**CAPACITY ALLOCATION AND DYNAMIC PRICING FOR AIR FREIGHT TRANSPORTATION**

(HAVA KARGO TAŞIMACILIĞINDA KAPASİTE ATAMASI VE DİNAMİK FİYATLANDIRMA)

by

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## LIST OF SYMBOLS

**ACRM** : Air Cargo Revenue Management
**AI** : Artificial intelligence
**ANN** : Artificial Neural Network
**CVaR** : Conditional Value at Risk
**GDP** : Gross Domestic Product
**GMAE** : Geometric Mean Absolute Error
**ICAO** : International Civil Aviation Organization
**IATA** : International Air Transport Association
**LF** : Load Factor
**MAD** : Mean Absolute Deviation
**MARE** : Mean Absolute Relative Error
**MaxAE** : Maximum Absolute Relative Error
**MdAE** : Median Absolute Error
**ME** : Mean Error
**MNB** : Mean Normalized Bias
**MPE** : Mean Percentage Error
**MSE** : Mean Square Error
**NARX** : Nonlinear Autoregressive Exogenous
**$R^2$** : Coefficient of Determination
**RM** : Revenue Management
**RMSE** : Root Mean Square Error
**SABRE** : Semi-Automated Business Research Environment
**SARSA** : State Action Reward State Action
**SUR** : Show Up Rate
**TDL** : Tapped Delay Line
**VaR** : Value at Risk

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## ABSTRACT

The air cargo industry is of significant importance to the global economy, employing a distinctive business model that makes it the most preferred mode of transportation, particularly for the rapid delivery of high-value goods. Airlines are constrained by limited cargo capacity, which presents a significant challenge for the industry. Maximizing revenue by selling capacity to the most profitable customers at the most advantageous price is an important issue that directly affects profitability. This study addresses the issue of capacity allocation, demand forecasting and dynamic pricing for air cargo firms. It is divided into three steps: the first is the allocation of capacity to allotment sales, the second involves the development of a demand-forecasting model that considers capacity excluding pre-sales, while the third stage entails the creation of a dynamic pricing model using the aforementioned forecast as an input. The unit revenue recommendations obtained from the dynamic pricing model were integrated to feed the capacity allocation model, which is the first stage of the study. Air cargo companies have limited capacity and wish to utilize it optimally. It is possible to pre-sell capacity through agreements or to make it available for future demand. The proportion of total capacity allocated to deals is crucial for more efficient capacity utilization. In the first stage of the problem, a model is proposed for the optimum allocation of capacity. The capacity solution to the problem is formulated with CVaR and ANN models, and the outputs of the models are then compared. The model that yields the optimal result is selected. Subsequently, a demand forecasting model is constructed, incorporating capacity as input. Regression analysis, time series methods, and ANNs were employed for demand forecasting. The values produced by the model were compared with the actual values, and the model that gave the best result was included in the solution. Due to the multitude of variables influencing the price in the air cargo sector and the intricate structure of the sector, it is exceedingly challenging and complex to determine the price dynamically in air cargo. To circumvent the difficulties inherent in this complexity, in addition to a comprehensive literature review, the opinions of industry experts were sought and the model inputs were determined. The problem solution was completed by employing SARSA algorithm for dynamic pricing. The study is concluded by evaluating the solutions and making suggestions for future studies.

**RÉSUMÉ**

Le secteur du fret aérien joue un rôle essentiel dans l'économie mondiale, grâce à un modèle d'entreprise particulier qui en fait le mode de transport privilégié, notamment pour la livraison rapide de marchandises de grande valeur. Les compagnies aériennes sont contraintes par une capacité de fret limitée, ce qui représente un défi important pour l'industrie. Maximiser les revenus en vendant la capacité aux bons clients au bon prix est une question importante qui affecte directement la rentabilité. Cette étude aborde la question de l'allocation des capacités et de la tarification dynamique pour les entreprises de fret aérien. Elle est divisée en trois étapes : la première est l'allocation de la capacité aux ventes de l'allotissement, la deuxième implique le développement d'un modèle de prévision de la demande qui considère la capacité à l'exclusion des préventes, tandis que la troisième étape implique la création d'un modèle de tarification dynamique utilisant les prévisions susmentionnées comme intrant. Les recommandations de recettes unitaires obtenues grâce au modèle de tarification dynamique ont été intégrées pour alimenter le modèle d'allocation des capacités de la première étape. Les compagnies de fret aérien disposent d'une capacité limitée et souhaitent l'utiliser de manière optimale. La capacité peut être vendue à l'avance dans le cadre d'accords ou mise à disposition pour répondre à la demande future. La mesure dans laquelle la capacité totale est allouée aux accords d'allotissement est cruciale pour une utilisation plus efficace de la capacité. Dans la première phase du problème, un modèle d'allocation optimale de la capacité est proposé. La solution de capacité au problème est formulée à l'aide de modèles CVaR et de réseaux neuronaux artificiels, et les résultats des modèles sont comparés. Le modèle qui produit le résultat optimal est sélectionné. Ensuite, un modèle de prévision de la demande est construit, dans lequel la capacité est incorporée en tant qu'entrée. Les méthodes des séries chronologiques, l'analyse de régression et les réseaux neuronaux artificiels ont été utilisés pour la prévision de la demande. Les valeurs obtenues par le modèle ont été comparées aux valeurs réelles, et le modèle présentant le résultat optimal a été sélectionné pour la solution. En raison de la multitude de variables qui influencent le prix dans le secteur du fret aérien et de la structure complexe du secteur, il est extrêmement difficile et complexe de déterminer le prix de manière dynamique dans le secteur du fret aérien. Pour contourner les difficultés inhérentes à cette complexité, en plus d'une revue exhaustive de la littérature, l'avis d'experts du secteur a été sollicité et les données d'entrée du modèle ont été déterminées. La solution du problème a été complétée par l'utilisation de l'algorithme SARSA pour la tarification dynamique. L'étude se termine par une évaluation des solutions et des suggestions pour les études futures.

**ÖZET**

Hava kargo endüstrisi, özellikle hızlı teslimat ve yüksek değer gerektiren mallar için en çok tercih edilen taşıma şeklidirler ve kendine özgü bir iş modeliyle küresel ekonomide çok önemli bir rol oynamaktadır. Havayollarının kargo kapasitesi sınırlıdır ve bu durum havayolları için kritik bir sorun teşkil etmektedir. Mevcut kapasiteyi en iyi şekilde kullanmak ve kapasiteyi doğru müşterilere doğru fiyattan satarak en yüksek geliri elde etmek karlılığı doğrudan etkileyen önemli bir husustur. Çalışmada hava kargo firmaları için kapasite tahsisi, talep tahmini ve dinamik fiyatlandırma problemi ele alınmıştır. İlgili problem üç aşamada irdelenmiştir. İlk aşamada kapasitenin ön satışa ayrılacak kısmı belirlenmiştir, ikinci aşamada ön satış haricinde kalan kapasiteyi de dikkate alan bir talep tahmin modeli önerilmiştir, son aşamada ise talep tahmininin girdi olarak kullanıldığı dinamik fiyatlandırma modeli oluşturulmuştur. Dinamik fiyatlandırma modeli sonucunda elde edilen birim gelir önerileri, ilk aşamadaki kapasite tahsisi modelini de besleyecek şekilde modellerin entegrasyonu sağlanmıştır. Hava kargo firmaları limitli kapasiteye sahiptirler ve bu kapasiteyi optimum şekilde kullanmak isterler. Kapasitenin anlaşmalar ile önceden satılması ya da gelecek talepler için satışa açılması mümkündür. Toplam kapasitenin ne kadarının önceden satışı yapılacak anlaşmalara tahsis edileceği, kapasitenin daha etkin bir şekilde kullanılması için oldukça önemlidir. Bu nedenle problemin ilk kısmında kapasitenin doğru şekilde ayrıştırılmasını sağlayacak model önerilmiştir. Problemin kapasite çözümü CVaR ve yapay sinir ağı modelleri ile formüle edilmiş ve modellerin çıktıları karşılaştırılarak optimum sonucu veren model seçilmiştir. Ardından kapasitenin de girdi olarak yer aldığı talep tahmin modellemesi yapılmıştır. Talep tahmini için zaman serisi yöntemleri, regresyon analizi ve yapay sinir ağları kullanışmıştır. Model sonuçları fiili değerler ile kıyaslanarak en iyi sonucu veren model çözüm için seçilmiştir. Hava kargo sektöründe fiyatı etkileyen çok sayıda değişken bulunması ve sektörün karmaşık yapısı nedeniyle, hava kargoda fiyatın dinamik olarak belirlenmesi oldukça çok zor ve karmaşıktır. Bu karmaşıklığın oluşturacağı zorlukları

önlemek adına, literatür incelemesine ek olarak sektör uzmanlarının da görüşlerine başvurulmuş ve model girdileri belirlenmiştir. Dinamik fiyatlandırma için SARSA algoritması kullanılarak problem çözümü sağlanmıştır. Çözümlerin değerlendirilmesiyle ve gelecek çalışmalar için önerilerde bulunularak çalışma tamamlanmıştır.

# 1. INTRODUCTION

As a result of globalization and developing technologies, the importance of air cargo transportation becomes more evident every day. It is important to move products faster for companies in an increasingly competitive environment.

It can be argued that air freight transportation is the optimal choice for several reasons, including its status as the preferred mode of transport for safer, more reliable, traffic-free, fast, and high-value products. On the contrary to these strengths, air freight companies have a limited capacity. Correct management of this limited capacity is of high importance for air freight companies. Airfreight companies are willing to use their opportunities efficiently and thus make more profit. Correct management of plane capacity has high importance in increasing the profits of air freight companies. Determining how much of the capacity will be allocated to contracted sales and how much to free sales is a very important decision for companies.

The application of dynamic pricing in the freight transportation industry can provide several benefits to both shippers and carriers. By capitalizing upon real-time market conditions and demand signals, it is possible to achieve more optimal pricing outcomes and operational efficiency.

The freight industry employs two distinct pricing methodologies: traditional class-based pricing and dynamic pricing. The objective of dynamic pricing is to create a database that will provide suggestions as to the optimum prices. Such a database will therefore have the effect of increasing profit margins. It is evident that this approach is incompatible with the conventional method, given the potential for providers to incur significant financial losses unless they implement an earlier increase in their expenditure. A multitude of variables can influence sales volumes, and the sheer volume of data to be processed makes it challenging to draw accurate conclusions without the use of automation. In contrast, dynamic pricing allows for the consideration of these factors, leading to the generation of a price that is deemed reasonable. However, the conventional approach involves the determination of prices on a fixed, manual basis, contingent upon the weight and volume of the shipment, as well as the distance traversed. Although some would consider this a beneficial aspect, it is not necessarily reflective of the true market value, which may result in overpricing or undervaluing (FreightCenter, 2023).

In this study, we reviewed the existing literature on capacity allocation and dynamic pricing in the air cargo transportation industry. Then, we proposed capacity allocation and dynamic pricing models suitable for the industry by consulting expert opinions. We subjected the selected models to a sample application in an air cargo company.

Our thesis consists of three main models: capacity allocation, demand forecasting, and dynamic pricing, as seen in Figure 1.1. In the first step, we presented the solution to the capacity allocation problem. In this context, the Conditional Value-at-Risk model (CVaR) and the Artificial Neural Network model (ANN) are employed. In the subsequent step, prior to proceeding to the dynamic pricing model, we addressed the demand forecasting problem, which is a critical input for the pricing model and we conducted an analysis of the Multiple Linear Regression model, Time Series (Winter's method), and ANN models. In the third step, we constructed a SARSA model for dynamic pricing. Finally, we concluded the paper with recommendations for future research.

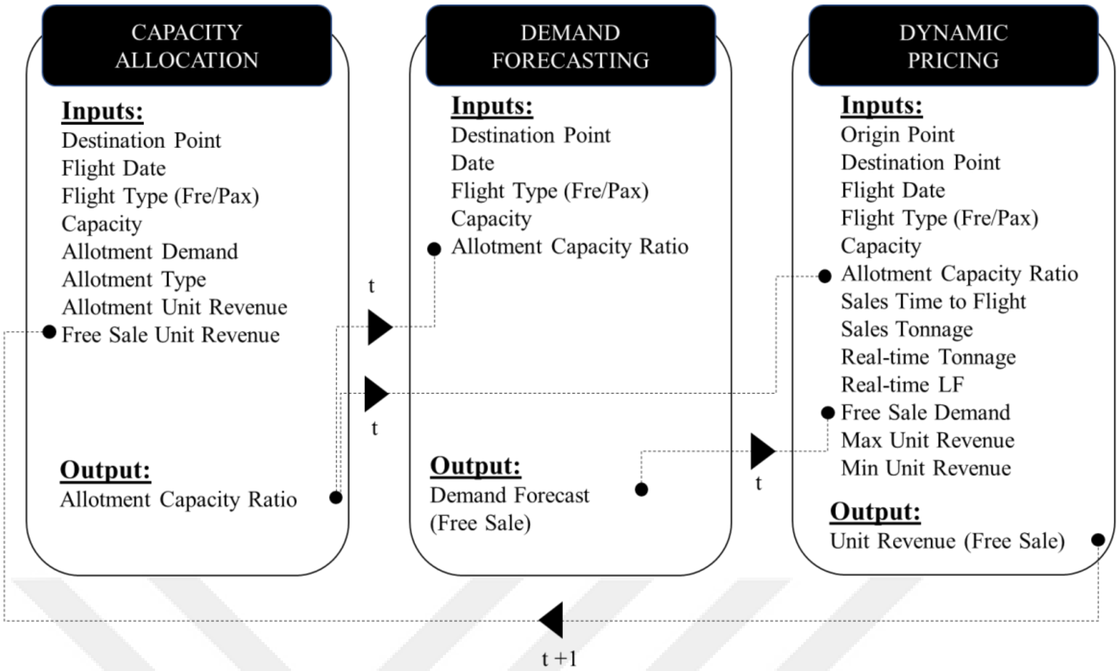


Figure 1.1: The Outlines the Steps of Our Work

The integration of expert opinions with literature reviews has enabled the development of demand forecasting, capacity allocation, and dynamic pricing models that are more aligned with real-world applications. These models have been evaluated through a case study involving data from a leading air cargo company in the industry. The distinguishing aspect of our model is its integrated structure, which sets it apart from other studies in the literature and renders it particularly well-suited for the air cargo sector.

