorithm is given in Figure 3.6. As can be seen, the characteristics of the new data obtained with the noise characteristic of the raw data are different from each other. Although it is a good way of data filtering, it is not appropriate to use this method only when frequency pairing is desired.

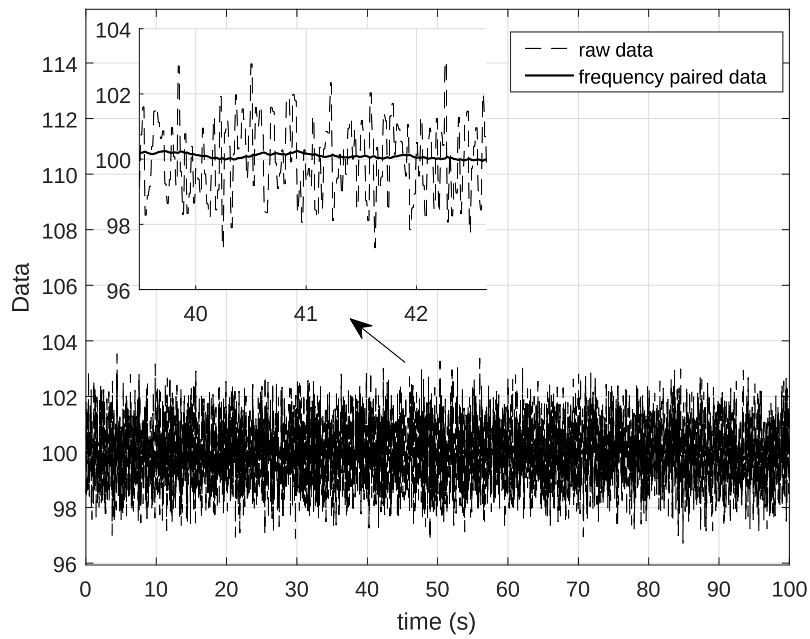

Figure 3.6: Data pairing algorithm for high frequency with pre-filtering.

Here, the raw data given at 50 Hz was moved to 100 Hz similar to derivation example. GNSS, RA and BA algorithm are among the sensors that may be below the operating frequency. In view of the general nature of these sensors, a recommendation can be made for the frequency matching method to be used. The frequency of data received from the GNSS transmitter is usually low. For this reason, a filter structure with a sensor data can be used to process data received over GNSS. For data with a higher frequency of data, RA and BA data would be appropriate to generate synthetic data using system states and IMU data in cases where no data update is required.

3.2 Reliability Ratio Calculation

It should be evaluated how accurate the measurements of the integrated sensor data whose frequencies are matched with the working frequency of the algorithm. It will be quite difficult to make this assessment literally for each sensor. In addition, the reliability of the sensor data will be estimated by taking into account the situation in which the system is existed and taking into account that these reliability estimates are generated when generating the output. In addition to the dynamic calculation of the reliability rates for the sensors, the reliability of some sensors in the design phase can be shaped by multiplying them with constant coefficients. In this case, reliability coefficients will be examined in two parts as static coefficients and dynamic coefficients.

Static coefficients can be defined as the coefficients between 0 and 1 which will be used for the weighting of the sensors after the tests and evaluations before the flight on the sensors. Static coefficients can also be formed from pre-flight environmental conditions. For example, in cloudy weather conditions, the possibility of incorrect reception of satellite signals increases. In such a case, the reliability rate of data received over GNSS can be reduced by the user. Similarly, the data received on the barometric altimeter in a windy weather is expected to contain high noise or even slip. Under such a condition, the reliability of the barometric altimeter can be reduced. For a radar altimeter, it might be a similar situation. The roughness of the ground shapes on the reference surface will affect the measurement on the radar altimeter according to the operating principle. For this reason, the reliability of the radar altimeter may be restricted when working on mountainous and rough terrain. The static coefficients are multiplied by the dynamically generated reliability rate for the respective sensor. At this point, the aim is to determine the dominant sensors or sensors within the algorithm.

The dynamic coefficients are generated simultaneously with the flight status over the current system status. These coefficients are formed by considering different parameters for each sensor because the sensor behavior is different from each other. In the formation phase, a sub-ratio is generated according to each effective parameter. These ratios are between 0 and 1, as in static coefficients. These sub-reliability rates are multiplied in order to evaluate all conditions that affect sensor measurement. As a result, the reliability of a sensor is obtained. How to establish these reliability ratios for each parameter is explained in the following sections.

3.2.1 Reliability of GNSS

Previously, different GNSS systems such as GPS, GLONASS and Gelieo were mentioned. Although there are differences between the working principles of these systems, the error characteristics will be common because they are based on the same logic. The two basic parameters that cause errors on GNSS systems are the number of satellites used for the solution and the acceleration in the axial direction. It is the standard deviation value produced by some advanced GNSS receivers on the position channel as a parameter associated with the number of satellites used. This value is generated by processing the difference between each number of satellites contributing to the solution with the solution produced. Therefore, it can be evaluated that the standard deviation value is added to the reliability ratio instead of the number of satellites used. The effect of the number of satellites used in the solution given in Table 3.1. Also the acceleration in the axial direction on the sensor reliability is shown in the Table 3.2.

Table 3.1: GNSS reliability with satellite number.

S_n	0	3	4	5	6	7	8	9	10
$\eta_{gnss,sn}$	0	0	0.2	0.5	0.75	0.85	0.87	0.9	0.95

Table 3.2: GNSS reliability with axial acceleration.

$a(m/s^2)$	0 30	40	60	70	80	90	100	110	120
$\eta_{gnss,acc}$	1	0.9	0.9	0.8	0.7	0.5	0.4	0.2	0.1

In addition to these parameters, the signal received on GNSS via the sensor that performs the data exchange with the sensor must be included in the calculation made for the reliability ratio. If this signal is not suitable, it will be correct to assign the reliability ratio to 0.

After definitions, reliability ratio for GNSS can be calculated in eq. 3.1.

$$\eta_{gnss} = \eta_{gnss,sn}\eta_{gnss,acc}\eta_{gnss,com} \tag{3.1}$$

3.2.2 Reliability of RA

As a result of the studies performed for the radar altimeter, it has been determined that the errors due to this section will change depending on the velocity, pitch angle and altitude. The tables of errors planned to be seen in these sections are shared below.

For the reliability ratio of a radar altimeter designed for low altitude, Table 3.3 as follows can be used. The table shows that the solution for altitudes below 0.75 meters cannot be produced and therefore the radar altimeter should not be used for altitudes below this value. It is also stated that RA should not be used for altitudes above 700 meters. It can be understood from the table that the data to be taken from RA between 1 meter and 550 meters will be completely safe. Although the values have been created for the RA model described in the previous section, different types of RA reliability tables can be created with changes to the values.

Table 3.3: RA reliability with altitude.

$h(m)$	0	0.75	1	5	550	650	700	10000
$\eta_{ra,h}$	0	0	0.2	1	1	0.25	0	0

It is known that the radar altimeter is working to measure over the signals sent to the surface. This signal transmission is conical with a certain angle limitation. In order for this measurement to be carried out in a healthy way, the signals must be sent perpendicular to the surface. If the angle of the radar altimeter with the surface exceeds the cone angle of the signal broadcast, there will be shifts on the elevation information received through RA. Generally, measurement errors can be seen in climbing and descending conditions. RA is fully reliable at the point where the pitch angle is zero. However, with the increase in the size of this angle, the reliability of RA will also decrease. The change in the reliability ratio according to magnitude of pitch angle is given in the Table 3.4. Here pitch angle is given in degree.

Table 3.4: RA reliability with pitch angle.

$\theta(deg)$	0	2.5	5	7.5	10	12.5	15
$\eta_{ra,\theta}$	1	0.97	0.93	0.9	0.86	0.83	0.80

Depending on the velocity in the forward direction, an error will occur on the radar altimeter depending on the Doppler effect. This error will increase with increasing speed data. As can be seen from the Table 3.5, the reliability of the radar altimeter is expected to decrease with the increase in speed data.

Table 3.5: RA reliability with forward velocity.

$V(m/s)$	0	50	100	150	200	250	300
$\eta_{ra,vel}$	1	0.98	0.97	0.95	0.93	0.91	0.90

Depending on the parameters that could cause errors on the radar altimeter, the individual reliability ratios were deduced. In addition to these parameters, the communication indicator will be added, which can only take 0 and 1 values. These reliability rates, which are obtained individually in terms of parameters, will determine the reliability ratio for RA dynamically by processing among themselves.

$$\eta_{ra} = \eta_{ra,h}\eta_{ra,\theta}\eta_{ra,vel}\eta_{ra,com} \tag{3.2}$$

3.2.3 Reliability of BA

The barometric altimeter is a sensitive sensor. It has been stated that there will be errors in the measurement with turbulence that can be seen on the flow around the Pitot tube or the pressure sensor. For some cases where this deterioration occurs, tables that can be used to calculate reliability rates will be examined according to the relevant parameters. Also BA is effective on selection of gains of VCDL. [15]

The first parameter that affects the reliability of the barometric altimeter will be the angle of attack. The change on this angle will greatly affect the flow on the air vehicle. Due to this effect, the pressure will be measured incorrectly and the calculation on the altitude after isentropic atmosphere transformations will be done incorrectly. The aerodynamic effect on the Pitot tube will be different in the flight with a positive angle of attack or negative attack angle. Therefore, the size of this error will depend on the sign and value of the angle of attack. As can be understood from the Table 3.6, if the angle of attack is 0, the reliability ratio will be 1. However, with the change in this angle, the reliability ratio will decrease in different slopes for different directions.

Table 3.6: BA reliability with angle of attack.

$\alpha(deg)$	-7	-3	-2	0	1	2	4	7	10
$\eta_{ra,\alpha}$	0.2	0.5	0.7	18	0.95	0.92	0.87	0.7	0.2

Similarly to the angle of attack, the sideslip angle also affects the magnitude of the pressure measured through the Pitot tube. This error due to the change of air flow on the Pitot tube is symmetrical due to the symmetrical orientation of the air vehicle and the related sensor. Therefore, design can be made independently of the sign of the slip angle. The reliability ratio due to the sideslip angle can be accepted as 1 on static stance. This value will decrease in accordance with the given Table 3.7, with the increase in the size of the slip angle.

Table 3.7: BA reliability with sideslip angle.

$\beta(deg)$	0	0.5	1	2	10
$\eta_{ra,\beta}$	1	0.7	0.3	0.1	0

The effect of the Mach number on the static pressure measurement is lower than the angle of attack and the sideslip angle. Under ideal conditions, the change in Mach number will not be effective on static pressure. However, the velocity of the flow around the Pitot tube depends mainly on the Mach number. By increasing the flow rate, the pressure around the Pitot tube will be reduced and a lower pressure will be obtained, therefore a lower altitude will be obtained from the sensor. In static stance, ie no flow on the sensor, the reliability ratio by caused from the Mach number will be 1. With increasing in Mach number, the reliability ratio will decrease. Related table is shared with Table 3.8

Table 3.8: BA reliability with Mach number.

M	0	0.2	0.4	0.6	0.8	1
$\eta_{ra,M}$	1	0.95	0.90	0.85	0.80	0.75

The fact that the angle of attack and the sideslip angle will have an effect on the static pressure is given in advance. Subsequently, the effects of changes in these angles on the reliability ratio were described. However, the change rates on these angles also have an effect on measurement. For the case where the total angular velocity value on the air vehicle is 0, the reliability ratio can be taken as 1. However, when angular velocity occurs on the system, the reliability ratio will be reduced depending on the magnitude of angular velocity. The change of BA reliability with angular velocity is given with Table 3.9.

Table 3.9: BA reliability with angular rate.

$w(deg/s)$	0	0.5	1	3	5	10	20	300
$\eta_{ra,w}$	1	0.95	0.9	0.85	0.6	0.3	0	0

On the barometric altimeter, reliability ratios for prediction of errors due to different effects have already been calculated. By multiplying these calculated rates, the reliability ratio for BA can be calculated dynamically. In addition to these parameters, the communication indicator will be included in the calculations which may take the values 1 and 0 only.

$$\eta_{ba} = \eta_{ba,h}\eta_{ba,\theta}\eta_{ba,vel}\eta_{ba,vel}\eta_{ba,com} \tag{3.3}$$

3.3 Bias Elimination for Sources

It is stated that it will be difficult to model the response of sensors according to environmental impacts and system conditions and that the addition of these expected differences to the algorithm before the process can make the measurement even more erroneous. However, in cases where the process becomes stable and the changes in the system state become sufficiently small, the combined data and the differences over the sensors can be eliminated depending on the reliability of the sensor data. Thus, the consistency between the sensors will be increased.