# 2. AIR FREIGHT TRANSPORTATION

The transportation sector represents one of the fundamental pillars of the country's economy. In the contemporary era, the expansion and advancement of the economy, in conjunction with the necessity to expedite the delivery of products, has elevated the significance of the transport sector (Amsterdam Optimization, 2003).

It is possible to divide the transportation sector into three passenger, freight, and information transportation. In this distribution, cargo transportation is the subheading of freight transportation.

Transport of cargoes, packages, mails, and some special cargoes by air can be referred to as air transport. Air cargo transport, ICAO (international civil aviation organization), and IATA (international air transport association) rules are made by applying the rules of the country, the limitations of the carrier.

Airfreight transportation starts with the willing seller and buyer of air freight transportation. Air transport includes a range of services during cargo transportation between origin and destination points. During the transportation process, shipper, forwarder, trucker, air freight carrier, consignee. The shipper needs to deliver his products to any part of the world at a low cost and on certain service standards. Forwarders are the structures that establish the bridge between the sender and the airway. Land transport is used to transport goods on the land before air transportation and/or to deliver the goods to the buyer when the airway transport is completed. The air freight company is responsible for storing, loading, and sending the product after the product is delivered to it. Figure 2.1 shows the air freight transportation process.

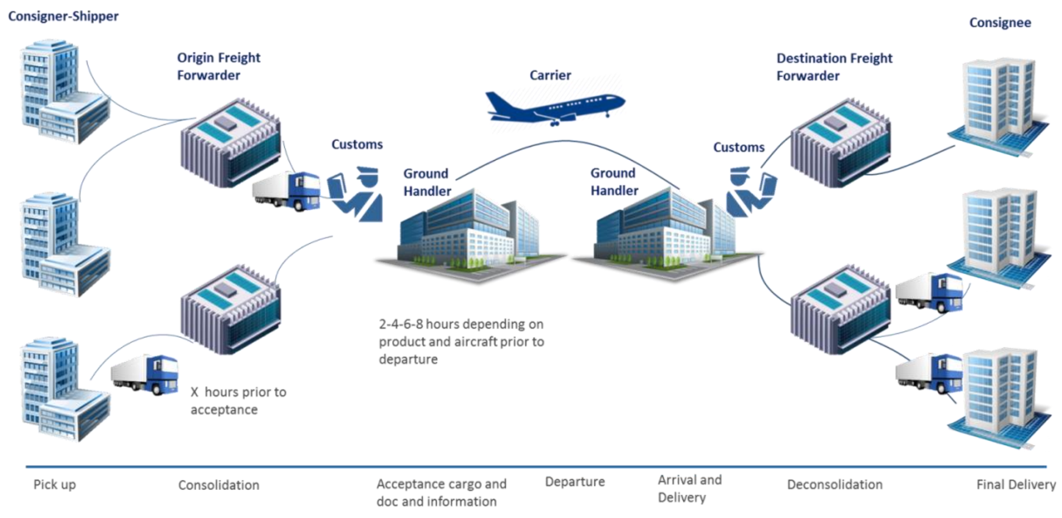


Figure 2.1: Air Freight Transportation Process

In the field of air freight transportation, two distinct categories of carrier exist: express cargo carriers and passenger and cargo combination carriers. Combination carriers are able to carry cargo, express parcels, and mail in the cargo hold of passenger aircraft or on aircraft that have been modified for cargo carriage (Li et al., 2012).

As air freight transport has more players, more complex processes, weight and volume restrictions, priority services, air freight transportation has more complex processes than passenger transportation because of the features such as the risk of products interacting with each other. For these reasons, the methods that should be used for air transportation should be different than passenger transportation.

Compared to other types of transport, although air transportation is more costly than other types of transport, it is more preferable than other transportation types because it is safe, there are less damage and losses during transportation, perishable products can be carried over long distances in a short time.

Air cargo plays a significant role in modern life, contributing to numerous aspects of contemporary society. In developed countries, the delivery of perishable goods from developing economies to markets is not possible in the absence of air transport. The transportation of time- and temperature-sensitive cargoes, such as pharmaceutical products (especially vaccines), is facilitated by the speed and efficiency of air transport.

In the contemporary era, the transport of live animals by air is regarded as the most expedient method of transportation for distances of considerable length. (Yalçınkaya et al 2019).

Increasing trade volumes of the countries, the fact that the speed is in critical condition due to the increasing competition among the companies positively affects air cargo transportation and also contributes to the growth of air cargo transportation. For areas where geographical transportation is difficult, air freight transportation is gaining the advantage thanks to the fast service and convenience provided.

The continued growth of air freight transportation can be attributed to a number of factors, including the increased prevalence of e-commerce, the expansion of urban areas, the efficiency of customs operations with air freight, the speed and reliability of the transportation method itself, and the general safety of the industry. The expansion of global trade, the growing demand for rapid and punctual delivery, as well as the low stock-keeping practices of companies undergoing frequent renovations have collectively driven the growth of airfreight transportation.

Air cargo companies can employ revenue management strategies to optimize the demand for their services. Air Cargo Revenue Management can be defined as the integrated management of cargo rates and available inventory in terms of belly space, payload, and containers. To success in revenue management means being able to transport and distribute a larger size and greater number of goods, which means more revenue.

# 3. REVENUE MANAGEMENT

The term "revenue management" is defined in numerous ways in the academic literature. Kimes (1989) defined revenue management as “Yield management is a method which can help a firm sell the right inventory unit to the right type of customer, at the right time, and for the right price. Yield management guides the decision of how to allocate undifferentiated units of capacity to available demand in such a way as to maximize profit or revenue”.

Research on revenue management goes back 40 years. In 1966, In order to streamline its operations, American Airlines implemented the SABRE computer reservation system (Semi-Automated Business Research Environment), which enables the company to efficiently manage seat reservations. Nevertheless, the spread of Revenue Management practices took place after the 1978 American Airline Regulation Act. Thanks to this law, price control in the airline sector has been loosened and rapid change has been experienced in the industry.  The development of revenue management is closely connected with the airline industry for the first business implementations on revenue management are in the airline industry.

RM system was later discovered and used by other sectors where services could not be stocked such as restaurants, hotels, retailing. Revenue management is a crucial aspect of the success of numerous companies and companies are making significant investments in this area.

### 3.1. Revenue Management for Air Freight Transportation

Revenue management (RM) is a method which using for increasing revenues. Revenue management is based capacity control. Methods and tools are used to increase profitability in revenue management (Hoffman 2013).

So that provides successful implementation, the following features are essential (Kimes, 1989). Revenue management consists of several problems such as forecasting, overbooking, pricing, and capacity control. Demand, no-shows, and cancellations can be forecast. Forecasting has a direct effect on the success of revenue management. Overbooking is used for avoiding from unused capacity. Pricing is another important problem for revenue management. Generally, cargo industry uses static pricing. Capacity control is used for maximizing the expected revenue. Capacity allocation is very important for capacity control. Cargo capacity can be allocated to customers with allotment contracts, or open for free sale. Figure 3.1 shows the components of RM for the air cargo business.

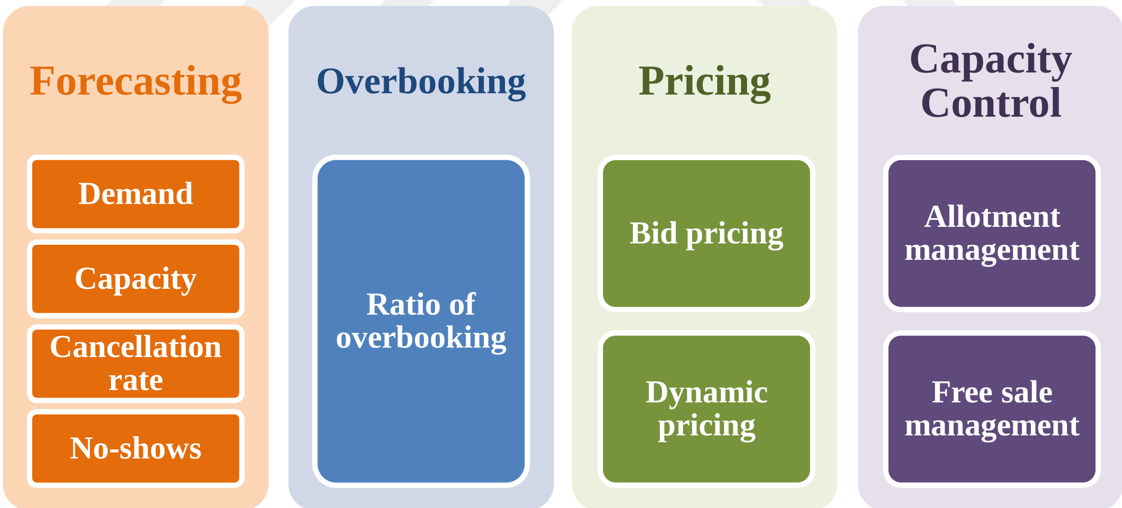


Figure 3.1: Air Cargo Revenue Management Components

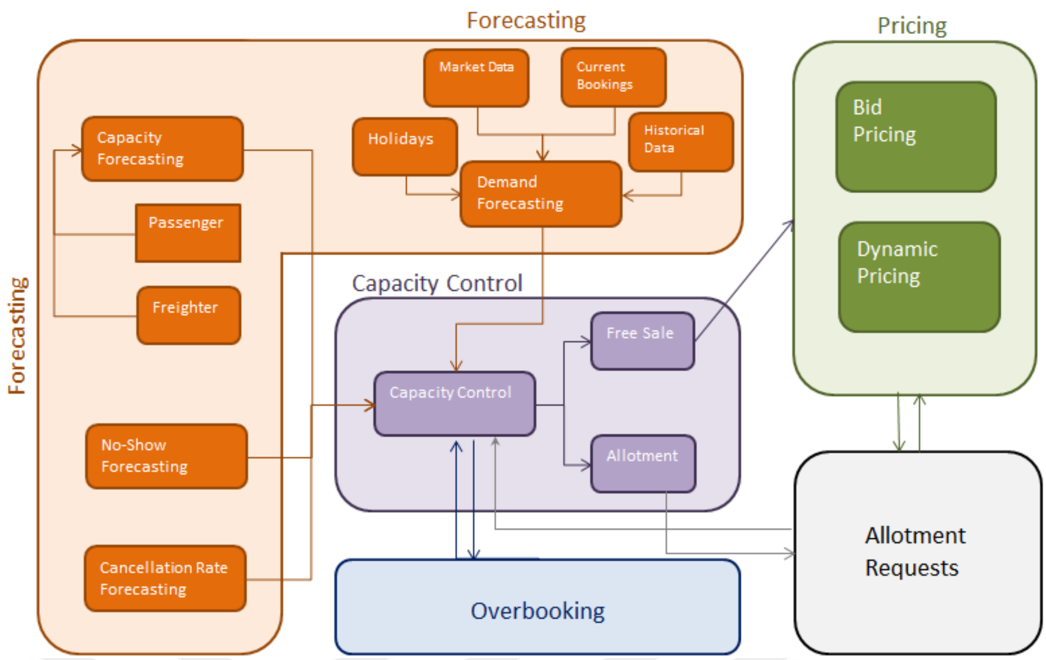


Figure 3.2: Relations between Air Cargo Revenue Management (ACRM) Components

Figure 3.2 shows the relationships between the ACRM components. Examining the relationship between ACRM fragments, it can be seen that the process begins with forecasting (Ilgün Ayhan & Alptekin, 2025). Demands can be estimated by using holidays, market data, current bookings, and historical data. When doing capacity forecasting it should be considered separately for passenger and cargo aircraft. Given the interdependence of passenger aircraft capacity with factors such as passenger numbers and baggage weight, it is more challenging to make accurate estimates. Demand and capacity as well as no-show and cancellation rates should be forecasted. All these estimation rates are essential for capacity control. Overbooking and allotment requests should also be taken into consideration. The capacity control section should specify both the capacity and the ratio of free sale capacity. The data obtained at the end of the capacity control section will also be used to evaluate allotment requests. Once the capacity control phase has been completed, the pricing phase commences for the free sale capacity that has been obtained.

Benefits from implementing revenue management to the air transport business are summarized below.

- ✓ increase in profit
- ✓ better utilization rate

- ✓ meets the needs of different customers types
- ✓ decreasing the risk of overbooking capacity
- ✓ increasing customer satisfaction and loyalty
- ✓ digitalization of systems

# 4. LITERATURE REVIEW

The studies carried out for air freight transportation until the mid-1980s focused on the identification of the operational process, air freight transportation system, and developments in the industry in general. Then, quantitative decision-making methods have been used in many studies in air freight operations. In recent years, there has been a notable increase in the number of studies conducted in the field of air freight (Feng et al., 2014).

Predicting demand, figuring out capacity for overbooking, and pricing are some of the key revenue management research fields. In air cargo transport, there are two primary dimensions of capacity: weight and volume. The capacity available for passenger aircraft transportation is not static; it can be influenced by the number of passengers, the overall baggage, etc. Demand also differs in both sectors; passenger demand can be defined by seasonal variations, while on the cargo side, numerous parameters affect demand, and it's far more challenging to predict. Due to all these difficulties, there are many publications on revenue management in air passenger transport, but few in air cargo transport.

Upon examination of the relevant literature, it becomes evident that revenue management studies, initially applied in the context of airlines, have subsequently been employed in a range of other sectors. However, their application in the field of air cargo remains relatively limited. The divergence in characteristics between air cargo transportation and passenger transportation is a significant factor in this discrepancy.

In the study of Klein et al. In 2020, they stated that air cargo capacity sales made the general RM rules more complicated. These complexities have been summarized as follows:

- The majority of air cargo capacity is sold on long-term contractual agreements, which are typically planned and executed in advance. Only the residual capacity is offered for sale on the spot market in the period of approximately 30 days prior to the scheduled delivery of the service in question. Previous research in the field of revenue management has concentrated on the control of sales in this market.
- Both the volume and the loadable weight of an airplane constitute a physical resource. Therefore, there are two dimensions need to be considered in capacity calculation.
- The volume and weight capacity of an aircraft may be subject to fluctuations due to a number of factors, including the capacity sold with long-term contracts, the number of passengers on the flight, and the prevailing weather conditions.
- The precise volume and weight specifications for cargo reservations are not determined until the service is provided, thereby contributing to an additional source of uncertainty.
- A cargo product is not typically identified by a specific itinerary; rather, it is loosely linked to an origin-to-destination pair, provided that it arrives on time. Consequently, the cargo firm has routing flexibility. The routing decision can be postponed if necessary.

Bartodziej et al. in their 2007 study in addition to cargo revenue management difficulties of Klein et al.'s study in 2020, they used the following items:

- It is typical for passengers to reserve return flights, yet the demand for cargo is generally one-way. This creates a geographically unstable environment for the cargo business.
- The subtlest distinction is that passengers themselves create their own itineraries. For example, there are certain series of flight connections that take the passenger from the start to the destination. In the context of cargo transportation, customers reserve capacity from a starting point to a destination, specifying a certain service level. Cargo customers are typically not concerned with the specific route of their packages. Consequently, cargo airlines have some flexibility in how and when to assign requests to specific flights. This flexibility gives rise to different planning models.

The processes of air cargo transportation are more difficult to manage and predict compared to air passenger transportation processes. Table 4.1 provides an overview of the distinctions between air cargo transportation and passenger transportation, as well as the associated revenue management elements.

The utilization of bid-price acceptance policies is a common occurrence within the domain of passenger revenue management. The fundamental concept of a bid-price policy is the determination of the optimal selling price at a specific point in time for a defined quantity of capacity. Pak and Dekker (2004) showed that if capacity and demand increase proportionally and the bid-prices are set accurately, a bid-price acceptance policy is asymptotically optimal. They provided a heuristic model to set the bid-prices this model based on a greedy algorithm. The solution technique that they offered was an easy-to-use bid-price acceptance policy in practice.

Table 4.1: Differences between Air Cargo Transport and Air Passenger Transport

| **Category** | **Air Cargo Transportation** | **Air Passenger Transportation** | **Affected RM Components** |
|---|---|---|---|
| Capacity | Uncertain | Certain | Capacity Control |
| Capacity | Multi dimentional | One dimentional | Capacity Control |
| Capacity | Possible stowage loss | - | Capacity Control |
| Demand | Short term | Long term | Forecasting |
| Demand | Volatility demand | Seasonality pattern | Forecasting |
| Demand | One-way transportation | Pax usually book a return trip | Forecasting |
| Product Variety | Much | Less | Pricing |
| Routing Option | Possible | - | Capacity Control, Forecasting, Pricing |
| Forecasting | Highly predictable | Hard to predict | Forecasting |

Hellerman discussed the two problems that are closely related to the dynamics of real applications in the air freight sector which explained in 2006 by Moussawai-Haidar. The first of these problems is how much of the total capacity should be allocated as an allotment and which allotment contract should be signed. The second problem is to decide dynamically whether the demand for spot will be accepted after allotment capacity. The study also considers the possibility of being no-show in the part separated as an allotment. Nonlinear modeling was used at this model. The model's objective function is to maximize the expected revenue from allotments and free sales, while simultaneously reducing the off-load cost. Second, a dynamic model was used for the management of free sake demands. Both allotment and free ssle requests are generated dynamically during the booking period.

In a study published in 2007, Becker and Dill examined the drivers of complexity in air cargo revenue management. At the end of the study, they advised approaches to handle these complexities.

Becker and Wald (2010) identified the major challenges for ACRM. Firstly, emphasized the critical success factors for ACRM then they suggested approaches to managed these challenges.

In a study published in 2010, Han et al. examined the allocation of capacity for single legs in the context of air freight revenue management. The authors concentrated on the management of bookings in relation to the capacity of free sale. They suppose that weight, volume and profit rate occurred randomly in booking request. They proposed a Markovian model for accept or reject process in the booking request.

The concept of capacity utilization is of significant importance in a multitude of fields. The issue of how to maximize capacity utilization requires further investigation. In their 2011 study, Wilken et al. tackled the problem of choosing a suitable peak hour and gave data concerning the capacity utilization of airports globally each year, using traffic ranking curves. They established a functional relationship between peak hours and the volume of annual air transport movements for each airport capacity category.

Amaruchkul and Lorchirachoonkul (2011) proposed a model that allocated cargo capacity to forwarders before the booking horizon with considering a single air cargo carrier. Their aim was to identifying the optimal allocations that would maximize the total contribution. In their work, they derive the probability distribution of actual usage using a discrete

Markov chain and then solve the problem using the dynamic programming method. In addition, they propose two heuristics to solve large-scale allocation problems.

Boonekamp (2013) developed two different models; the first model based on described by Kevin Pak, and the second model was a practical model that based on information get from experts. Fairly straightforward booking control policies are used in paper. Theatrical potential of these models when implemented as revenue management solutions, are evaluated by comparing with first come first serve acceptance policy. The theoretical benefit of these models was obtained by more than 20%.

Haidar (2014) demonstrated the optimal resolution of a single-leg cargo revenue management issue. He then proceeded to determine the optimal quantities of volume and weight to be sold on an allotment basis. He addressed this challenge using a dynamic programming approach, which has proven effective in solving medium-size industry problems. He formulated a discrete-time capacity control model for the allotment requests was formulated, with the objective of determining which of the allotment requests is accepted.

Feng et al. in their study in 2014, they conducted a literature study for air freight operations and compared the samples. They discussed the studies in the literature with three main headings: airway perspective, forwarder perspective, service supply chain perspective. The largest part of the studies examined is from the airway perspective. Activities in this category are classified under four sub-headings: RM, flight routing and scheduling, terminal operations, and aircraft loading. In order to define the characteristics of air freight operations, they investigated the use of mathematical models in the literature and revealed the differences in the operation of air freight from passenger operation. They emphasized the gap between current studies and actual practices in the past. Finally, they summarized the issues that could create new research opportunities for future studies.

In 2015, Huang and Lu proposed a multi-dimensional dynamic programming model to illustrate a network revenue management problem within the context of air freight. Weight, rate of shipments and volume was stochastic in the model. The objective of the study is maximizing the expected revenue of air freight firms by using dynamic model.

To overcoming the computational challenge, they developed two models based on linear programming.

In a study published in 2017, Lin et al. examined the booking and execution procedure in the air freight industry with the objective of evaluating the applicability of a buy-back policy. They built a revenue model that includes the Black-Scholes pricing model and Hellermann's capacity option model by applying a buy-back policy.

A substantial corpus of literature exists on the subject of decision-making under capacity contracts. Tao et al. (2017) conducted a study on capacity reservation policy and revenue management in the air freight industry. The study addressed the pricing and reservation problems associated with capacity in the air freight industry. A Stackelberg game model was constructed to simulate the behaviors of carriers and forwarders. After establish a Stackelberg game model, they derived optimal pricing and reservation policy respectively to maximizing expected profits.

Brandth (2017), tried to understand the load planning problem that cargo airlines faced. He created a decision support system to maximizing revenue, minimizing operational costs and minimizing physical handing of effort by developed a suitable solution approach computed within a reasonable time.

In order to maximize profits, Delgado and his colleagues proposed a multi-stage stochastic programming model for allocating cargo on passenger networks. The authors addressed the uncertainty of cargo capacity on passenger aircraft and considered demand uncertainty. The authors focused on the allocation of booked capacity across different legs, with the use of the belly cargo as the sole mode of transportation.

He (2019) examined the impact of capacity flexibility on the optimal booking limits for a number of customers. In particular, the paper considered the advantages of using booking control limits. The flexibility in question includes downside, upside, and timing flexibility in capacity. Firstly, he analyzed a static case, in this case low-price customers made bookings before, after that he studied a dynamic case. In became possible with this case that different segments customers make bookings in any order.  The findings of this study indicate that the benefit of booking limit control is contingent upon the level of flexibility in both upside and downside scenarios. In the former, more flexibility can either enhance or diminish the benefit of booking limit control. Conversely, in the latter, greater flexibility consistently enhances the benefit of booking limit control.

In their 2020 study, Huang and Chang developed a solution algorithm for the ACRM problem based on dynamic programming. This algorithm approximates the expected revenue function using a joint approximation heuristic. In their study, the researchers consider the stochastic volume and weight of the shipments. The heuristic method is based on generating the space control policy for Amaruchkul et al (2007) study. In order to alleviate computational strain, the computation of the Bellman equation is conducted within the framework of dynamic programming. This is done concerning a predefined number of sampling points that are distributed evenly within the dynamic programming state space. The simplification addresses the dimensionality challenge commonly observed in dynamic programming models. Consequently, the methodology is now capable of computational applicability.

While numerous methods exist within the extant literature to estimate various parameters, there are few forecasting studies for air cargo. Attraction models, analytic hierarchy process, fuzzy logic, time series, regression, Delphi technique, ANNs, genetic algorithms can be given as examples of methods used in forecasting in the literature.

Grosche et al (2007) used two different attraction models to estimate passenger volumes between city pairs. Their study included both geo-economic and independent factors. In the first attraction model, cities with several airports in one city were not included in the study. In the second attraction model, city pairs with multiple airports were included in the study and passenger volumes were estimated.

Asilkan and Irmak (2009) attempted to predict future used car prices using ANN. They used data from used car sales websites as input to the ANN. As a result of their study, they found that using ANNs to predict future used car prices gives successful results for the model they built.

Forecasting the market demand for a newly developed product is an important research topic. Aydın et al. (2014) conducted an analysis on this issue in their study. In their study, they aimed to develop a market demand model with a fuzzy approach in relation to market potential estimation and survey data. In their study, they proposed a fuzzy method for forecasting the market demand of the newly developed product and developed forecasting models with bad, normal and good scenarios. The proposed methodology is based on fuzzy regression and discrete choice analysis, with a focus on a fuzzy choice model. To measure the effectiveness of their proposed method, they used their proposed method to forecast the demand for new tablets entering the market. They compared the results with those obtained using the MNL model. The comparison showed that the results of the fuzzy approach estimated with the normal scenario were close to the model estimated with MNL. However, the MNL model does not predict for bad and good scenarios.

In their 2006 study, Feng and Xiao reviewed the literature on air cargo operations in detail and identified gaps in the literature by interviewing airlines and forwarders. The aforementioned scholars identified several gaps in the extant literature, including but not limited to capacity allocation and pricing strategies. They also underscored the importance of data-driven decisions in their study.

Du et al. (2024) present a comprehensive study that addresses the dynamic pricing problem faced by airlines seeking to maximize expected cargo revenue on a single-leg flight. The weight and volume of cargo shipments are inherently uncertain, and their precise values are not readily available at the time of booking. To model this uncertainty, the researchers employed a Markov decision process, a statistical method in which the probability of an event is calculated based on the occurrence of preceding events. By adopting this methodological approach, the researchers were able to derive a necessary condition for identifying the optimal pricing strategy.

Patel et al.'s 2023 study aspires to comprehend and delineate the pricing strategy model for freight transportation goods. The authors conducted a deliberation on the subject of freight transportation systems, with a particular emphasis on the impact of dynamic pricing models on systems that have been implemented within the market. A rigorous examination of the multifaceted characteristics inherent in various pricing strategies ensued, to elucidate their correlation to parameters exerting influence on the price of the service in question. The study investigated the potential advantages of integrating dynamic pricing models and methodologies to enhance business returns, boost revenue generation, and optimize operational efficiency. Additionally, it explored the integration of sales, marketing, and customer lifetime value enhancement models. These multifaceted considerations collectively contribute to essential components of the freight transportation system, which serves as the foundation for all logistics and supply chain systems worldwide.

In their 2021 study, Feng et al. considered the problem of an airline setting prices dynamically while possessing limited information about demand, such as moments and the median of the distribution. This study examined the airline's capacity to sell its services over a two-stage sales period. The researchers employed a dynamic pricing model based on distributional robust stochastic programming to minimize expected regret value under a worst-case distribution. This approach accounts for partial information availability, a common scenario in practical applications.

Capacity management plays an instrumental role within the domain of the air cargo industry. A proper allocation of capacity can lead to an increased utilization rate, which in turn increases total revenue. In the present study, the primary objective is to meticulously ascertain both the contracted sales and free sales rates for capacity planning. The secondary objective is the dynamic pricing of capacity allocated for free sale. Prior to the development of the dynamic pricing model, a demand forecasting model was developed to forecast demand, as it is one of the crucial inputs of the model.

In today's world, it is very important to make accurate predictions for the future. Although it is impossible to obtain perfect forecasting results since not all factors affecting the parameter to be forecasted can be reflected in the model, it is very important to use the model that gives the most realistic results for forecasting. In order to manage the available resources more effectively, it is closely related to making accurate future forecasts. In our study, we utilized expert opinions in addition to the literature review while determining the model inputs in order to make more accurate forecasts while forecasting demand.

In the context of the air cargo sector, characterized by its intensely competitive nature, it is imperative for businesses to meticulously craft their pricing strategies. Doing so allows them to ensure their continued viability, gain a competitive advantage, and enhance their profitability. The second objective of the study is to create a dynamic pricing model. We used the results of the capacity allocation and demand forecasting models to set up the dynamic pricing model. In our study, in addition to the literature review, we also included expert opinions. We used the unit revenue from the dynamic pricing model as input for the capacity allocation model for the future periods, so we created an integrated model.

We have proposed a model for three of the most important issues for revenue management in air cargo: demand forecasting, capacity allocation, and pricing. The model under consideration diverges from the extant literature on the subject in several notable aspects: firstly, it is distinguished by an integrated structure and scope, and secondly, it utilizes a reinforcement learning algorithm for the purpose of dynamic pricing. The incorporation of expert opinions has enhanced the model's capacity to mirror real-life scenarios. The application of the model to real data from a prominent airline in the air cargo industry facilitated the accurate interpretation of the model outputs.