By reshaping the difference between the combined data and the source sensors through a filter, and then adding them to the source sensor data, the difference between the sensors can be properly closed. The filter coefficients can be used to set the time of the transfer of the transfer function. Thus, the differential closing speed will be much greater at points where the sensor reliability is high.

During the climbing or maneuvering, the process of closing the difference will not be suitable for the correct handling of the process. In order to do this, it is necessary to check that the system must be at steady-state flight in addition to the reliability rates.

The filter structure that can be used to close the difference between the sensors during continuous operation is shared with 3.7. Value of gain to be used for the integrator part in filter structure can be designed for the case where the reliability ratio is 1. The results obtained after this design is shared with 3.8.

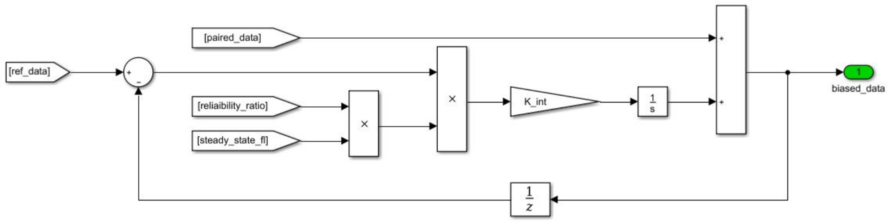

Figure 3.7: Algorithm structure for bias elimination.

The algorithm that is given by structural figure can also be expressed mathematically in eq. 3.4.

$$D_{b,k+1} = (D_{ref,k} - D_{b,k}) \times \eta \times K \times \Delta t + D_{p,k} \tag{3.4}$$

where:

$D_{b,k+1}$	= next biased data
$D_{b,k}$	= current biased data
$D_{ref,k}$	= current reference data
η	= reliability ratio
K	= gain
Δt	= step time
$D_{p,k}$	= current paired data

As can be seen from the figure, as the coefficient of the integrator increases, the system becomes faster and the difference between the reference data and the frequency-paired data is faster. This coefficient can be selected via the following chart. However, there are two other parameters that affect the gain. The first of these parameters is the information to be obtained about how well the sensor is measuring. The reliability ratios of the sensors can be used for this coefficient. In this case, the convergence rate of the difference between the sensor and the reference data will be reduced if the reliability ratio is low. In this way, it will be prevented to make a false difference convergence. The other factor can be shaped according to the fact that the flight is in steady-state level flight.

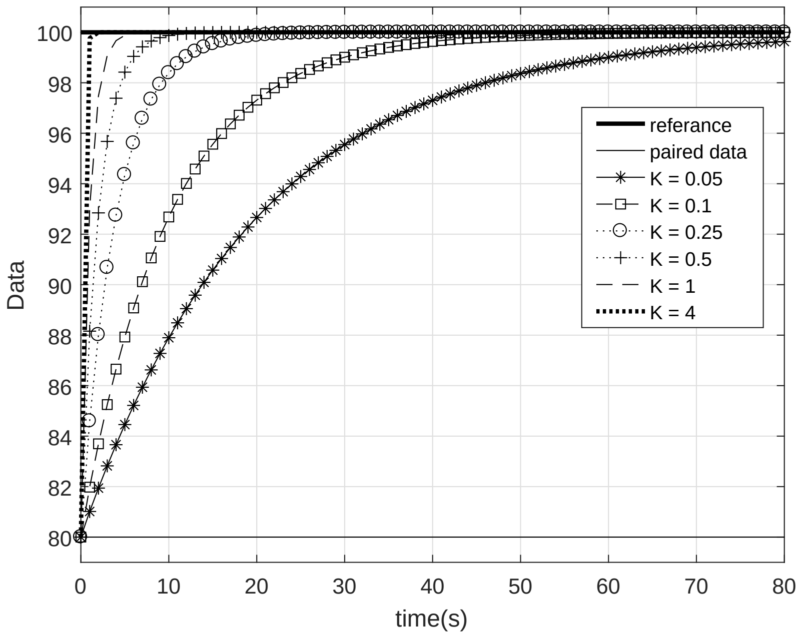

Figure 3.8: Bias elimination behaviors for different gains.

3.4 Data Merging

Reliability ratios were calculated in previous sections. Besides, raw sensor data at different frequencies were processed and moved to the same frequency. In addition, by eliminating the differences that can be seen between the sensor data in steady-state cases, the data are suitable for the combination. In this section, all sensor data will be rated using the previously determined reliability ratios. After this ratio, the total reliability value for the sensors will be 1. All processed sensor data will then be multiplied by the specified reliability coefficients. By collecting the results obtained, the merged output of the sensors will be obtained.

Descriptions can also be expressed by eq. 3.5 and eq. 3.6. For this purpose, reliability ratios and processed sensor measurements should be vectorized.

$$\eta = \begin{bmatrix} \eta_{gnss} & \eta_{ra} & \eta_{ba} \end{bmatrix}^T \tag{3.5}$$

$$h_{processed} = \begin{bmatrix} h_{gnss,processed} & h_{ra,processed} & h_{ba,processed} \end{bmatrix}^T \tag{3.6}$$

After the creation of the required vectors, the formula which can be used to form the merged altitude can be given by eq. 3.7.

$$h_{merged} = h_{processed}^T \frac{\eta}{\mid \eta \mid} \tag{3.7}$$

3.5 Filtering

In the previous section, a common altitude source was obtained by weighting the sensors. This data will be used as reference altitude information. There is noise of different sensors on the reference height information obtained. In order to absorb all these noises, and to act on the accuracy of IMU data in the short term, the filtering will be performed between the integrated data and the derivative data. This operation can be used with Kalman Filter or with vertical axis damping filter. The final elevation information obtained will be used in the "bias elimination" section via feedback. In this case, the loop will be closed and if the system is out of stability, all integrated data will correspond to the selected main altitude information. Other sensors that are simultaneously calibrated with the process will continue to transmit data even if one of the sensors is in a situation which is not available or will be disconnected [16].

There are many methods used for filtering. One of these methods is the vertical channel damping loop. The structure of the related algorithm is given by the Figure 3.9. Filtering properties can be adjust according to the changes of the parameters K1, K2 and K3 [17].

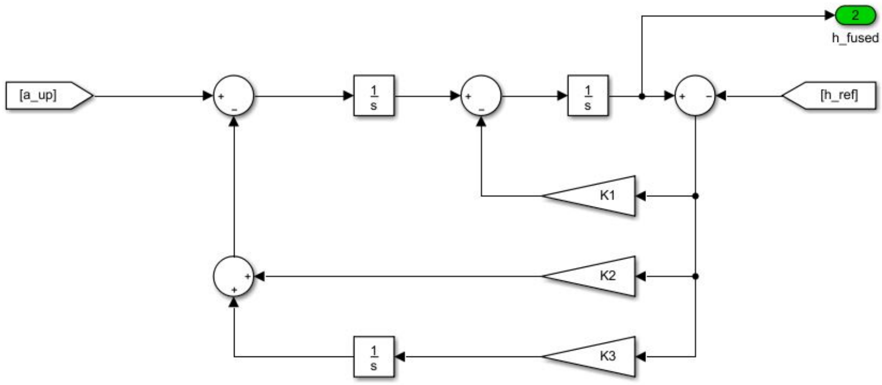

Figure 3.9: Vertical channel damping loop algorithm structure.

VCDL can be also referred by a mathematical equation.

$$h_{f,k+1} = ((a_{up} - (h_{ref,k} - h_{f,k})(K_2 + K_3\Delta t))\Delta t - (h_{ref,k} - h_{f,k})K_1)\Delta t \tag{3.8}$$

where:

$h_{f,k+1}$	= next fused data
$h_{f,k}$	= current fused data
$h_{ref,k}$	= current reference data
a_{up}	= second derivation of data that can be obtained by a sensor
K_i	= gain
Δt	= step time

4. TEST RESULTS

In the previous sections the algorithm definition is made with details. After this definition, the algorithm must be tested. To perform the validity of algorithm, firstly a scenario must be created. This scenario should contain different states for the algorithm to be tested extensively. In this section, a simultaneous test will be carried out with the feeding of the related parameters to the fusing algorithm during the running of the scenario. Two different scenarios were created for the realization of this situation and the parameters produced for these scenarios are given in each part of the algorithm.

4.1 Scenario 1

The first scenario to test the algorithm has different flight altitudes and conditions. Throughout the scenario, many altitudes are flying and there are vertical maneuvers between these altitudes. However, horizontal turns are also included. The altitude profile of the scenario to be used is shared with the Figure 4.1.

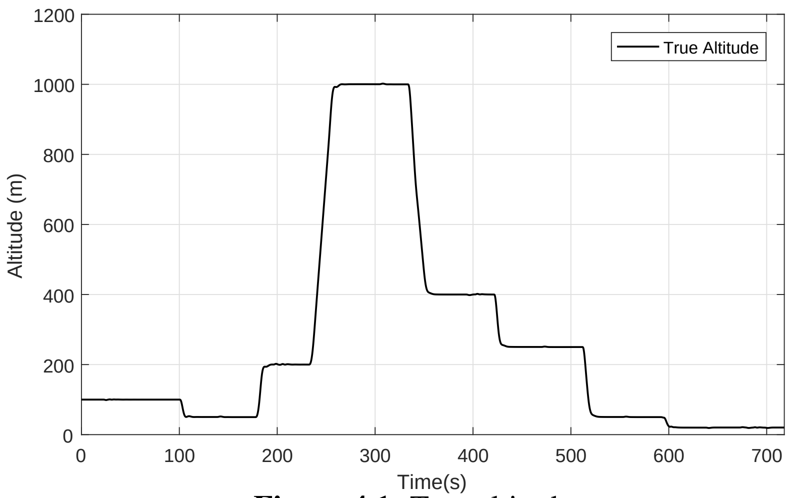

Figure 4.1: True altitude.

4.1.1 Frequency pairing

After the true altitude data is passed through the sensor models, the frequency match is made. Figure 4.2 shows the graphs of the data obtained for this process for GNSS, RA and BA. It is seen that the GNSS and RA data converge to the actual data during different flight behaviors. Besides, RA data cannot be produced over a limit altitude. The barometric altimeter shows incorrect measurement during maneuvering throughout the flight.

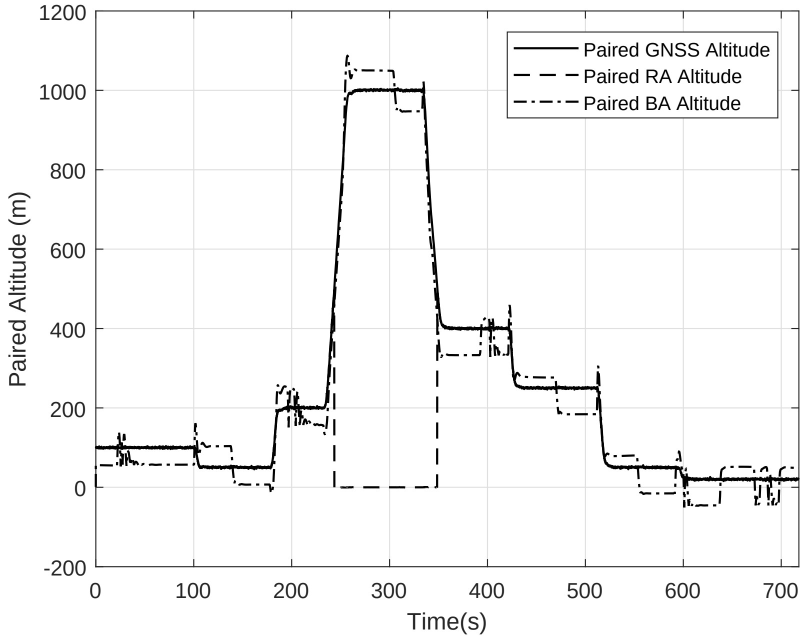

Figure 4.2: Paired altitudes for GNSS, RA and BA.

4.1.2 Reliability ratios

It is predicted that the sensor measurements will be different in different situations of flight. In parallel with this prediction, reliability rates were calculated with the help of other parameters that can be observed during the flight. The results are shared with Figure 4.3.

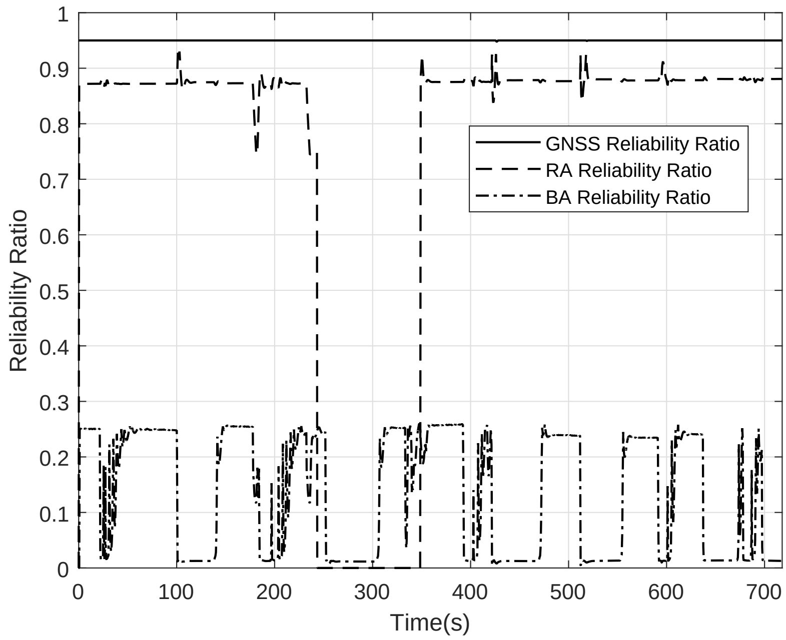

Figure 4.3: Reliability ratios for GNSS, RA and BA.

It should be noted that the static reliability ratios determined before the running were chosen as 1 for GNSS, 0.95 for RA and 0.3 for BA. The results are shared with the graph below. Through the graph, it can be obtained that the reliability ratio of the RA decreases to 0 at the times where RA is not create solution, the reliability of the BA decreases during the maneuver and with the adequate satellite number usage during the flight, the GNSS reliability remains at a spesific level.

4.1.3 Bias elimination

Bias additions were made by using frequency paired parameters and reliability rates. The results for GNSS, RA and BA were shared respectively.

As can be understood from the Figure 4.4, the difference between the solution provided by GNSS and the solution obtained by processing the data is quite small. This is due to the high accuracy of the GNSS and therefore the high reliability. As can be seen in the figure, the bias in the following parts of the flight is higher than the GNSS correction in the beginning.

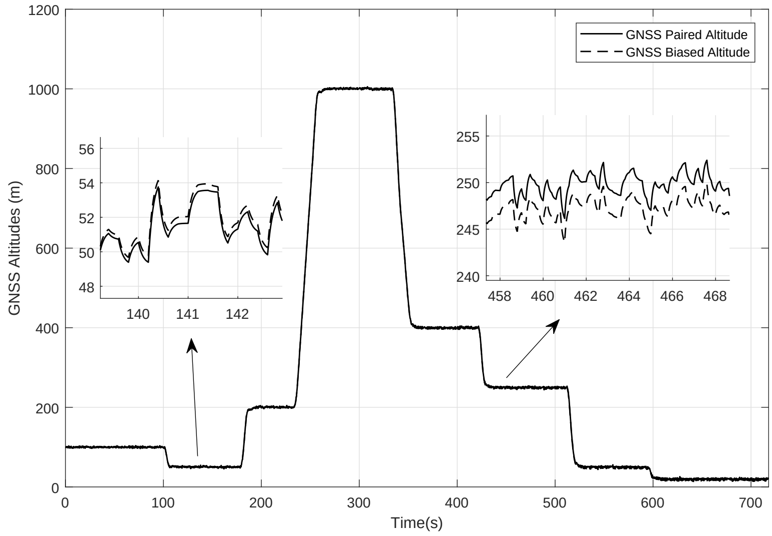

Figure 4.4: Bias addition for GNSS.

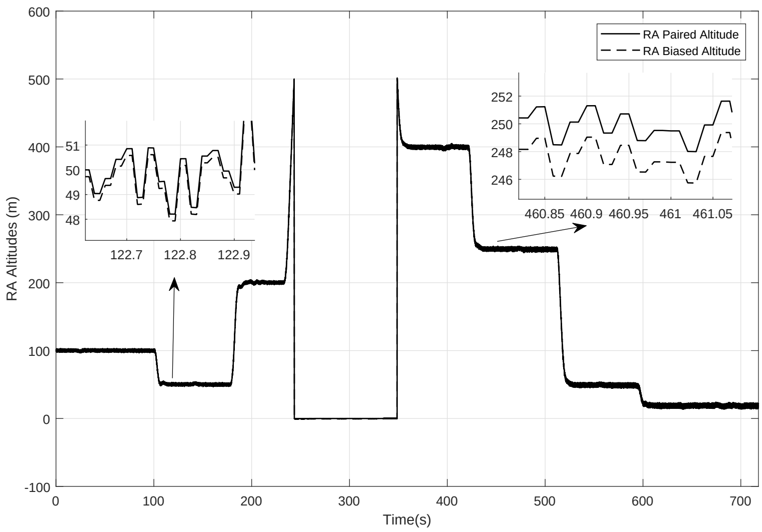

Figure 4.5: Bias addition for RA.

Similar to GNSS, the correction for RA is very high according to Figure 4.5. Like GNSS, the high reliability of RA has caused this situation. Low bias error at the beginning of the flight, exceeds 2 meters in the fallowing sections of flight.

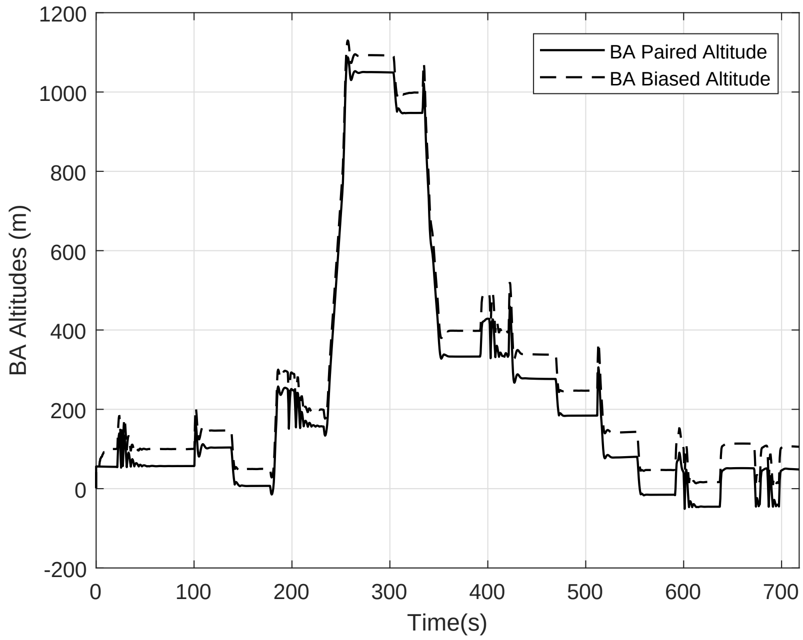

Figure 4.6: Bias addition for BA.

The barometric altimeter is the most sensitive of the selected sensors. The difference between the actual altitude and the other measurement errors seen during the maneuver confirm this in Figure 4.6. In addition, by applying the bias process on BA, the amount of correction in the steady state level flight is much higher than that of RA and GNSS.

4.1.4 Data merging

Differences added values calculated in the previous section and merged data using reliability ratios were shared with Figure 4.7

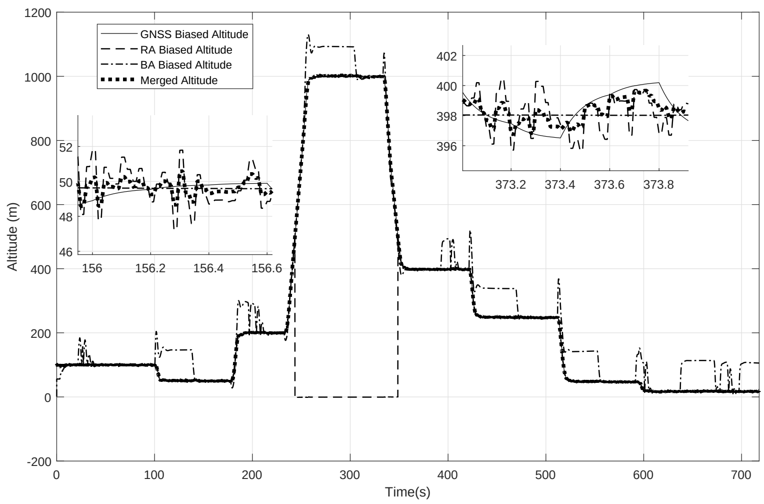

Figure 4.7: Merged altitude with biased GNSS, RA and BA.

It can be understood from the graph that the merged data obtained depends on the data obtained from different sensors. Besides, the combined altitude information obtained on the Figure 4.8 is compared with the true altitude information.

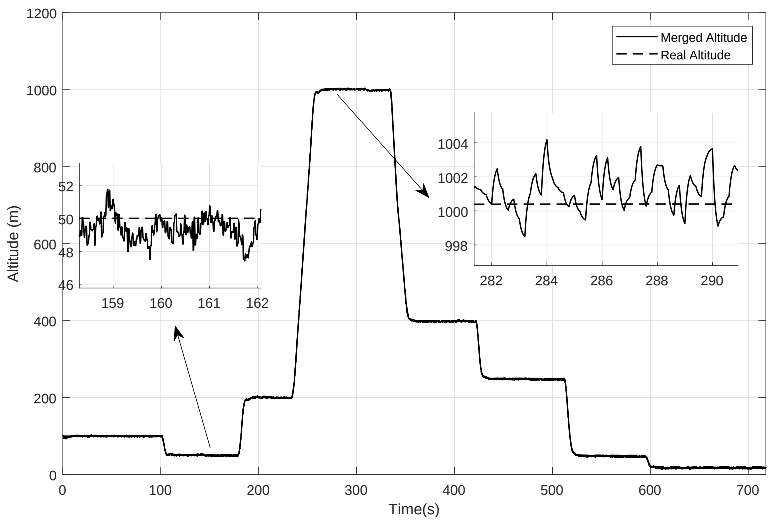

Figure 4.8: Merged altitude with true altitude.

When the merged altitude and the true altitude information are compared, it is seen that the difference is very small. This high-accuracy estimate, made in the early part of the flight, maintained itself at an altitude of 1000 meters, even in the absence of RA.

4.1.5 Filtering

The data filtered using the IMU with the VCDL structure was shared with the Figure 4.9.

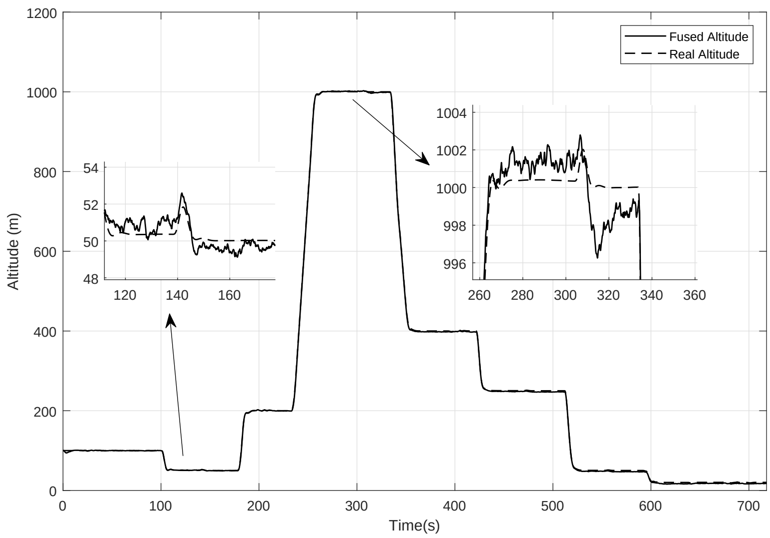

Figure 4.9: Fused altitude with true altitude.

As seen in the figure, the noise on the altitude combined with the filtering was reduced and the reliability of the system was increased. Besides, the difference between the true data and the filtered data is very low. It should be noted at this point that, when one of the sensors performs an unreal measurement, the IMU will not allow this error to be taken into account in the short term.

4.2 Scenario 2

In the previous scenario, the accuracy of the algorithm has been tested according to different flight conditions and altitudes. Algorithm structure has been successful in this test and showed that it can work with weighting on reliability ratios on a normal flight. This section will examine the resistance of the algorithm against a fault on some sensors during flight. For this purpose, a scenario was created in which the communication with GNSS would be lost at t=200s. In addition, in t=300s the connection with RA will be lost and will remain the only sensors with which the BA and IMU algorithm can be used. The altitude profile of the scenario is shared with Figure 4.10.