# 5. AIR FREIGHT CAPACITY ALLOCATION

When it comes to transporting goods by air, the product being sold is capacity. After the flight date and time that were scheduled have passed, the capacity becomes unusable. Unused capacity can be considered as a product that cannot be sold the appropriate management of capacity within the domain of air cargo transport will make a positive contribution to increasing revenue and profitability.

In air cargo, the capacity can be sold with periodic allotment agreements or it can be offered for sale as free sales. Air cargo companies may consider allotment sales as a means of reducing the risk of their aircraft being empty. At this point, it is critical to determine how much of the aircraft capacity will be reserved for allotment sales (Ilgün and Alptekin, 2016).

The management of capacity is influenced by a number of factors, including volatility in capacity and the existence of multiple capacity constraints. Furthermore, the absence of demand certainty is also a contributing factor. It is possible that the incoming request may be cancelled, and hard block allotment agreements can be employed to mitigate the impact of some cancellations. However, it is not possible to eliminate the risk entirely. Overbooking is carried out to prevent the idle capacity of the aircraft due to demand cancellation. Nevertheless, overbooking increases the probability of offloading, which may subsequently result in customer complaints and the deterioration of customer relationships.

Airlines utilize a variety of channels for the sale of their cargo capacity, which can be categorized into two distinct categories as pre-allocation, and free sales. It is possible for airlines to sell their capacity to shippers directly, but a large extent of air freight firms sells their capacity to forwarders. In the context of air freight operations, forwarders are allocated capacity on specific routes in accordance with their previous year's performance. Allocation information is a requirement for forwarders to plan their next planning periods. Forwarders are keen on purchasing dedicated capacity in the next seasons when they have constant cargo sources, so they enter into contracts with air freight firms. In light of the potential for overbooking and cancellation by forwarders, air freight firms must consider the viability of various policies to maximize their expected revenue. Air cargo companies manage their network capability via several divisions, each of which runs its own regional operation. For every division, there are many representatives assigned to capacity management. For each route, there are a number of forwarders who are responsible for purchasing the capacities. At the commencement of a planning period, the cargo capacity planning department allocates network capacity to every branch. Afterward, representatives allocate the capacity to forwarders on the managed routes. Air freight firms frequently come up against challenging problems. Although it is possible that insufficient capacity to meet the orders on some routes, other routes have idle capacity (Feng et al., 2015).

Upon entering into a contract with an air freight carrier, a freight forwarder is entitled to a proportion of the carrier's total capacity. This capacity may be allocated in whole or in part, and is subject to the market demand at the time of its utilization.

The issue of capacity allocation becomes significant when a carrier sells its capacity to multiple forwarders and orders exceed the airline’s fixed capacity (Feng et al., 2015). Despite the abundance of literature on nonlinear resource allocation problems, there are only a few papers that present mathematical models for the air freight allocation problem (Amaruchkul and Lorchirachoonkul, 2011).

## 5.1. Model Description for Air Cargo Allocation Problem

Air cargo companies are limited by capacity. Therefore, the financial success of air cargo companies depends on the ability to use capacity efficiently. Capacity limitation can be examined under three headings as tonnage, volume, and position for air cargo companies. Multi-dimensional capacity makes capacity management difficult in air cargo companies. It is possible to maximize the revenue of the air cargo company by providing the right capacity allocation and correct pricing in air cargo. The fact that the capacity can no longer be used after the flight has been carried out and that there is no return in this sense shows how critical the correct planning is.

Our study aims to determine the free sales and allotment capacity within the total capacity.

## 5.2. Solution Algorithms

ANN and CVaR models are used to achieve this objective. These models and their results will be discussed in detail in the rest of the section.

### 5.2.1 Artificial Neural Networks

Artificial intelligence (AI) first emerged in the United States in 1956 at a scientific conference where the objective was to devise computer programs capable of demonstrating intelligence (Uysal, 2009).

ANNs are one of the areas of artificial intelligence research. With the technological developments and changing conditions, the usage areas of computers increase. Computers are in a position to make predictions using data instead of just processing and calculating data. ANNs are aimed to transfer these abilities to the computer-based ability of the human brain to think and work. ANNs originated from the biological nervous system. ANN structures are similar to biological cells.

The application of ANNs enables the resolution of intricate issues, the categorization of data based on previous inputs to the network, and the formulation of predictions (Uysal, 2009). ANNs are made up of three layers as input layer, hidden layers and output layer. The ANN structure is given in Figure 5.1.

The information is initially introduced into the network via the input layer. It then undergoes conversion into output through the application of information weight values within the hidden layer, before being transmitted to the output layer. The network is trained to find the correct weights that will be used to process the information. In the initial stage of the training process, the randomly assigned weights are modified in accordance with the learning rule of the network in response to each sample presented to the network. The aim is to find the most suitable weight value for the network. It is not known what the specified weights mean individually. It can be said that the intelligence of the network is these weights because the network gives the result concerning the inputs using these weights. The capacity of the network to learn and simulate an event is contingent upon the artificial intelligence model selected for the sample (Öztemel, 2012).

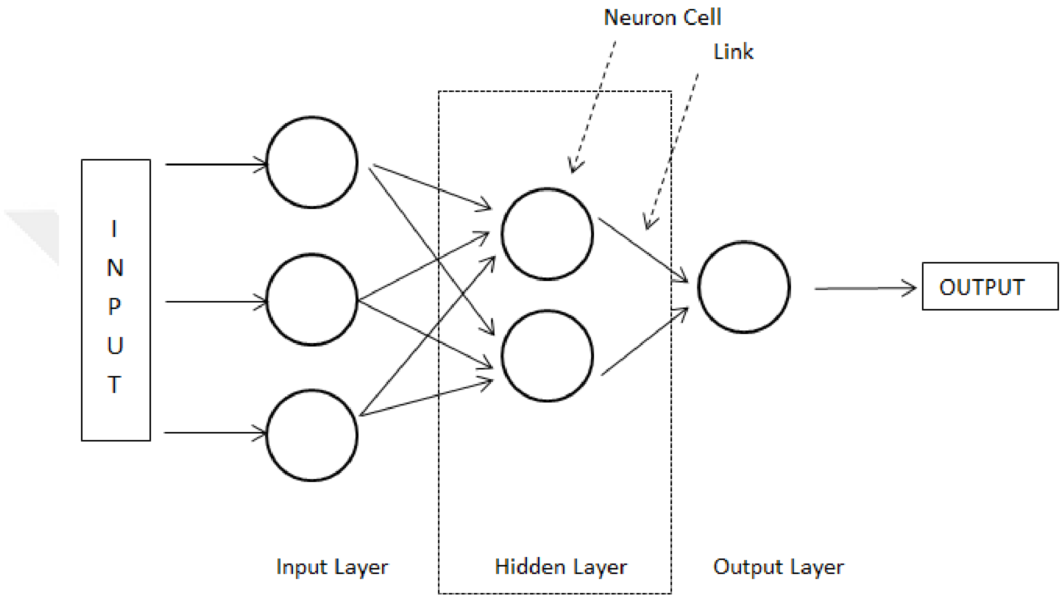


Figure 5.1: ANN structure

In ANNs, the time interval in which weights are constantly renewed is achieved as learning to achieve the desired result. In simple terms, learning is the shaping of weights to meet the required performance criteria (Karaali, 2006). The learning process in ANNs may be viewed as a reward-and-punishment mechanism. If the network reacts correctly to the data, its weights are strengthened; otherwise, weights are weakened (Şahin, 2002). In case the system reacts appropriately to the input, it is possible to create output values similar to the input encountered by the system by strengthening the relevant weights. When unwanted outputs are produced, the model is tried to be prevented from producing unwanted outputs by reducing the weights. The model learns to react differently when similar inputs are available (Kabak et al, 2007).

There are numerous types of ANNs. Given the ongoing development of new ANNs, it is not possible to provide an exact figure for the total number of ANNs in existence. (Javatpoint, n.d.).

**NARX Neural Networks (Nonlinear Autoregressive Exogenous)**

The Nonlinear Autoregressive Exogenous (NARX) model was proposed by Lin and colleagues in 1996 as an ANN model for use in problems where the desired output depends on data in the past. NARX is a dynamic ANN comprising numerous layers of feedback and forward calculation. The letter "X" in the model's designation denotes the exogenous variables, which are external variables that are included within the model. In a dynamic ANN, historical values of one or more temporal series can be employed to forecast future values.

The results of the study indicate that NARX is a more efficient and effective feedback network structure than those employed in traditional systems. (Aşkın et al. 2011). In comparison to traditional feedback network structures, NARX networks demonstrate accelerated convergence and enhanced learning efficacy. Diaconescu 2008). This study examines seasonal market demand in different destinations. In our model, it would be appropriate to use the NARX model in our study. The NARX model is based on the linear ARX model, ARX model is widely used in time series. Output is applied to the input as feedback. In contradistinction to alternative feedback networks, NARX networks are distinguished by the reception of feedback from the output layer of neurons, as opposed to the reception of feedback from the entirety of the hidden layers. The NARX model is expressed by the following equation (Yavuz, 2018):

$$y(t) = f(y(t-1), y(t-2), \dots, y(t-ny), x(t-1), x(t-2), \dots, x(t-nx)) \qquad (5.1)$$

y (t-1), y (t-2),…, y (t-ny) in the equation 5.1 refers to network outputs. X (t-1), x (t-2),…, x (t-nx) in the equation 5.1 refers to network inputs. In this context, "ny" and "nx" denote the number of previous outputs and inputs, respectively, that will be utilized for the purpose of providing feedback. The value of Y(t), which is linked to the output signal, is computed by integrating the signal of the preceding output value with the return of the previous independent input signal (external).

NARX Architectures: NARX networks can be designed using parallel or series-parallel architectures (Yavuz, 2018).

5) Parallel NARX architecture: The estimated output value is then fed back into the feed-forward network, where it is subjected to further processing. The estimation of the subsequent value is contingent upon the inputs to the network and the preceding outputs. TDL (Tapped Delay Line) refers to temporal delay and serves to feed the network with previous input values. A parallel NARX architecture is given figure 5.2.

The recycling of the output (regressor) consists of the estimated output values of the system (Arık, 2011).

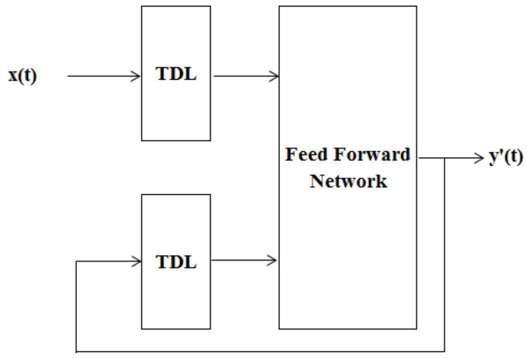


Figure 5.2: Parallel NARX Architecture

b) Series-parallel NARX architecture: The output is fed back to the input of the feedforward neural network in accordance with the standard NARX architecture. Since real output exists during the training of the network, the regressor of the output consists of the real output values of the system. The two principal benefits of this approach are that the introduction to the feed-forward network is more accurate and, secondly, the resulting network has a completely forward feed architecture. Furthermore, static backpropagation can be used for training. (Yavuz, 2018). A series-parallel NARX architecture is given figure 5.3.

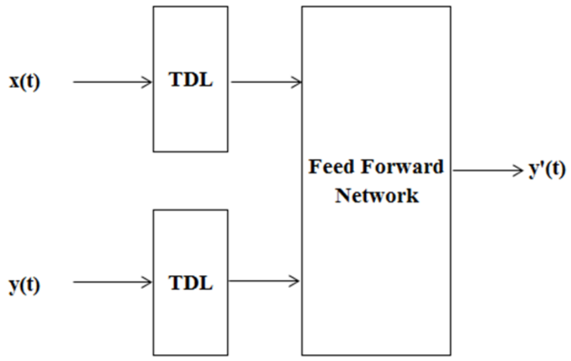


Figure 5.3: Series-Parallel NARX Architecture

In this architecture x(t) shows the exogenous parameters of the past, y(t) refers to the time series to be estimated. y'(t) expresses the estimated values (Yılmaz, 2015).

### 5.2.1.1 Solving the Air Cargo Capacity Allocation Problem with ANN

It is to be expected that air cargo demand will vary in accordance with seasonal patterns. Consequently, the number of requests for and the volume of cargo shipped may fluctuate during certain months, either above or below average levels. The incorporation of seasonality into the model is intended to enhance its predictive accuracy. The sales structure and demand may vary considerably between different destinations. In some destinations, allotment transports constitute a significant proportion of the available capacity, whereas in others, this may be the opposite. In order that the model may yield differing outputs according to the destination, the destination has been incorporated into the model as an input. Cargo or passenger aircraft are other parameters that may affect the model. For this reason, fleet type is also taken as input. As a result of the model, it will be determined how many percent of the current capacity will be reserved for allotment sales and what percent will be put on sale as free sales. Therefore, the amount of capacity is another input that is essential for the model. Allotment requests and allotment type are added to the model as input, since the allotment requests and where these requests are made are also important. Allotment and free sale unit revenues are also added to the model as input. Allotment capacity ratios of previous years were taken as output in the model. As a result of the model, the capacity allotment rate is estimated.

Remain capacity will be determined as free sale capacity. The data set used in the ANN model is shown in the figure 5.4.