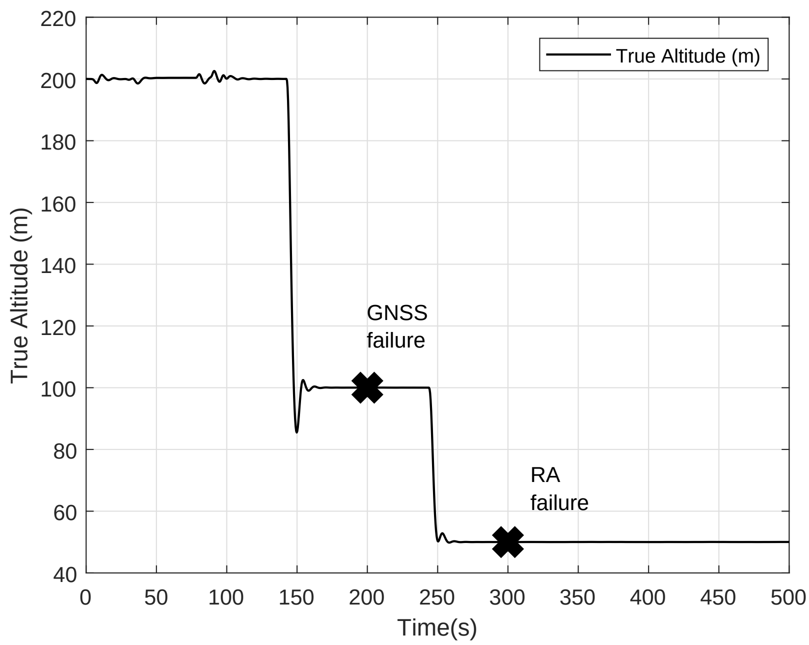

Figure 4.10: True altitude.

4.2.1 Frequency pairing

The data obtained by pairing the frequencies of the raw data received on the sensors is given by Figure 4.11. Similar to the first scenario, GNSS and RA have a noise level and a slight difference is seen with the actual altitude. In addition, it is seen that there is a difference between the altitude information obtained from the barometric altimeter and the actual altitude information.

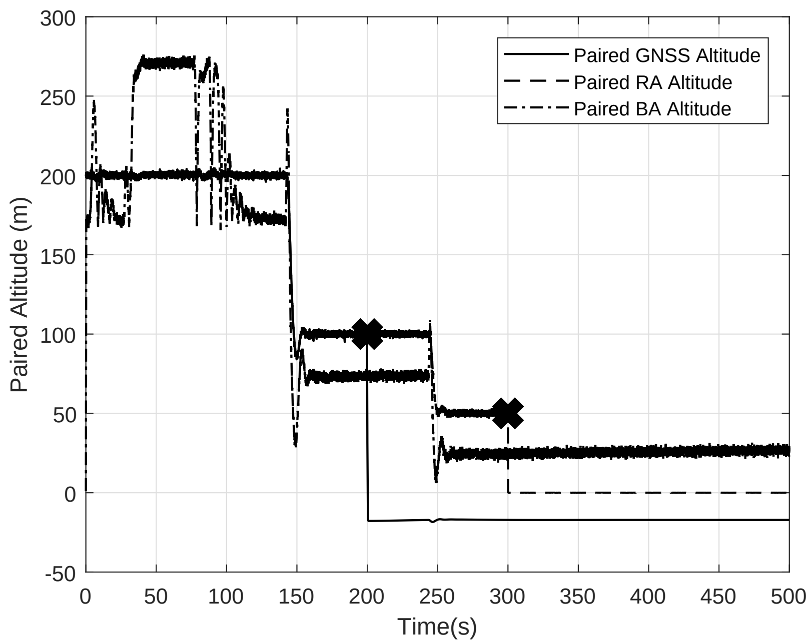

Figure 4.11: Paired altitudes for GNSS, RA and BA.

As can be seen on the graph, the data received over GNSS was intercepted at t=200s. Following this, altitude information cannot be obtained via RA after t = 300s.

4.2.2 Reliability ratios

The change in the reliability rate throughout the flight is given with Figure 4.12. It is seen that reliability of GNSS ratio has decreased to 0 at t=200s and remained at this value throughout the flight. In addition, the reliability of RA is reduced to 0 at t=300s. From this point, the algorithm will operate using only BA and IMU data.

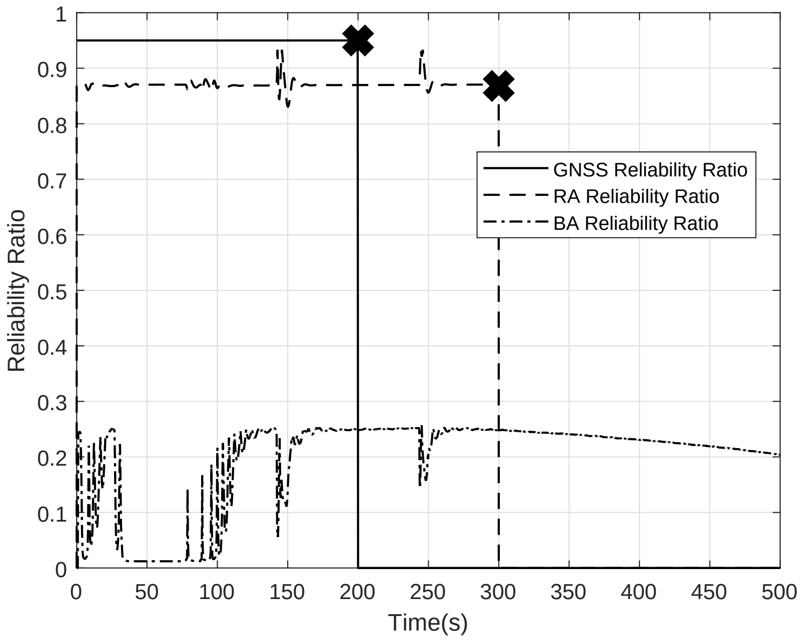

Figure 4.12: Reliability ratios for GNSS, RA and BA.

4.2.3 Bias elimination

Bias additions were made by using frequency paired parameters and reliability rates. The results for GNSS, RA and BA were shared respectively.

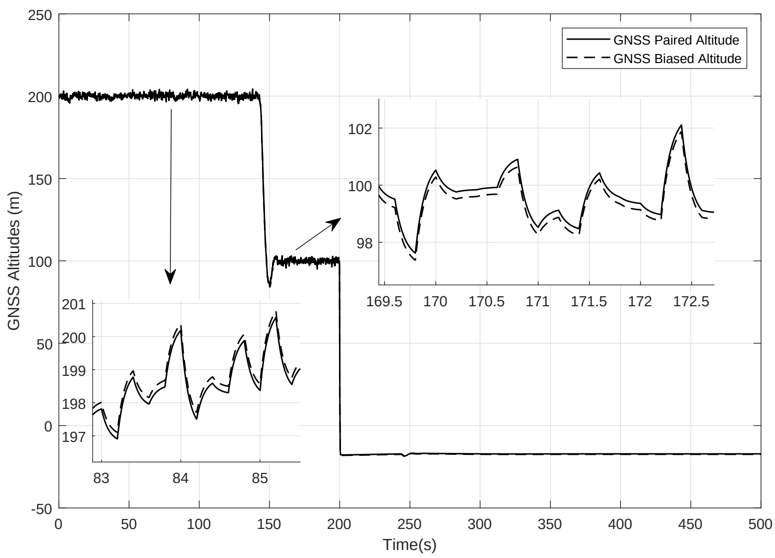

Figure 4.13: Bias addition for GNSS.

The addition of bias on GNSS is shown in Figure 4.13. It was observed that this difference was dynamically changed during the time that valid data was received through the sensor. The reliability ratio was reduced to 0 with data interruption. For this reason, the integrator gain in the bias addition block was 0. In this case, the difference remained constant in the continuation of the flight.

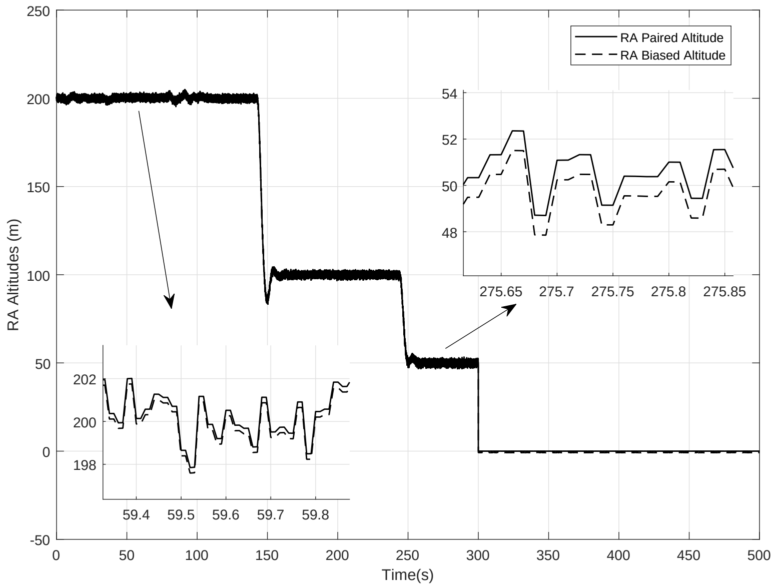

Figure 4.14: Bias addition for RA.

Similar to GNSS, the difference on RA has also changed dynamically throughout the flight as can be shown in Figure 4.14. This change continued until the communication with RA broke. From this point on, the bias on RA remained constant with the reliability rate falling to 0.

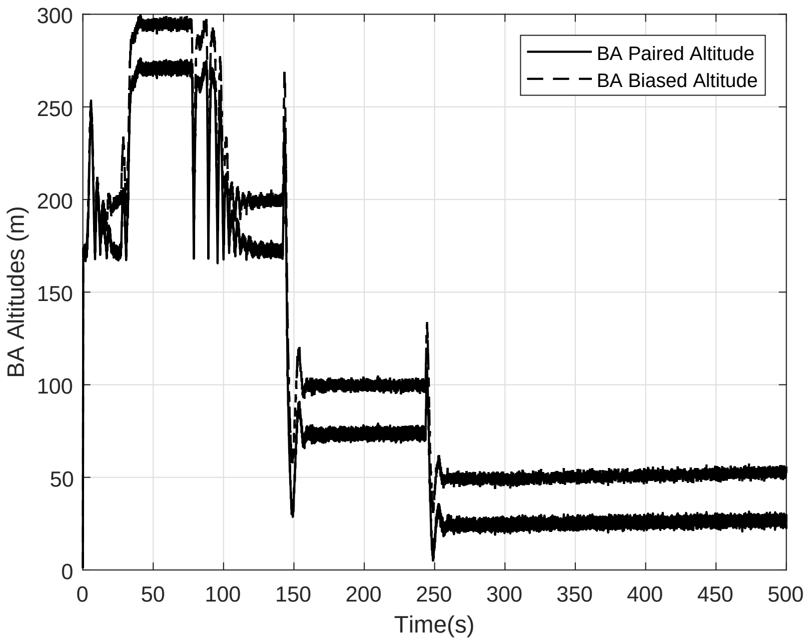

Figure 4.15: Bias addition for BA.

The change on the barometric altimeter is shown in the Figure 4.15. In the first part of the flight, the difference on BA data was closed using the accuracy of RA and GNSS data. With the interruption of the GNSS data, the production of the reference data to be processed by IMU will only be performed using RA and BA data. With the interruption of RA data, BA remains as the only source of reference data and will be processed with IMU regardless of the reliability ratio.

4.2.4 Data merging

The difference calculated in the previous section was shared with Figure 4.16 using combined values and reliability rates.

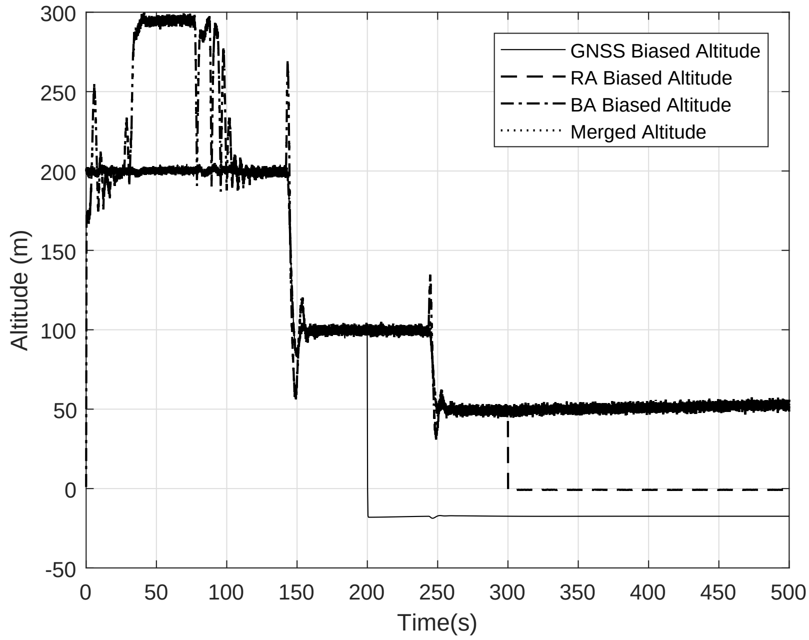

Figure 4.16: Merged altitude with biased GNSS, RA and BA.

For the first 200 seconds, the merged altitude was generated using GNSS, RA and BA, as shown in Figure 4.17. From this point GNSS has been disabled. In the figure, it is observed that the noise is increased after this moment on the combined data. It is seen that this noise level increases with the unusable situation of RA at t=300s.

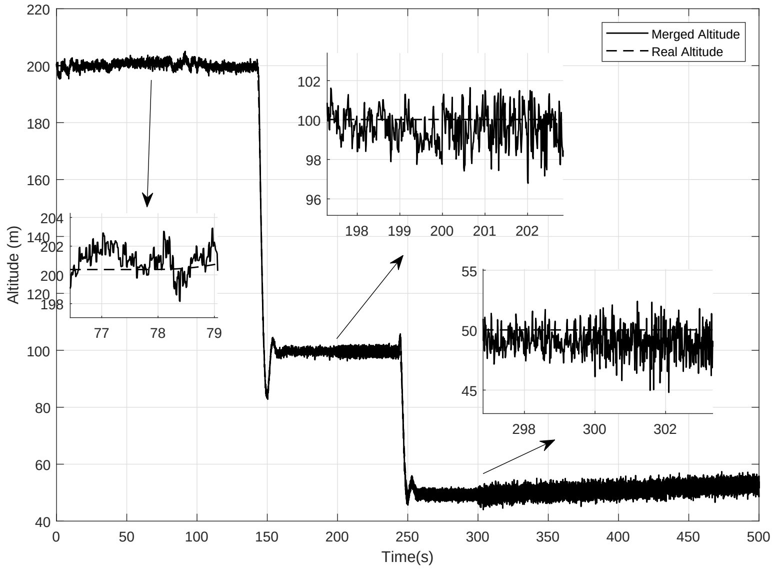

Figure 4.17: Merged altitude with true altitude.

When compared to the actual data, the corrected reference data appears to be very close to reality. This accuracy has been validated in unusable situation of GNSS. By interruption of the data that is obtained from RA, it is seen that the barometric altimeter measurements the faulty is sufficient to make estimation the in altitude.

4.2.5 Filtering

The data filtered using the IMU with the VCDL structure was shared with Figure 4.18.

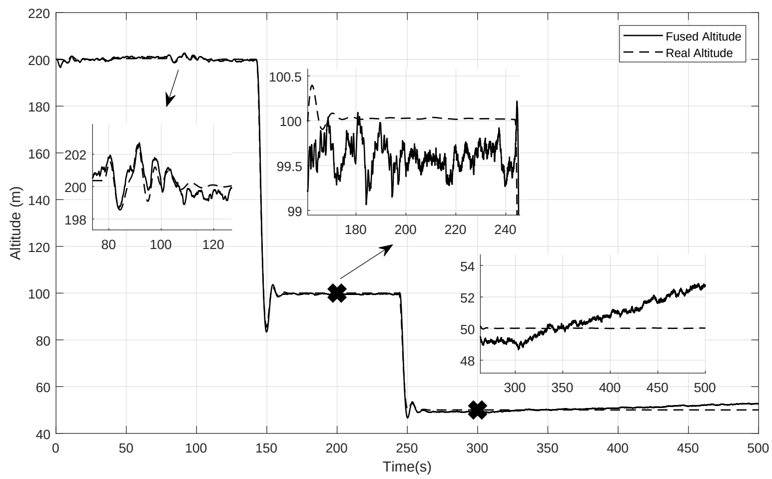

Figure 4.18: Fused altitude with true altitude.

The disturbance on the combined elevation data obtained as in the first scenario was reduced by the filtering method. While the data consistency in the first part of the flight was largely achieved, only a slight difference between the actual value and the reference value was obtained in the case where only BA data were used as the reference altitude. This shift can be considered as a success for a sensitive sensor BA, which has a very long time of 200 seconds.

5. CONCLUSION

The measurement of a physical parameter cannot be performed precisely and accurately. The reason for this can be defined as the loss of transformation during the measurement and disturbances on the physical magnitude. Although the exact result can not be obtained accurately, the number and type of sensors which have high accuracy measurements have increased considerably. The methods used by these sensors for measurement also vary. This allows different sensors to be measured by using different characteristics of the same physical parameter. One of the indicated physical parameters is the altitude information. This information is one of the most important parameters in terms of providing flight continuity for air vehicle.

This study, which is intended to estimate altitude information using different sensor informations, was started with the identification and modeling of sensors. For this operation, the sensors to be used during operation are selected. These sensors will be GNSS, RA and BA. In addition, acceleration and angular velocity information received via IMU will serve within the algorithm. Following the selection of sensors, the operating principles, areas of use and error behavior are explained. After these explanations, the mathematical models of the sensors have been extracted in order to create the algorithm design.

Three elevation sources have been prepared for using for algorithm input. In addition, the acceleration and angular velocity information obtained via IMU are also modeled. Besides all these, attitude, velocity and position information are derived bu using navigation equations for using in algorithm. Following the preparation of system states and sensor information, the process of creating the algorithm for altitude estimation has been initiated.

In order for the algorithm to work, it is necessary to match the frequencies of the altitude information received via the sensors first. Different methods can be used for this process. In this study, data derivation with IMU and pre-filtering methods are given as examples. In the next step, the error behavior of the sensors according to different flight conditions is defined. In this context, the situations that may cause the sensors to make a mistake are determined and the reliability ratio has been calculated for each sensor considering these conditions. A high degree of reliability will be considered as an indicator of confidence in sensor measurement. There will be measurement differences between the sensors. A filter structure was created to dynamically eliminate these differences and the difference was slowly closed using the reference data. After this process, the data obtained by removing the bias errors between the sensors were weighted by using the reliability ratios and the reference information of the merged altitude was obtained. After this, the combined altitude data containing the noise characteristic of all three sensors were filtered through the IMU and filtered through the acceleration data on the vertical axis.

The algorithm is tested after design. Two different test scenarios were created to check the accuracy of the algorithm. The first of these scenarios includes different altitudes and flight conditions. In the second scenario, it was assumed that some sensors lost their data production capabilities during flight. For both scenarios, the altitude estimation along the flight is expected to be obtained close to the actual data. The data obtained after the scenario runs were shared in Section-4. For both test scenarios, altitude estimation was found to be very close to the actual data.

In addition to the study, several issues should be expressed. First of all, it is stated that there may be a difference between the altitude information seen on different sensor measurements. These differences need to be decreased at the beginning of the flight. When performing this operation, a process to be performed over reliability ratios may be inaccurate due to incorrect measurement by one of the sensors. In order to avoid this situation, the altitude source to be used during the closing of the difference between the sensors must be selected carefully. This source can be the altitude obtained by deriving acceleration and angular velocity that is obtained from IMU for the case where the system's initial position and speed conditions are known. This recommendation is supported by the low value of navigation divergence due to errors on the IMU in the short term. It is also appropriate to use a sensor data with high reliability as the reference elevation data at the beginning of the flight. By eliminating the difference between the sensors, the reference altitude information to be fed to the bias elimination block can be output as the algorithm.

An open loop structure was used during the study. Therefore, the altitude information obtained as the algorithm output is not used in the air vehicle decision making center. In this study, although the effects of system states on the algorithm output were investigated, the effect of the algorithm output on the system states was not investigated. Testing this algorithm in a closed loop can be a test to further increase the reliability of the algorithm.

Tests of the algorithm in closed loop can be performed in simulation environment. For this purpose, a simulation environment must be prepared for an aircraft. This simulation environment should involve propulsion, aerodynamics and gravity models. The forces and moments obtained as outputs of these models should be processed together with the physical properties of the system. After performing kinetic calculations, kinematic calculations should be made and flight mechanics equations for the simulation environment should be coded. In addition, the model of the sensors and subsystems to be used in flight should be created. Following the preparation of the simulation environment, system inputs and outputs should be created within the algorithm. In order to work in harmony with the simulation environment, the inputs and outputs of the algorithm must be integrated into the simulation. Simulation should be finalized by coding navigation and guidance calculations within the algorithm. Harness can be made with a defined task plan and the defined fusion algorithm can be controlled. Furthermore, the fusion algorithm can be tested by integrating it into an existing aircraft algorithm.

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APPENDICES

APPENDIX A.1 : Scenario 1
APPENDIX A.2 : Scenario 2
APPENDIX B.1 : Algorithm Web Address

APPENDIX A.1

Additional graphs for scenario 1 are shared below.

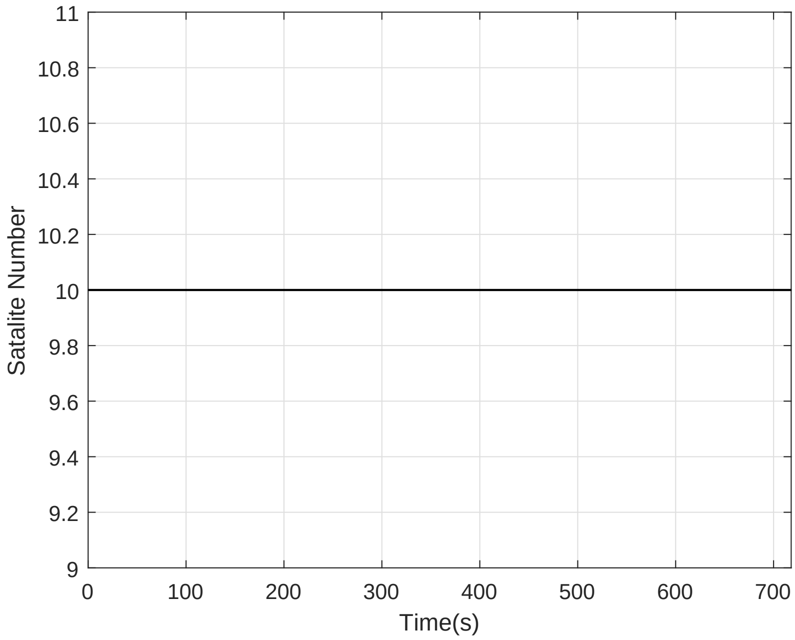

Figure A.1: Satalite number with time for scenario 1.

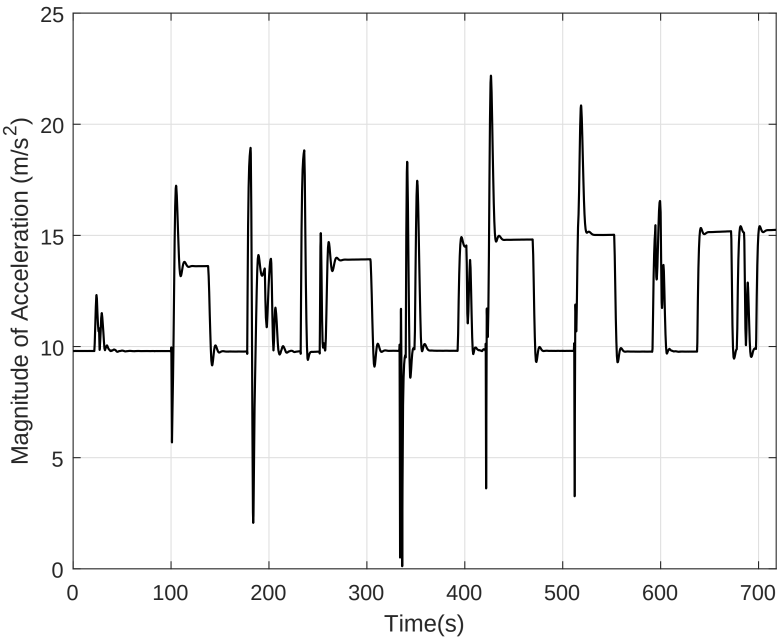

Figure A.2: Magnitude of acceleration with time for scenario 1.