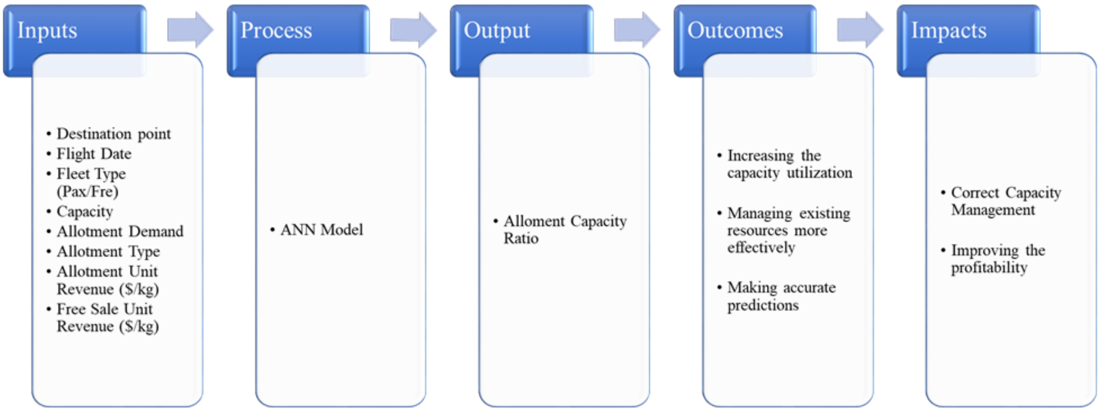


Figure 5.4: ANN Model Input & Output Parameters

Firstly, the inputs and output that to be used in the model should be added to the MATLAB application. For this, normalization process is used.

There are many types of normalization in the literature such as minimum rule, maximum rule, sigmoid etc. With the normalization process, it is possible to evaluate different data on the same scale (Deveci, Yavuz, 2012).

<u>D_Min_Max normalization:</u> It enables the data to be converted into values in the range [0,1 0,9]. The formula for D_Min_Max normalization is given in equation 5.2 (Deveci, Yavuz, 2012).

$$\acute{d} = 0{,}8 * \frac{d_i - d_{min}}{d_{max} - d_{min}} + 0{,}1 \qquad (5.2)$$

<u>Statistical normalization:</u> Arithmetic mean and standard deviation are calculated for each variable. The equation was given in 5.3 (Deveci, Yavuz, 2012).

$$\acute{d} = \frac{d_i - \mu_i}{\sigma_i} \qquad (5.3)$$

<u>Min-Max normalization</u>: used to ensure the linearization of data linearly. The calculation is given in 5.4 (Deveci, Yavuz, 2012).

$$\acute{d} = \frac{d_i - d_{min}}{d_{max} - d_{min}} \tag{5.4}$$

Median normalization: In the method, the median value of each entry is calculated. The formula used for median normalization is given in equation 4.5 (Deveci, Yavuz, 2012).

$$\acute{d} = \frac{d_i}{Median(a_i)} \tag{5.5}$$

Sigmoid normalization: classifies the data between [0, 1] or [-1, 1]. There are several types of sigmoid functions in the literature.

In the model, two-year data set with specified input data is used as training input for 4 different destinations. Two-month data were used as test data. Normalization was performed in the data set. For normalization D_Min_Max normalization was used. Then, ANN model was created using MATLAB NNTOOL. Model trials were carried out using different models, neuron numbers and layer numbers. The data obtained as a result of the trials were compared with the actual data and $R^2$ ratios were calculated. The model that demonstrated the highest $R^2$ ratio was selected as the base model.

The model demonstrating the greatest $R^2$ ratio was the NARX model. Selected neural network training result is given in the figure 5.5.

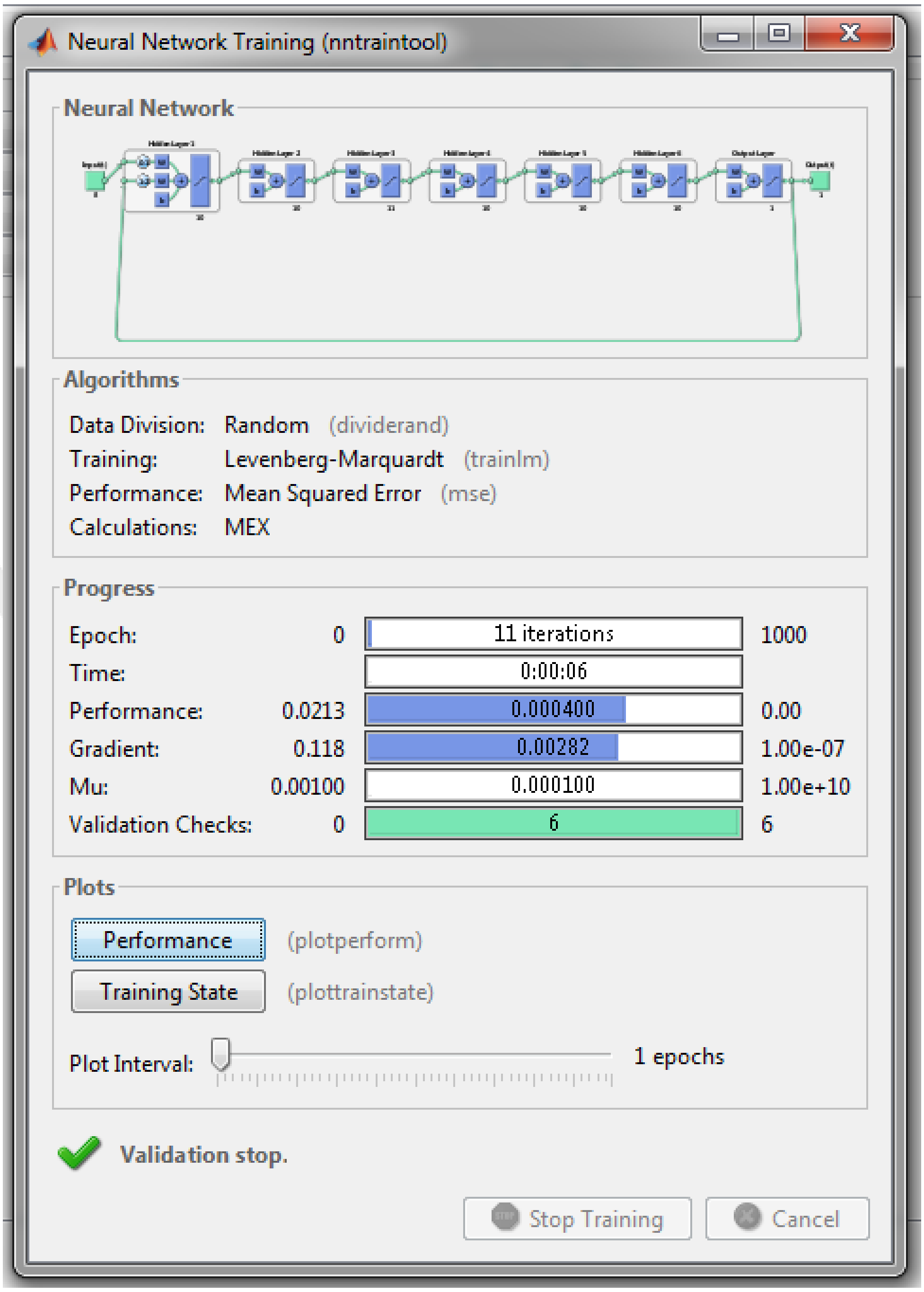


Figure 5.5: Nntool Screen with Training Results

For examining the results obtained from different network, $R^2$ ratios between model results and actual results were calculated. When the calculated $R^2$ values were examined, the highest $R^2$ value was obtained as 0.9335 in the NARX model with 7 hidden layers. Network structure established with NARX network is given in figure 5.6.

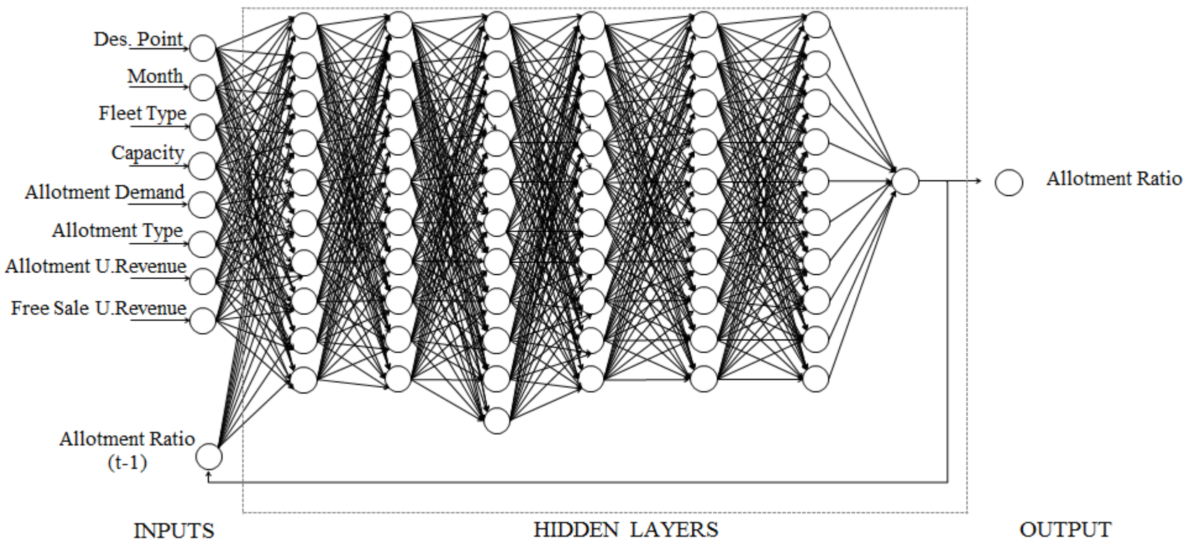


Figure 5.6: NARX Network Structure With 7 Hidden Layers

The first two months of 2020 were analyzed with the objective of establishing an allotment ratio forecast. This analysis was performed using a forecasting model based on a NARX network comprising seven layers. To assess the reliability of the forecast data, the actual results for the specified period were analyzed. As illustrated in Figure 5.7, a scatter plot is presented, showing the actual and the predicted allotment ratios. The table 5.1 presents the other statistical data obtained when the estimation result and the actual data of the model were compared.

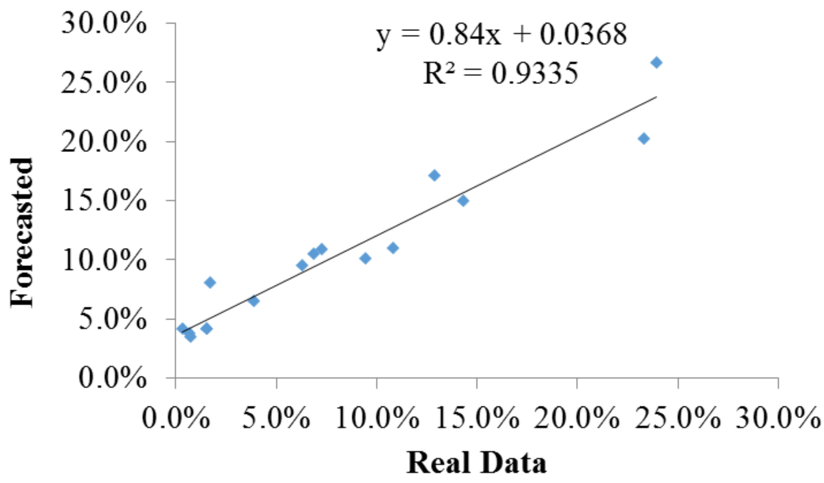


Figure 5.7: Actual and Predicted Allotment Ratio Scatter Plot

Table 5.1: Statistical Results of ANN Model

| Sample | Destination Point | Actual | Forecast | Error | Absolute Value of Error | Square of Error | Absolute Values of Errors Divided by Actual Values | Errors Divided by Actual Values |
|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0,003 | 0,041 | -0,038 | 0,038 | 0,001 | 12,340 | -12,340 |
| 2 | 1 | 0,015 | 0,041 | -0,026 | 0,026 | 0,001 | 1,680 | -1,680 |
| 3 | 1 | 0,017 | 0,080 | -0,063 | 0,063 | 0,004 | 3,652 | -3,652 |
| 4 | 1 | 0,007 | 0,037 | -0,030 | 0,030 | 0,001 | 4,357 | -4,357 |
| 5 | 2 | 0,015 | 0,041 | -0,025 | 0,025 | 0,001 | 1,652 | -1,652 |
| 6 | 2 | 0,069 | 0,104 | -0,035 | 0,035 | 0,001 | 0,515 | -0,515 |
| 7 | 2 | 0,073 | 0,108 | -0,035 | 0,035 | 0,001 | 0,488 | -0,488 |
| 8 | 2 | 0,128 | 0,171 | -0,042 | 0,042 | 0,002 | 0,330 | -0,330 |
| 9 | 2 | 0,007 | 0,034 | -0,027 | 0,027 | 0,001 | 3,641 | -3,641 |
| 10 | 3 | 0,094 | 0,101 | -0,007 | 0,007 | 0,000 | 0,069 | -0,069 |
| 11 | 3 | 0,143 | 0,149 | -0,007 | 0,007 | 0,000 | 0,046 | -0,046 |
| 12 | 3 | 0,239 | 0,266 | -0,026 | 0,026 | 0,001 | 0,110 | -0,110 |
| 13 | 3 | 0,233 | 0,202 | 0,031 | 0,031 | 0,001 | 0,134 | 0,134 |
| 14 | 4 | 0,039 | 0,065 | -0,026 | 0,026 | 0,001 | 0,675 | -0,675 |
| 15 | 4 | 0,062 | 0,095 | -0,032 | 0,032 | 0,001 | 0,517 | -0,517 |
| 16 | 4 | 0,108 | 0,109 | -0,001 | 0,001 | 0,000 | 0,009 | -0,009 |

| | |
|---|---|
| Mean Error (ME) | -0,0243 |
| Mean Absolute Deviation (MAD) | 0,0282 |
| Mean Square Error (MSE) | 0,0010 |
| Root Mean Square Error (RMSE) | 0,0317 |
| Mean Normalized Bias (MNB) | -1,9 |
| Median Absolute Error (MdAE) | 0,0283 |
| Maximum Absolute Error (MaxAE) | 0,0628 |
| Mean Absolute Relative Error (MARE) | 1,8884 |
| Geometric Mean Absolute Error (GMAE) | 0,0213 |

The allotment ratio estimation model that was created using the NARX network produces fairly realistic estimates. A graph was created that depicted the actual and forecasted allotment ratio values with the NARX network with seven hidden layers, as given in Figure 5.8.