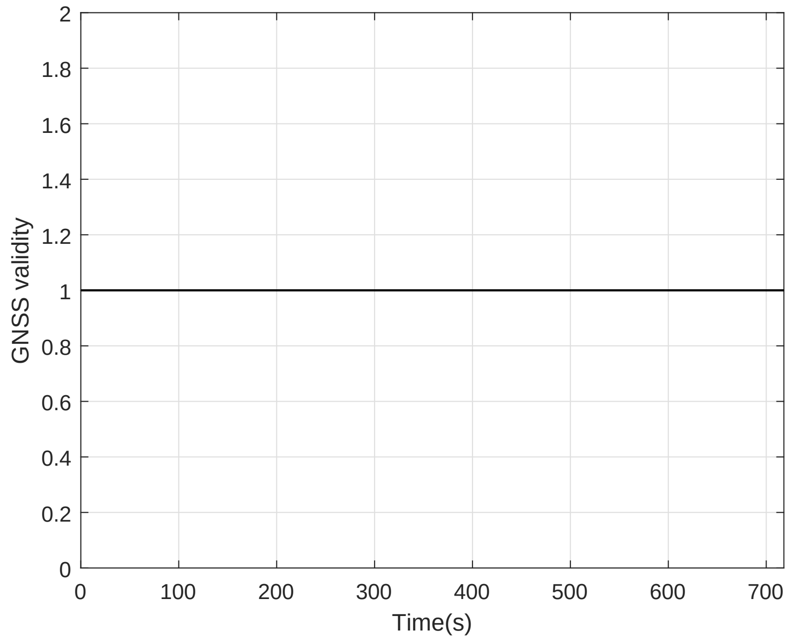

Figure A.3: GNSS validity with time for scenario 1.

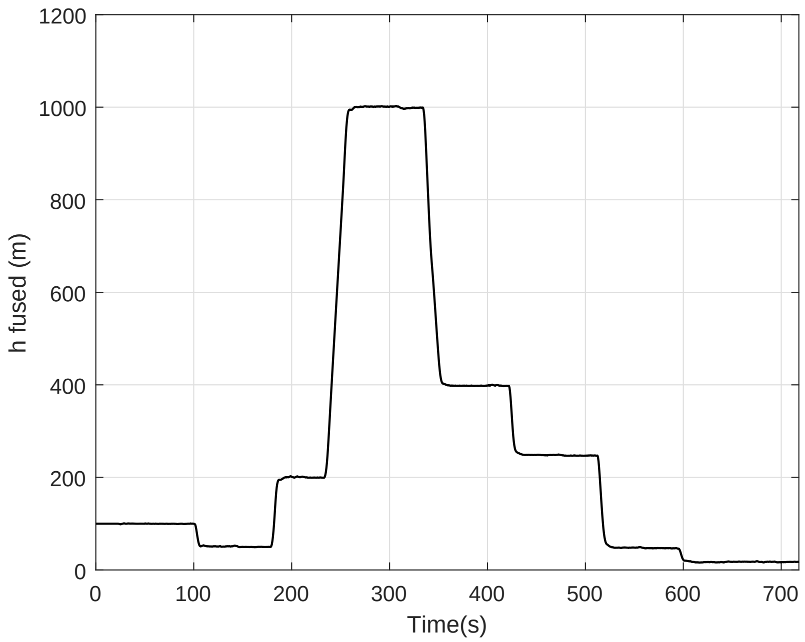

Figure A.4: Fused altitude with time for scenario 1.

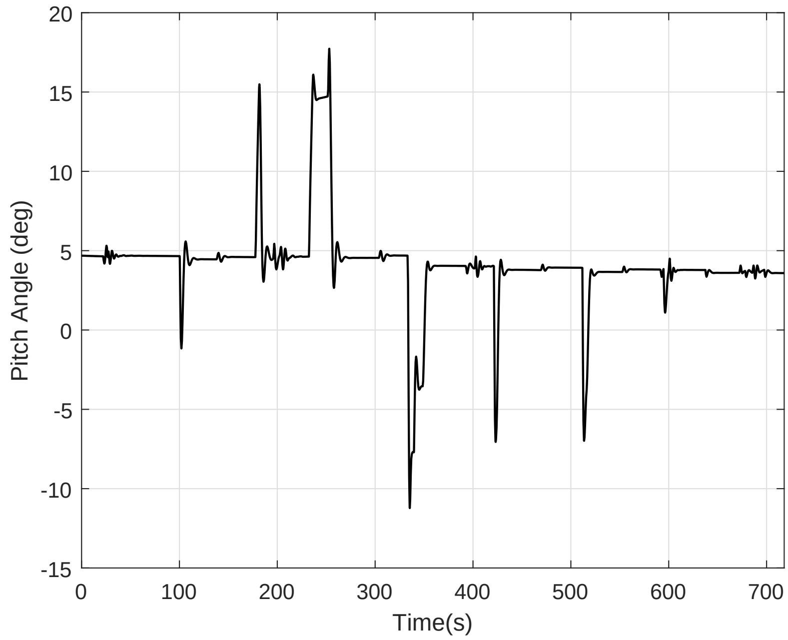

Figure A.5: Pitch angle with time for scenario 1.

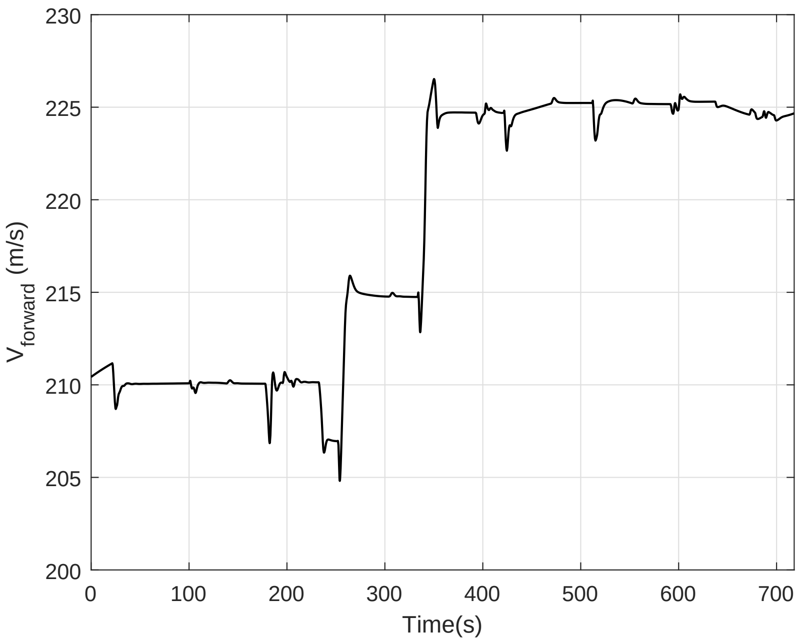

Figure A.6: Foward velocity with time for scenario 1.

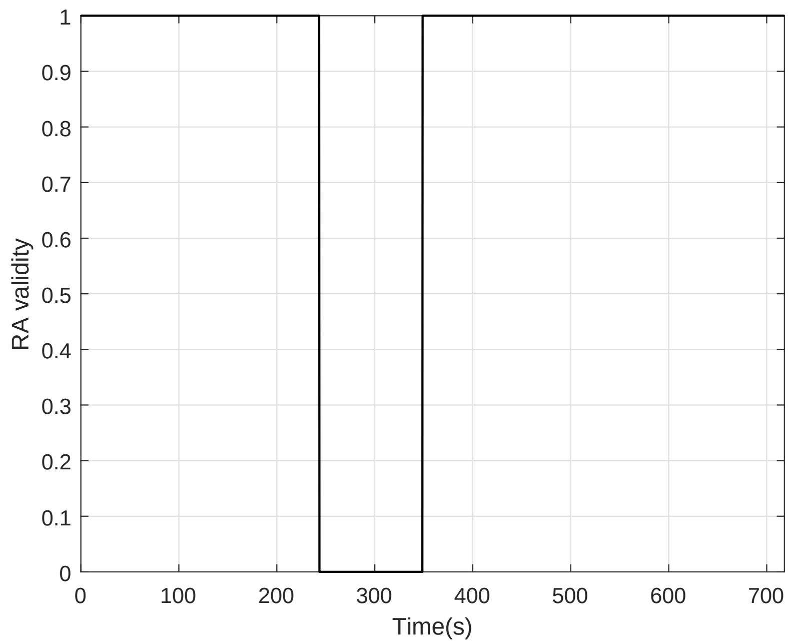

Figure A.7: RA validity with time for scenario 1.

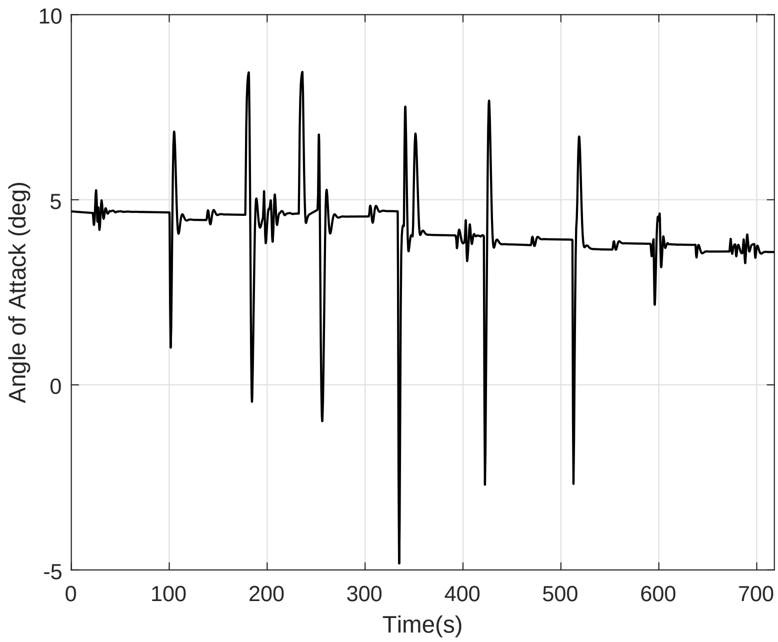

Figure A.8: Angle of attack with time for scenario 1.

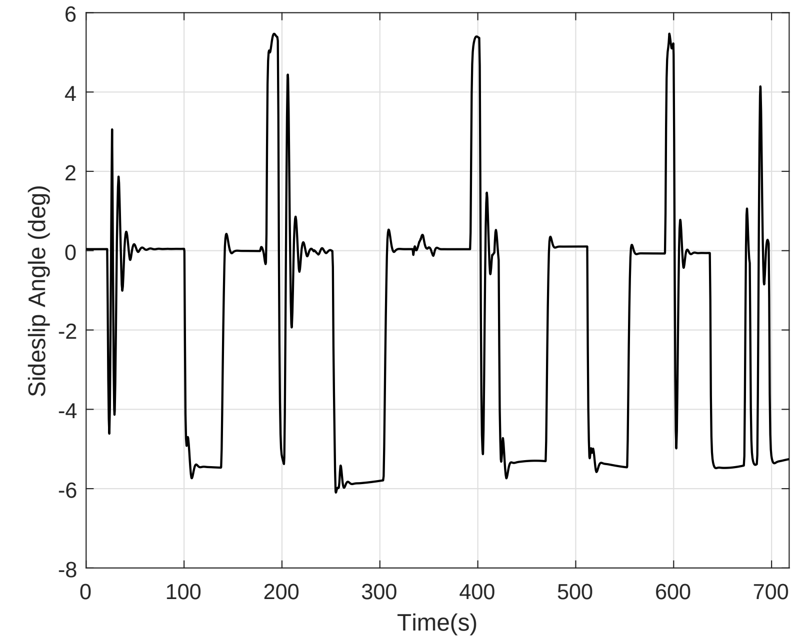

Figure A.9: Sideslip angle with time for scenario 1.

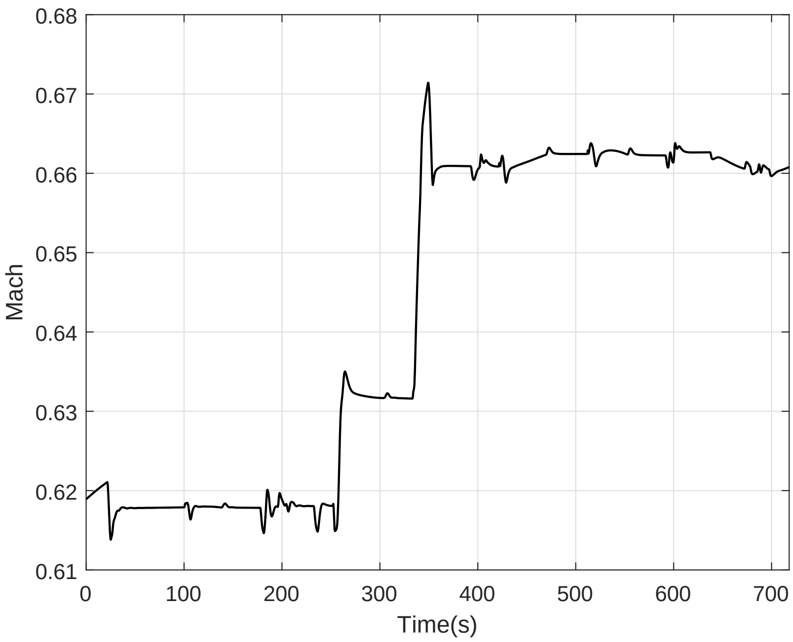

Figure A.10: Mach with time for scenario 1.

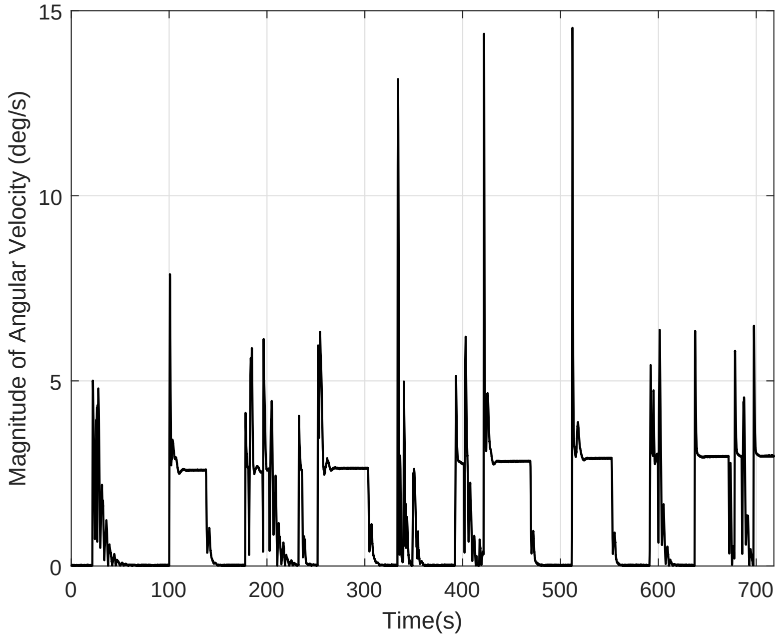

Figure A.11: Magnitude of angular velocity with time for scenario 1.

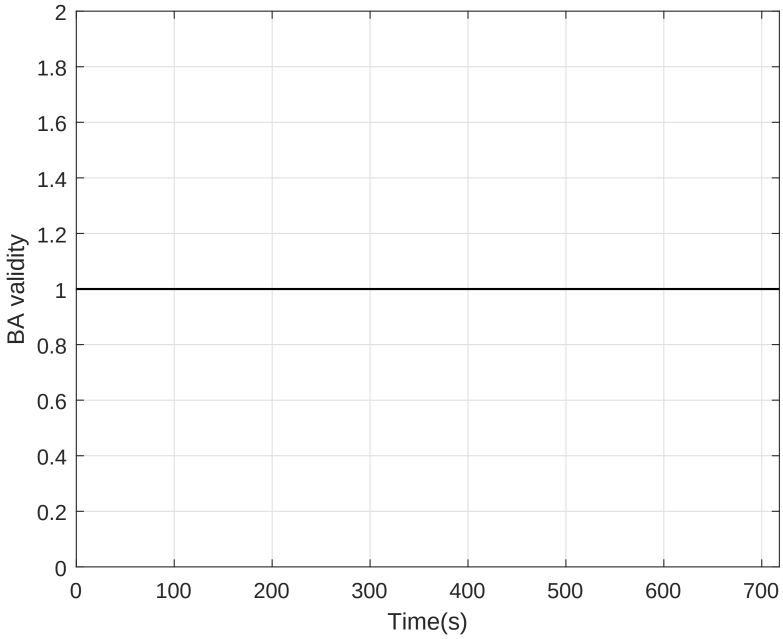

Figure A.12: BA validity with time for scenario 1.

APPENDIX A.2

Additional graphs for scenario 2 are shared below.

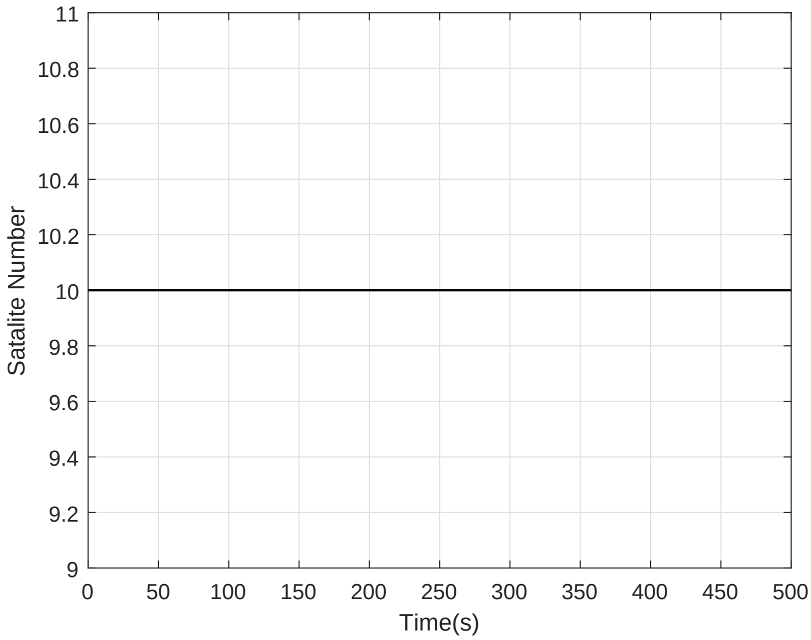

Figure A.13: Satalite number with time for scenario 2.

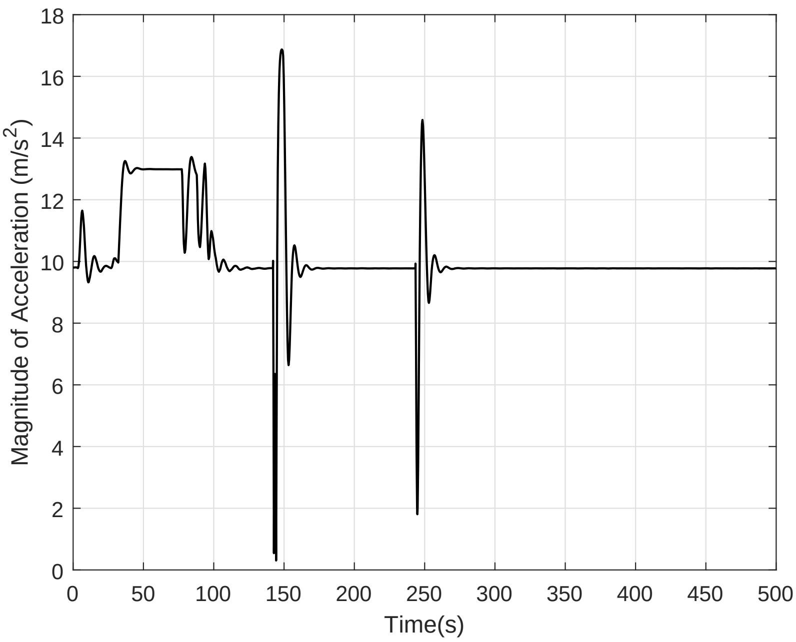

Figure A.14: Magnitude of acceleration with time for scenario 2.

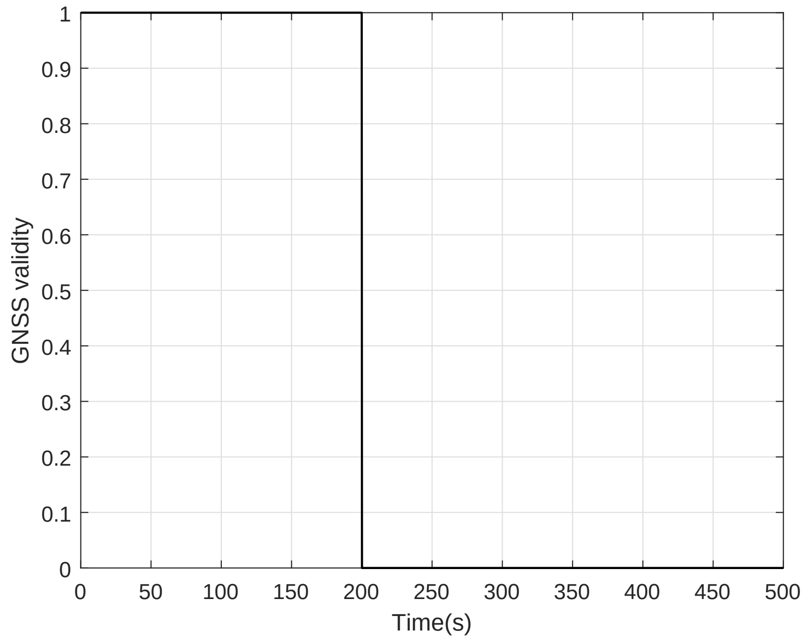

Figure A.15: GNSS validity with time for scenario 2.

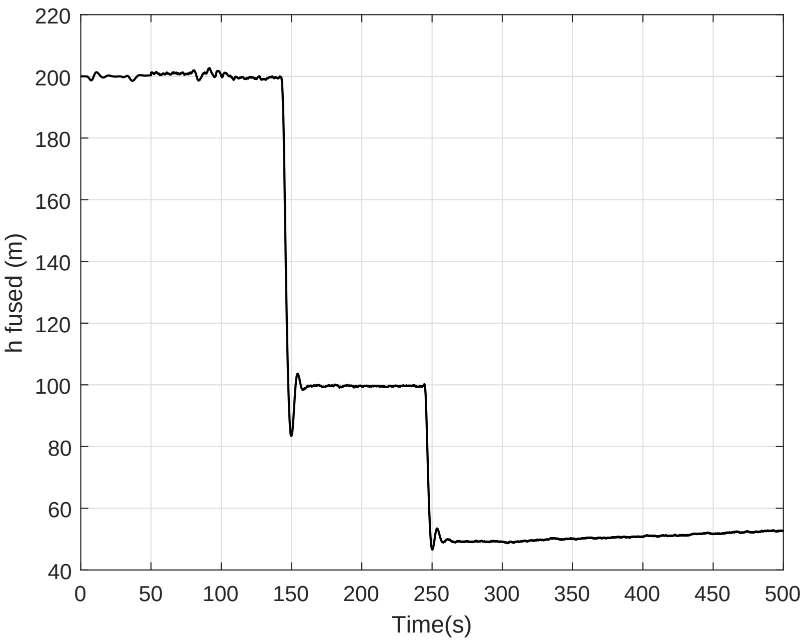

Figure A.16: Fused altitude with time for scenario 2.

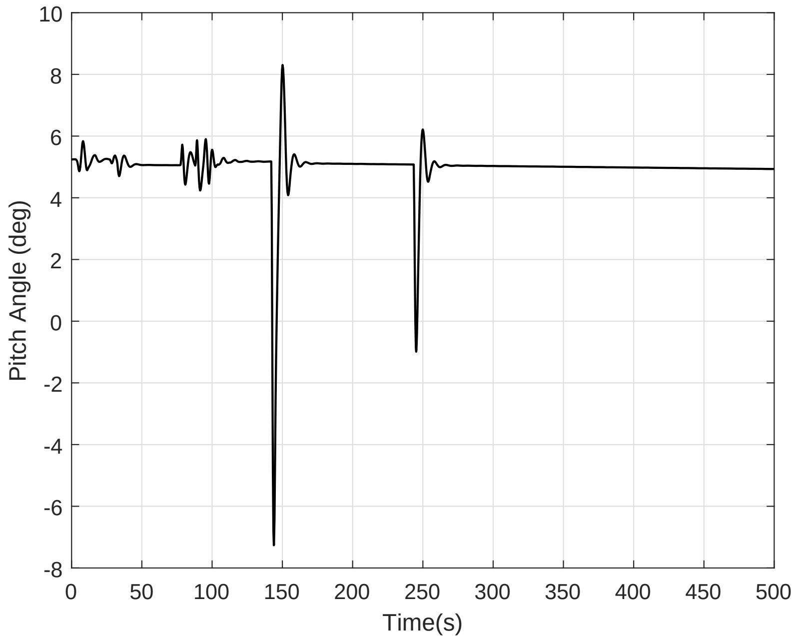

Figure A.17: Pitch angle with time for scenario 2.