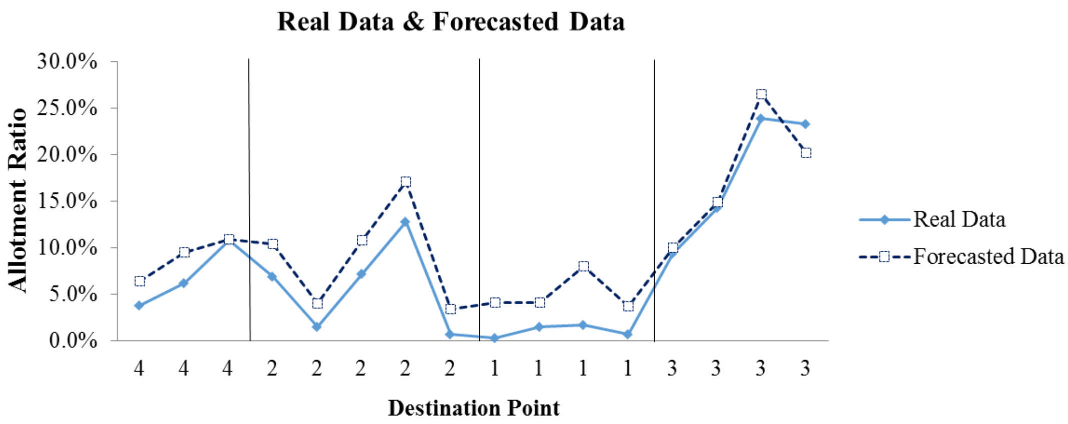


Figure 5.8: Predicted and Actual Allotment Ratios

### 5.2.2 Risk and Risk Measurement

In the theory of finance, risk is the probability of the reduction in the economic benefit that may result in a monetary loss, an expense or a loss related to a transaction (SPK, 2002). One of the potential risks associated with the transportation of air cargo transportation is the improper capacity allocation. As a result of this, the company may suffer economically.

It is of paramount importance for organizations to have a robust risk management system in place that is capable of defining the risks they face, measuring, monitoring and controlling these risks. Risk management is one of the areas where also regulatory and supervisory authorities also focus in terms of ensuring stability in the market and reducing systemic risk (SPK, 2002).

Risk measurements assist in the determination of the relative merits of risky options, facilitate the calculation of risk, inform the estimation of the capital requirements of an institution, and are employed for the purpose of reporting institutional risks (Kızılok, 2010).

Different risk measurement techniques are used in the decision-making process. Among these techniques, Value at Risk (VaR) and Conditional VaR (CVaR) methods will be explained in the next section.

#### 5.2.2.1 Value at Risk VaR

Value at risk represents a methodology for the estimation of the expected maximum monetary loss over a specified period and at a specified probability level. Value at risk is a methodology designed to illustrate the overall exposure to risk of a financial institution or firm in a straightforward and comprehensible manner. In contrast to traditional approaches, it allows risk amounts to be correlated with the probability of risk occurrence (SPK, 2002).

The calculation is performed in accordance with the following procedure:

$$VaR = M \cdot \alpha \cdot \sigma \tag{5.6}$$

M : Position amount

α : Fixed confidence factor

σ : Standard deviation

In accordance with the square root of time rule, which is based on the idea that uncertainty will increase as the holding period of financial assets increases, for a duration exceeding one day, the standard deviation is to be calculated as the value calculated for the aforementioned interval for 1 day multiplied by $\sqrt{T}$.

$$\text{T-day standard deviation} = \sigma \cdot \sqrt{T} \tag{5.7}$$

VaR value for position held for days of holding time T:

$$VaR = M \cdot \alpha \cdot \sigma \cdot \sqrt{T} \tag{5.8}$$

Financial professionals also use VaR as a basic model for determining the required capital to meet market risk. Widely used by banks, financial institutions and businesses, VaR is a risk measure that helps firms make agreements and decisions with other businesses (Denuit et al. 2005). VaR refers to the threshold value for losses, but does not provide information about what will happen when this threshold is exceeded.

**5.2.2.2 Conditional VaR - CVaR**

In 1999, Philippe Artzner and others developed a model, designated CVaR, in response to criticisms levied against the VaR method. CVaR is essentially defined as the expected loss in the event that the potential loss is in excess of the VaR.

$$CVaR[x] = E\{x \mid x > VaR[x]\} \tag{5.9}$$

CVaR is calculated by averaging the losses in excess of those captured by VaR. This measure is always greater than normal VaR. The principle of risk diversification posits that the combination of various assets in a portfolio should result in a reduction or, at the very least, a maintenance of the total risk at the same level. So,

$$\text{Risk (A+B)} \leq \text{Risk (A)} + \text{Risk (B)} \tag{5.10}$$

Albeit simple, definition (4.9) has little usage in an optimization. Rockafellar and Uryasev (2000) studies' key result is proof that CVAR can be stated as the definition (5.11) (Wada et al 2017):

$$CVaR_{\alpha}[X] = min_{\theta \epsilon R} \left\{\theta + \frac{1}{1-\alpha} E[(x-\theta)_{+}]\right\} \tag{5.11}$$

The VaR calculation method is often criticized because it gives non- coherent risk measurement results in fat-tailed distributions. In the studies conducted on VaR, it is observed that the method generally fails to meet the condition of sub layering. VaR is generally not a coherent risk measure, as it cannot provide the subdivision feature. However, conditional value at risk provides this feature (sub -additive) and is therefore a consistent risk measure. CVaR of a portfolio can be succinctly defined as the mean loss that the portfolio will incur in the worst-case scenario of X%. VaR can be succinctly defined as the best of the worst-case scenario.

#### 5.2.2.3 Solving the Air Cargo Capacity Allocation Problem with CVaR

In the following section, the problem is going to be presented in the context of optimization. The data set employed herein is based on actual data furnished by a cargo airline for four distinct destinations. The destinations are especially chosen from different regions and points with different characteristics. The database that we use for CVaR includes; flight date, fleet type (passenger flight or cargo flight), flight destination, capacity, free weight and allotment carried tonnage, free weight and allotment unit revenue. Show up rate (SUR) is representing the carried tonnage divided by reserved amount. The data set used in the CVaR model is shown in the figure 5.9.

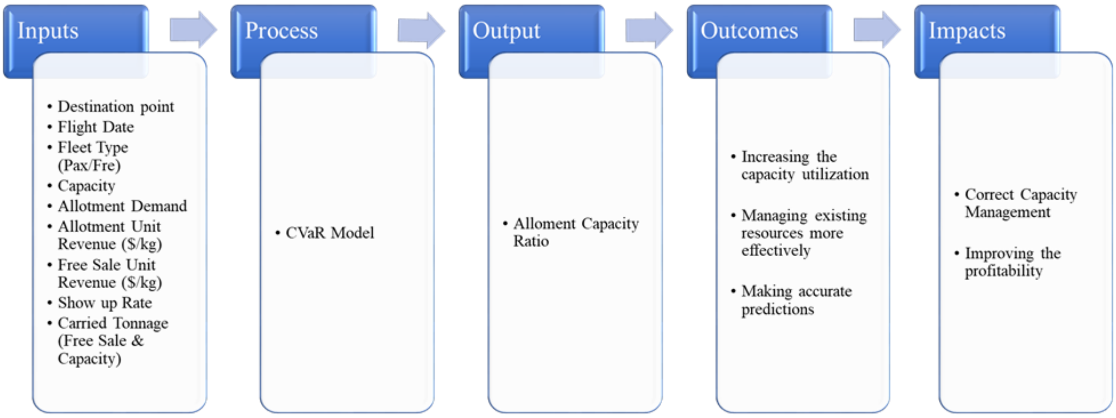


Figure 5.9: CVaR Model Input & Output Parameters

Due to allotment contracts is generally certain for sales, all the uncertain parameters of the model come from free sales. In the context of hard block space agreements, the customer is obligated to remit payment even in circumstances where the purchased capacity remains unused. In the context of soft block space agreements, in instances where customers do not utilize the stipulated capacity, they are not subject to penal sanctions but the agreement unit fee is higher. Precisely at this point, an additional penalty cost was added to the model for agreements without penal sanctions, and it was aimed to make the model more reasonable and reduce the risk of the plane being empty.

The ensuing model entries are listed below:

k: Destination

j: Sample

$T_A^k$: Allotment tariff for destination k

$X_A^k$: Allotment amount for destination k

$T_F^{jk}$: For destination k and sample j free weight tariff

$X_F^{jk}$: For destination k and sample j free weight amount

$D_A^k$: Allotment demand for destination k

$D_F^{jk}$: for destination k and sample j free weight demand

$SUR_A^k$: Allotment show up rate for destination k

$SUR_F^{jk}$: for destination k and sample j free weight show up rate

$\lambda$: Risk profile

$\alpha$: Confidence level

$u^{jk}$: Auxiliary variable to linearize the model

$C$: Flight capacity

$PC^k$: Penalty cost for destination k

$$Min_{X_A^k\ X_F^{jk}}\ -T_A^k X_A^k SUR_A^k + X_A^{ik}\left(1 - SUR_A^k\right)PC^k +$$

$$\begin{Bmatrix} \lambda\left[\frac{1}{N}\sum_{j=1}^{N}\sum_{k=1}^{M} - T_F^{jk}X_F^{jk}SUR_F^{jk}\right] + \\ (1-\lambda)\left[\theta + \frac{1}{N(1-\alpha)}\sum_{j=1}^{N}\sum_{k=1}^{M} u^{jk}\right] \end{Bmatrix} \tag{5.12}$$

$$\text{s.t } 0 \leq X_A^k \leq D_A^k, \tag{5.13}$$

$$u^{jk} \geq 0, \qquad j = 1, \dots, N \quad k = 1, \dots, k \tag{5.14}$$

$$u^{jk} + \theta + T_F^{jk}X_F^{jk}SUR_F^{jk} \geq 0, \qquad j = 1, \dots, N \quad k = 1, \dots, k \tag{5.15}$$

$$X_A^k SUR_A^k + X_F^{jk}SUR_F^{jk} \leq C, \qquad j = 1, \dots, N \quad k = 1, \dots, k \tag{5.16}$$

$$0 \leq X_F^{jk} \leq D_F^{jk}, \qquad j = 1, \dots, N \quad k = 1, \dots, k \tag{5.17}$$

$$0 \leq \lambda \leq 1 \tag{5.18}$$

$$SUR_A^k = \begin{Bmatrix} 1, & SUR_A^k > 1 \\ SUR_A^k, & SUR_A^k \leq 1 \end{Bmatrix} \qquad k = 1, \dots, k \tag{5.19}$$

$$X_F^{jk}, D_F^{jk}, SUR_F^{jk}, T_F^{jk} \geq 0 \qquad j = 1, \dots, N \quad k = 1, \dots, k \tag{5.20}$$

$$X_A^k, SUR_A^k, D_A^k \geq 0 \qquad k = 1, \dots, k \tag{5.21}$$

This model has been resolved individually for disparate fleet types and various values of the $\lambda$ parameter. Parameter $\lambda$ is representing the risk profile. The value of the parameter (λ) is a critical component in this analysis. When the value of λ is equal to 1, the risk-neutral approach is represented. In this case, risk is given importance. However, when the value of λ is less than 0.5, it signifies a high level of risk aversion. The objective function (5.12) has three terms. First term represents the revenue from allotment sales, the second one is penalty cost, and the last one represents the revenue from free sales.

Constraint (5.13) states that the allotment amount can not exceed the allotment demand for each destionation. Like the constraint (5.13), constraint (5.17) states that free sales amount can not exceeed the demand for selected destionation. Capacity constraint (5.16) expressed that the total of sales made without charge and those for which payment has not been made cannot exceed the avaliable capacity on the flight.

The model was solved in GAMS program using test data. The obtained model results are compared with actual data. The first step in this process involved estimating allotment ratios for the first two months of 2020. This was accomplished through the application of the established forecasting model, which was based on CVaR. The actual outcomes of the selected timeframe were employed to ascertain the reliability of the forecast data in relation to the observed data. As illustrated in Figure 5.10, a scatter plot is presented, showing the actual and predicted allotment ratios and other statistical data obtained when comparing the estimation result and actual data of the model are summarized in the table 5.2.