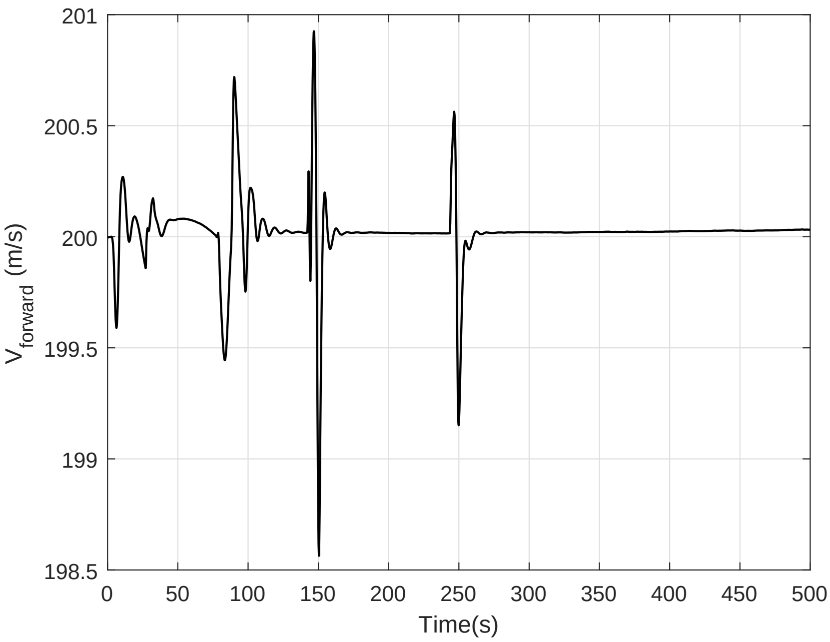

Figure A.18: Foward velocity with time for scenario 2.

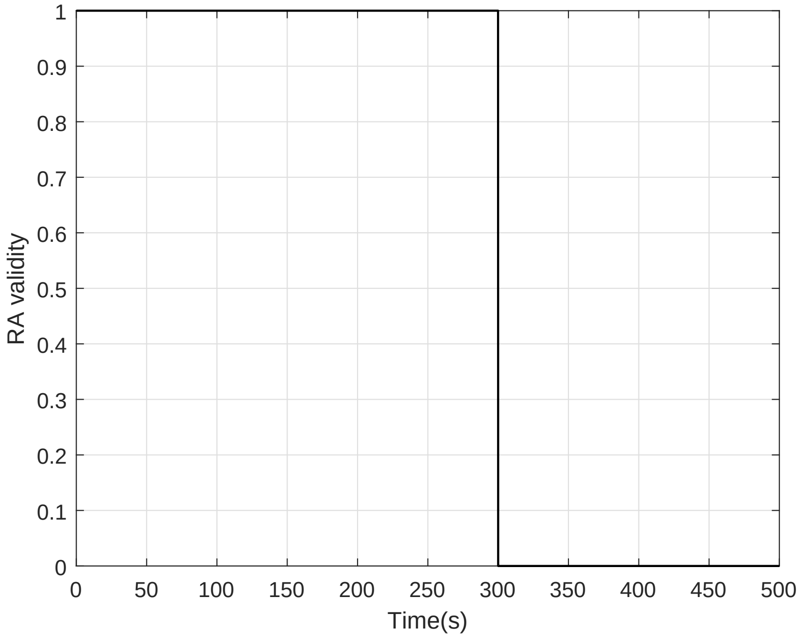

Figure A.19: RA validity with time for scenario 2.

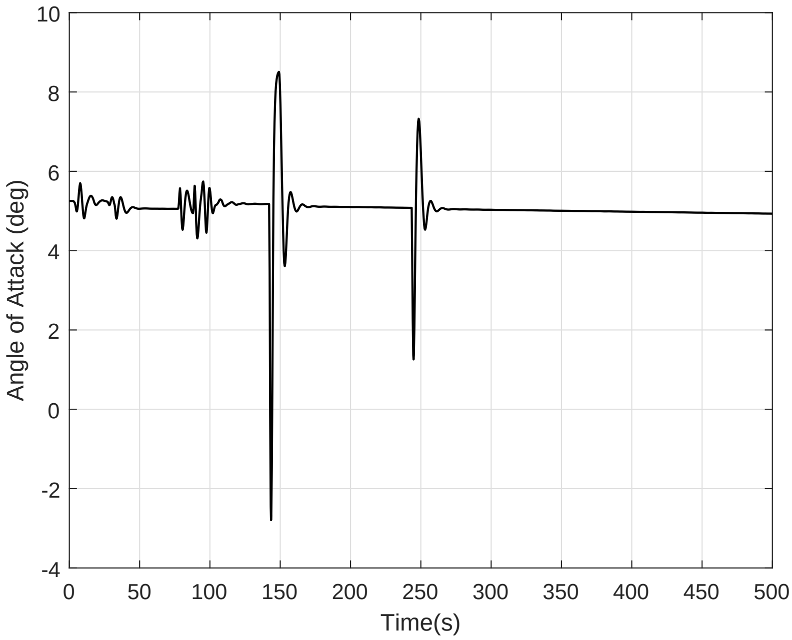

Figure A.20: Angle of attack with time for scenario 2.

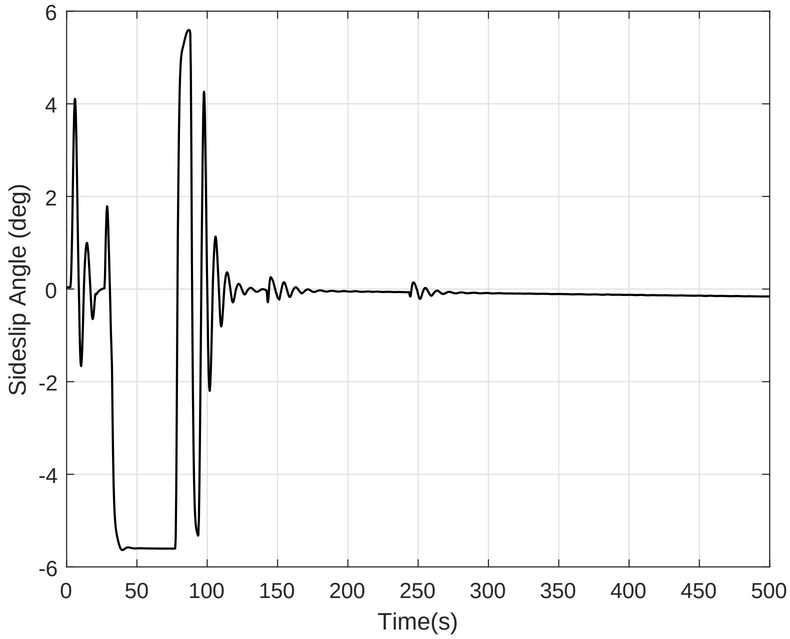

Figure A.21: Sideslip angle with time for scenario 2.

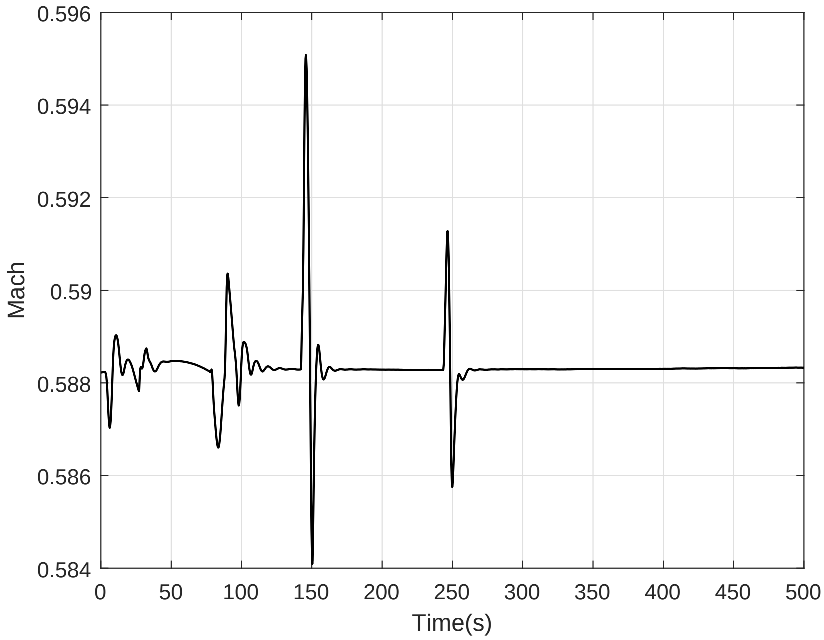

Figure A.22: Mach with time for scenario 2.

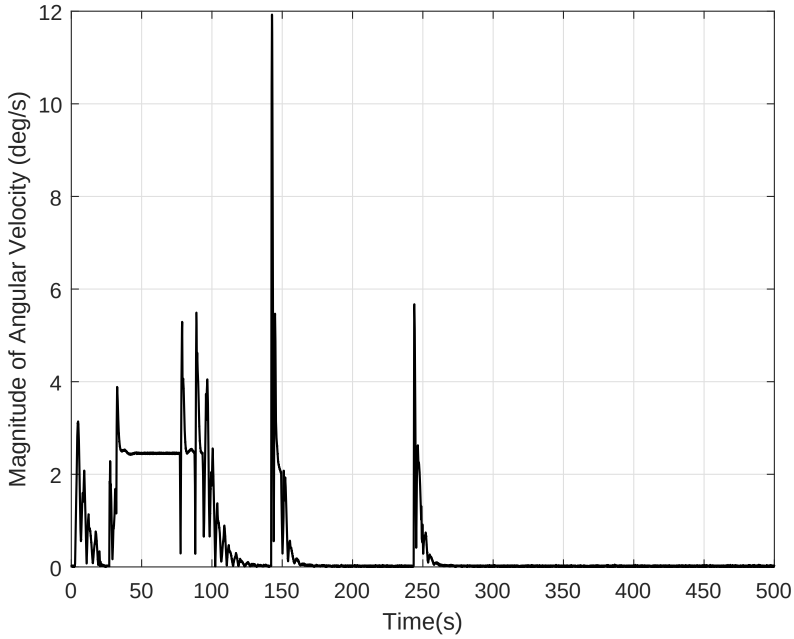

Figure A.23: Magnitude of angular velocity with time for scenario 2.

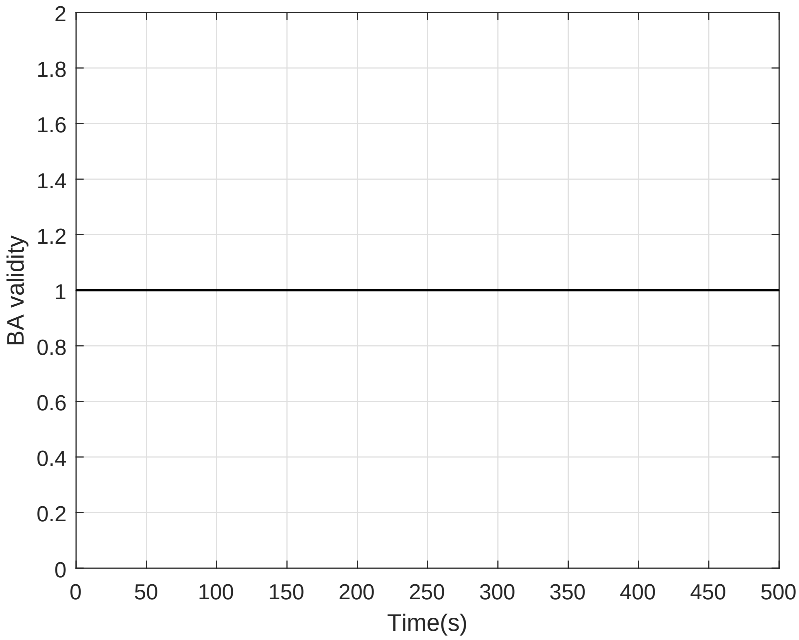

Figure A.24: BA validity with time for scenario 2.

APPENDIX B.1

https://github.com/kankayan/MasterThesisAlgorithm/blob/master/NK_Sensor_Fusion_Algorithm.rar

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