Table 5.2: Statistical Results of CVaR Model

| Sample | Destination Point | Actual | Forecast | Error | Absolute Value of Error | Square of Error | Absolute Values of Errors Divided by Actual Values | Errors Divided by Actual Values |
|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0,003 | 0,263 | -0,260 | 0,260 | 0,068 | 85,084 | -85,084 |
| 2 | 1 | 0,015 | 0,263 | -0,248 | 0,248 | 0,061 | 16,173 | -16,173 |
| 3 | 1 | 0,017 | 0,263 | -0,246 | 0,246 | 0,060 | 14,293 | -14,293 |
| 4 | 1 | 0,007 | 0,263 | -0,256 | 0,256 | 0,066 | 37,398 | -37,398 |
| 5 | 2 | 0,069 | 0,324 | -0,255 | 0,255 | 0,065 | 3,713 | -3,713 |
| 6 | 2 | 0,015 | 0,000 | 0,015 | 0,015 | 0,000 | 1,000 | 1,000 |
| 7 | 2 | 0,073 | 0,324 | -0,251 | 0,251 | 0,063 | 3,459 | -3,459 |
| 8 | 2 | 0,128 | 0,324 | -0,195 | 0,195 | 0,038 | 1,520 | -1,520 |
| 9 | 2 | 0,007 | 0,324 | -0,316 | 0,316 | 0,100 | 42,931 | -42,931 |
| 10 | 3 | 0,094 | 0,442 | -0,348 | 0,348 | 0,121 | 3,700 | -3,700 |
| 11 | 3 | 0,143 | 0,442 | -0,299 | 0,299 | 0,089 | 2,095 | -2,095 |
| 12 | 3 | 0,239 | 0,442 | -0,203 | 0,203 | 0,041 | 0,848 | -0,848 |
| 13 | 3 | 0,233 | 0,442 | -0,209 | 0,209 | 0,044 | 0,895 | -0,895 |
| 14 | 4 | 0,039 | 0,265 | -0,227 | 0,227 | 0,051 | 5,890 | -5,890 |
| 15 | 4 | 0,062 | 0,265 | -0,203 | 0,203 | 0,041 | 3,248 | -3,248 |
| 16 | 4 | 0,108 | 0,265 | -0,157 | 0,157 | 0,025 | 1,459 | -1,459 |

| | |
|---|---|
| Mean Error (ME) | -0,2286 |
| Mean Absolute Deviation (MAD) | 0,2305 |
| Mean Square Error (MSE) | 0,0584 |
| Root Mean Square Error (RMSE) | 0,2416 |
| Mean Normalized Bias (MNB) | -13,9 |
| Median Absolute Error (MdAE) | 0,2467 |
| Maximum Absolute Error (MaxAE) | 0,3479 |
| Mean Absolute Relative Error (MARE) | 13,9814 |
| Geometric Mean Absolute Error (GMAE) | 0,2022 |

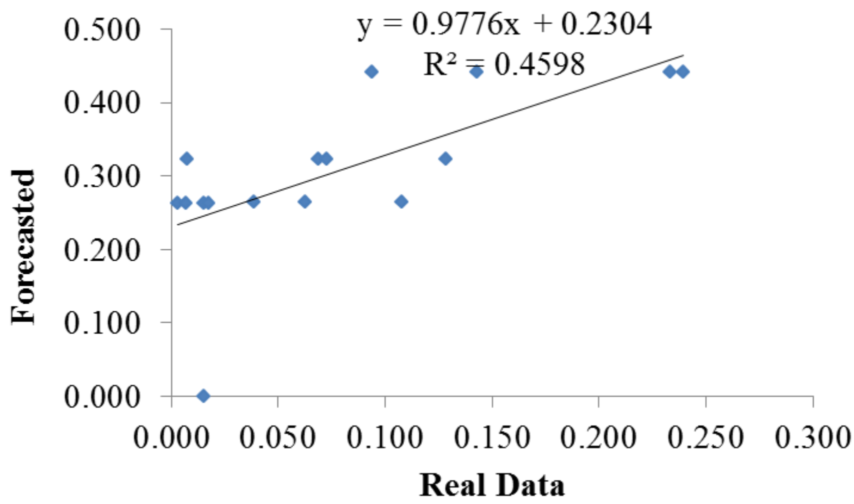


Figure 5.10: Actual and Predicted Allotment Ratio Scatter Plot

In the next section allotment ratio estimation model that created using the NARX network produces fairly realistic estimates. The deviation rate of the CVaR model estimate from the actual data was higher than that of the ANN model. In the next section, comparisons of these two models will be given. Figure 5.11 illustrates the forecast and actual allotment ratio values that were generated through the implementation of the CVaR model.

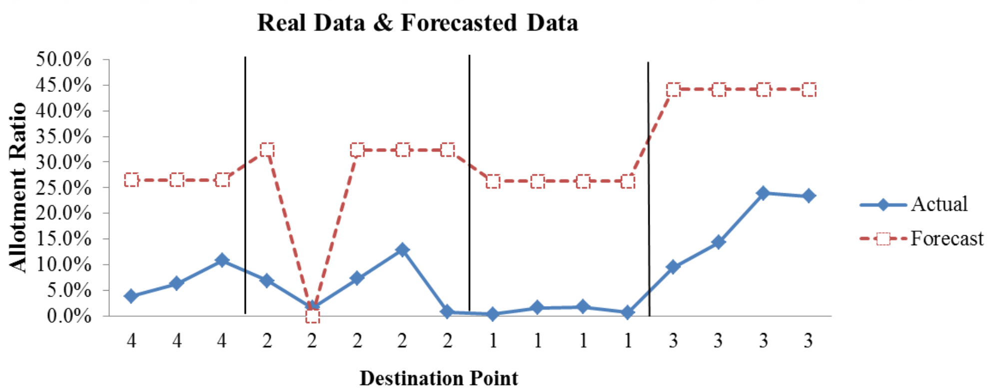


Figure 5.11: Predicted and Actual Allotment Ratios

### 5.3. Model Results Comparison for Air Cargo Allocation Problem

In this section, a comparison will be made between the CVaR and ANN model results. A subsequent examination of the relationship between the model results and the actual results is presented here, along with the coefficient of determination $R^2$ values. The $R^2$ value created by the forecasted results produced by the artificial neural network (ANN) model is 0.9335, while the $R^2$ value created by the conditional value at risk (CVaR) model is 0.4598. The forecasts generated by the artificial neural network (ANN) model yielded a ratio that approximated unity, and the allotment ratio could be explained by the model at a rate of 93.35%. As illustrated in Figure 5.12, the predicted data, as derived from the CVaR and ANN models, are displayed alongside the actual data.

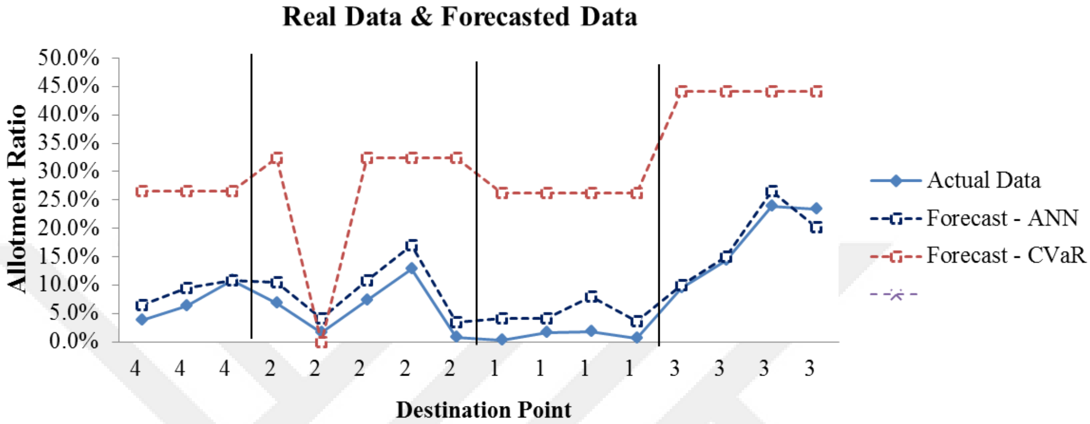


Figure 5.12: Predicted and Actual Allotment Ratios

Table 5.3 shows that the ANN model outperforms the CVaR model in all statistical results. The superiority of the ANN model can be attributed to its capacity to model complex events, its aptitude for modeling complex nonlinear connections in data, its ability to adapt to changing trends, its resistance to noisy data, and the availability of sufficient past data for model training.

Table 5.3: Statistical Results of Forecasting Models

| Forecast Comparison Measure | CVaR Model | ANN Model |
|---|---|---|
| Geometric Mean Absolute Error (GMAE) | 0,20 | 0,02 |
| Mean Absolute Deviation (MAD) | 0,23 | 0,03 |
| Mean Absolute Relative Error (MARE) | 13,98 | 1,89 |
| Maximum Absolute Relative Error (MAxAE) | 0,35 | 0,06 |
| Median Absolute Error (MdAE) | 0,25 | 0,03 |
| Mean Error (ME) | -0,23 | -0,02 |
| Mean Normalized Bias (MNB) | -13,86 | -1,87 |
| Mean Square Error (MSE) | 0,06 | 0,00 |
| Root Mean Square Error (RMSE) | 0,24 | 0,03 |

# 6. DEMAND FORECAST

Forecasting is the act of predicting future events. Forecasting is a significant issue in a multitude of disciplines, including industry, politics, economics, science, health, social sciences, and finance. Forecasting problems are typically categorized as long, medium or short-term (Ilgün, 2016).

To ensure precise predictions, it is imperative to ascertain the most suitable forecasting technique for the problem structure to be predicted, as asserted by Monks (1987). A taxonomy of forecasting methods can be established, classifying them into three broad categories: qualitative, quantitative, and intelligent forecasting methods. Quantitative forecasting methods require the incorporation of real data collected at distinct temporal points. The basis of the method is a good analysis of the data. Qualitative methods use the knowledge and experience of experts (Arscher, 1980). Forecasting can be conducted using either qualitative or quantitative methods, with the latter encompassing a range of techniques. In some cases, both qualitative and quantitative methods are employed concurrently. Additionally, ANNs, fuzzy logic and genetic algorithms, collectively referred to as intelligent methods, have been utilized in academic literature for the purpose of forecasting the future. Table 6.1 shows the characteristics of the forecasting methods and compares their strengths and weaknesses.

In our study, we used historical data to forecast demand for future periods. To create data-driven forecasting models, we used time series and regression analysis from quantitative methods and ANN models from intelligent methods.

Table 6.1: Features of Forecasting Methods

| | **Qualitative Methods** | **Quantitative Methods** | **Intelligent Methods** |
|---|---|---|---|
| **Feature** | It is subjective and based on personal views and experiences. | Mathematical | Operations that require thinking and intelligence are performed by the computer. |
| **Strengths** | Changing conditions can be reflected in the model There may be no historical data. | Objective and consistent Takes into account a lot of data and information at once | Can be used in complex models. Can be used in non-linear models |
| **Weakness** | Prediction accuracy may be low as it involves personal judgement | Measurable data may not always be available Accuracy of results depends on data used | Difficulty in obtaining information about the internal structure of the system |

## 6.1. Demand Forecasting Model Description for Air Cargo

In the air cargo sector, it is necessary to forecast the demand in order to establish future capacities, aircraft leasing decisions, the number of workers to be employed, unit prices, etc. In order to make these decisions correctly, it is essential that the future forecast is as close to reality as possible. In this section, we will apply various algorithms to forecast the free sale demand and evaluate the results.

For the demand forecasting model, first, the model inputs were determined. To include economic expectations in the study, the model includes GDP ratios as input variables. Upon examination of the results of the study, it was found that the GDP data did not yield a statistically significant result and thus was excluded from further analysis. Following consultations with experts working in the air cargo sector, the model inputs were determined to be as follows: destination point, date, aircraft type (passenger/cargo), capacity, and allotment capacity ratio produced from the capacity allocation model are included in the study as input. The forecasts of free sale demand, which are derived in this section, will be incorporated into the dynamic pricing model as an input.

The demand forecasting process employed multiple linear regression, time series (Winter's model), and artificial neural networks (ANNs). Figure 6.1 presents a visual representation of the inputs and outputs of the demand forecasting model.

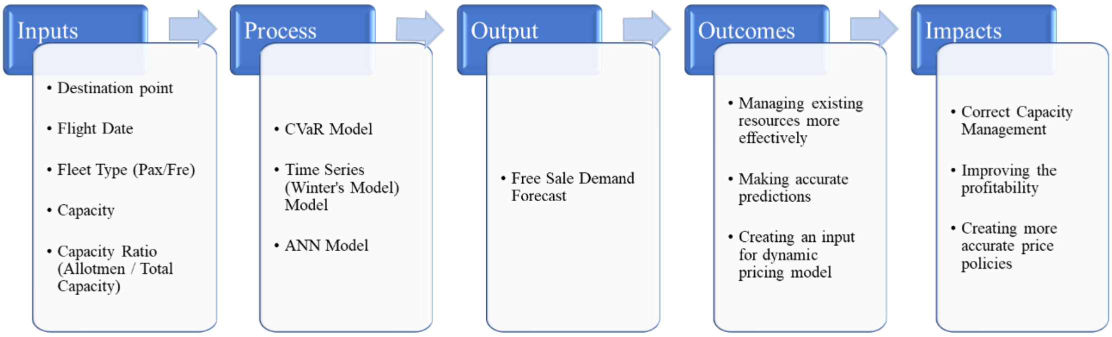


Figure 6.1: Demand Forecast Model Input & Output Parameters

## 6.2. Solution Algorithms

The demand forecasting process incorporates a variety of statistical models, including multiple linear regression models, Winter's model, and ANN models. These models and their results will be discussed in detail in the rest of the section.

### 6.2.1 Regression Model

A regression model may be applied to a data set where the independent variables exhibit a degree of relationship to the dependent variable. This method of analysis can be defined as the explanation of the average relationship between the dependent variable, Y, and the independent variable(s), X, through the use of a mathematical function. The model that has been developed to explain this relationship is known as the ‘regression model’. (Tabachnick & Fidell, 2007).

Regression analysis is a statistical analysis method that is widely used in many different fields, e.g. medicine, economics, chemistry, physics, biology and social sciences. Its objective is to examine and model the relationship between two or more variables that may have a relationship. The variable that is the object of estimation is referred to as the dependent variable. The other variables that are utilized to estimate the value of this variable are designated as independent variables (Uçgun, 2023).

The linear regression model is constructed in accordance with the following equation: $Y = X\beta + \varepsilon$. The dependent variable vector, Y, is of dimension (n*1), while the independent variable matrix, X, is of dimension (n*p). The unknown parameter vector, β, is of dimension (n*1), while the random error vector, ε, is of dimension (n*1). In this context, n signifies the total number of observations, while p denotes the number of parameters (Atkinson and Riani, 2000).

The optimization of a regression equation is predicated on the judicious selection of independent variables. The relationship between the independent and dependent variables must be carefully evaluated and, where necessary, controlled. The former must demonstrate a strong correlation with the latter and must not be influenced by other variables. Furthermore, it is also important that the data sets are sufficiently large, that there is no multicollinearity and that outliers are not present (Tabachnick & Fidell, 2007).

A number of assumptions are inherent in the linear regression model, which is the most commonly used method in regression analysis. This approach involves making several assumptions regarding the error terms. Primarily, it is assumed that the error terms are statistically independent of one another and that they follow normal distributions, and that the error variance is constant and does not vary between data sets (Uçgun, 2023).

A multiple regression analysis was performed using the inputs determined for the model. The outcomes of the model were subject to statistical assessment. The regression statistics are given in table 6.2.

Table 6.2: Regression Statistics

| *Regression Statistics* | |
|---|---|
| Multiple R | 94% |
| R Square | 88% |
| Adjusted R Square | 88% |
| Standard Error | 58.941 |
| Observations | 627 |

### 6.2.2 ANN Model

A number of ANN algorithms were evaluated for their suitability as a model for the study. The NARX model was selected as the most appropriate model, as it demonstrated the most favorable results and was therefore incorporated into the study. ANN model is solved by using Matlab nntool. Screenshots of the ANN models are given in figures 6.2 and 6.3.

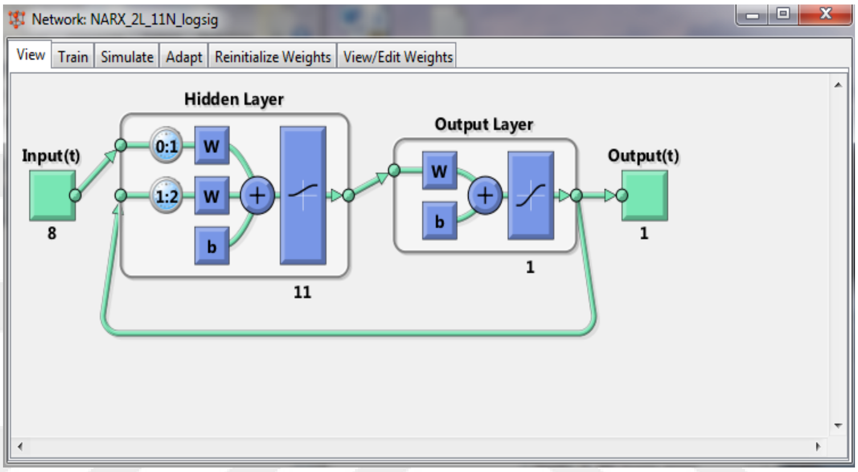


Figure 6.2: NARX Neural Network Structure

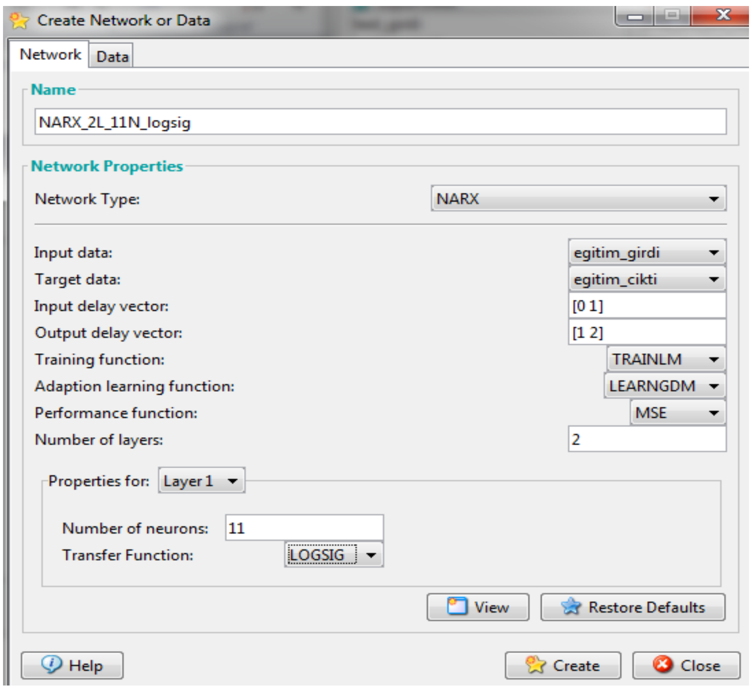


Figure 6.3: Network Properties of NARX Model

### 6.2.3 Time Series Model

Putting numerical observations in to an order based on time is called time series (Dilek, 2010). Times series aims to build a model from existing data. In time series, time generally refers to equal intervals; such as, every day, every hour. Examining the situations that have a positive or negative impact on an event occurring today allows making predictions for the future and forming an opinion on future periods.

Time Series are divided into four main components. The aforementioned components can be classified as follows: trend, seasonal, cyclical, and irregular.

Trend; In the context of sociological and cultural studies, a trend is a long-term movement. Positive or negative growth are determined by examining of general trend of a time series. Trend has a vital place for the estimation of the progress in time series.
Seasonal components: Many time series have seasonal components. Seasonal components are periodic movements and indicate similar behaviors for equal time intervals. Forecast models which is includes seasonal components would enable the creation of more accurate models for future forecasting.

Cyclical components: Fluctuations around the trend curve over a long period create these components.

Irregular components: A time series element based on random events that are independent of the period.

A significant proportion of forecasting problems require the use of time series data. In order to make forecasts in Time Series, the problem must first be defined. The problem definition is followed by the collection and the process of analyzing the pertinent data, selecting the most appropriate model, validating the model, constructing the prediction model and examining the performance of the model is a crucial aspect of any scientific study (Montgomery et al, 2007).

In the field of time series analysis, numerous methodologies exist for making forecasts for future periods. These forecasts are based on observations from previous periods and the current period. In essence, time series analysis methods are categorized into two main groups: univariate and multivariate analysis methods. In univariate time series, the data belong to a single variable that undergoes change over time. The data is used to inform future forecasts. The aforementioned methods include the following: trend analysis, moving averages, exponential smoothing, adaptive succession, and Box-Jenkins estimation. In multivariate time series analysis, the cause-and-effect relationship between two or more time series is identified and utilized for forecasting and control purposes (Ilgün, 2016).

Prior to selecting the most suitable time series method for the study, a meticulous investigation of the subject matter was conducted in order to ascertain the most appropriate approach. A data analysis was conducted on the past four years in order to be used in the demand forecasting model. The overarching goal was to develop an in-depth comprehension of the distinctive attributes that define this series. The analysis yielded results that demonstrated the presence of comparable patterns in the data on a monthly basis. This indicates the presence of a seasonal effect in the data. It was observed that the demand series exhibited an upward trend in addition to the seasonal effect. As the series contains both seasonality and a trend, it was decided that the Winter's Method, one of the exponential smoothing methods, should be used for forecasting purposes.

In the Winter's exponential smoothing method, initial values are identified through regression analysis.

The general smoothing formula is presented in equation 6.1 (Chopra ve Meindl, 2010).

$$L_{t+1} = \alpha(\frac{D_{t+1}}{S_{t+1}}) + (1-\alpha)(L_{t-1} + T_{t-1}) \qquad (6.1)$$

The formula for smoothing the trend is provided in equation 6.2 (Chopra ve Meindl, 2010).

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1-\beta)T_t \qquad (6.2)$$

The formula for smoothing seasonality is presented in equation 6.3. (Chopra ve Meindl, 2010).

$$S_{t+p+1} = \gamma(D_{t+1} - L_{t+1}) + (1-\gamma)S_{t+1} \tag{6.3}$$

The formulae used for future forecasting are given in equation 6.4 and equation 6.5 (Chopra ve Meindl, 2010).

$$F_{t+1} = (L_t + T_t) * S_{t+1} \tag{6.4}$$

$$F_{t+n} = (L_t + nT_t) * S_{t+n} \tag{6.5}$$

α, β, γ constants should be chosen at values that minimize the estimation error. The first step in determining the seasonality index is to define the specific season under consideration.

## 6.3. Model Results Comparison for Demand Forecasting Problem

In order to understand which model gives better results, the results of the model outputs were evaluated in comparison to the actual observed data. The model results are shown on the graph in Figure 6.4. The statistical outcomes of the models are presented in Table 6.3.

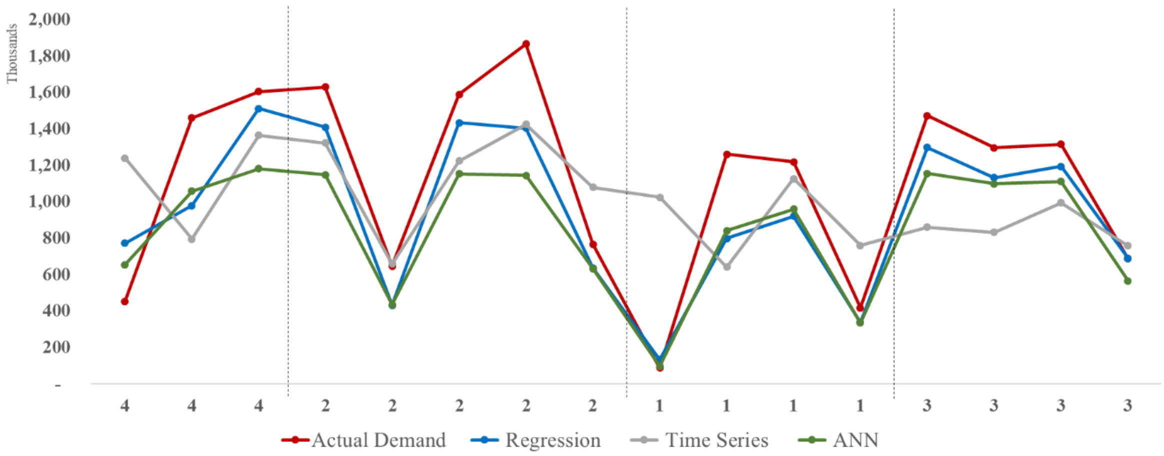


Figure 6.4: Predicted Demand Forecasts and Actual Values

Table 6.3: Statistical Results of Forecasting Models

| | Multiple Linear Regression | Artificial Neural Network | Time Series Winter's Model | Adjusted Time Series Model |
|---|---|---|---|---|
| $R^2$ | 88% | 91% | 15% | 62% |
| ME | 116.800 | 262.918 | 103,999 | 175.236 |
| MAD | 183.832 | 289.005 | 411,765 | 298.053 |
| RMSE | 229.814 | 338.400 | 482.661 | 341.486 |

A thorough examination of the dataset and outputs revealed that the predictions generated by the time series model exhibited a satisfactory degree of accuracy. Nevertheless, a number of outliers were identified, with the results demonstrating a notable discrepancy from the actual data. Consequently, the time series model was adjusted through the exclusion of these data points. This adjustment led to the acquisition of the corrected time series model results. Upon analysis of the results obtained from the various models, it can be seen that the regression analysis provides the closest fit to the actual data, while the ANN model produces the closest fit to the regression analysis. In the light of these results, the multiple linear regression model was selected to be used in demand forecasting.

The efficacy of multiple linear regression is more pronounced in scenarios characterized by low variance, while neural networks demonstrate superior performance in contexts marked by high variance. Consequently, the multiple linear regression model may have yielded more favorable outcomes in our model.

## 7. DYNAMIC PRICING

The determination of an optimal pricing strategy for a company's range of products or services represents a complex process that should be integrated into the larger framework of revenue management. Within the context of business management, pricing can be defined as the method by which the optimal price for products and services is determined. This strategic process is intertwined with a plethora of other considerations, including pricing, distribution channels, revenue, economic patterns, competition, market demand, service characteristics, and product. Pricing strategies play a pivotal role in enabling businesses to ascertain prices that yield maximum revenue and profit. These strategies are also instrumental in aligning with consumer and market demands, thereby optimizing shareholder value. Pricing strategies should be created analytically, systematically and optimally to meet customers' expectations (Helmond, 2020).

Pricing decisions are the most important decisions affecting a firm's profitability. There are goals such as increasing return on investment, gaining new customers and reaching maximum sales volume with effective pricing. Firms must have sufficient information and data to be able to determine product prices in a way that provides maximum revenue or to determine the amount in an optimum way. Firms need information about the competitive situation of the market as well as information about customer behavior and financial status of these customers (Özdemir, 2015).

The price at which a product or service is offered on the market will determine the quantity and range of products or services made available. A plethora of pricing strategies have been employed in the business world. These include cost-based pricing, value-based pricing, break-even pricing, dynamic pricing, loss-leader pricing, competitive pricing, premium-based pricing, target return pricing, everyday low pricing, good value pricing, freemium pricing, loss-leader pricing, skimming pricing, packaging pricing, high-low pricing and margin pricing (Helmond, 2020).

Dynamic pricing practices are often used for products that need to be sold within a certain period and in industries where it is impossible or too costly to raise the inventory level. The primary objective of dynamic pricing strategies is to optimize revenue by adjusting prices in accordance with customer demand, current inventory levels, and customer characteristics.

A variety of studies on pricing must be conducted by businesses in order to manage their revenues. Revenue management is a critical component of pricing strategy. The pricing process is referred to as pricing decisions in a consistent and effective manner. The primary purpose of the pricing process is to identify a pricing strategy that will maximize expected revenue while adhering to the established constraints. It is important to note that these constraints may be limited by the company. Furthermore, these constraints may also be physical in nature, such as limited capacity and inventory (Bilişik, 2015).

Implementing dynamic pricing in the cargo industry can offer several advantages to both shippers and carriers. Dynamic pricing offers benefits to shippers by helping to reduce transportation costs through lower rates during off-peak times or optimizing shipping schedules to capitalize on these savings. Additionally, it aids in inventory and supply chain management by incentivizing customers to buy during off-peak periods or offering discounts on slow-moving inventory. For carriers, dynamic pricing supports revenue maximization by adjusting rates based on market shifts and demand fluctuations. This approach allows carriers to set rates considering factors like capacity, location, and seasonal trends, ultimately enhancing pricing outcomes and profitability (FreightCenter, 2023).

When the revenue management is applied, pricing analyzes are made to be the highest and the customer can buy the product. When the revenue is managed, the price change is seen as Dynamic Pricing. Here, determining how often and how much to change the price requires very difficult and comprehensive analyzes. For the analyzes, marketing, economics, statistics and operations research disciplines are used together (Bilişik, 2015).

The change in price while managing the revenue appears as Dynamic Pricing. Here, determining how often and how much the price will change is very difficult and requires comprehensive analysis. Customers have the opportunity to access low-cost power at affordable prices when dynamic pricing is an option. However, high prices may be seen during periods of high demand and limited capacity.

The implementation of dynamic pricing necessitates the existence of market power, the ability of customers to vary their demand in accordance with fluctuations in price, and the prevention of resale at varying prices (Medium, 2023).

To explain the dynamic pricing simpler with a visual, figure 7.1 shows the price and demand charts for static and dynamic pricing. On the left is the price and demand graph of a statically priced product. The shaded area in the graph shows the revenue obtained. The graphic on the right is the result of dynamic pricing. Additional revenue was obtained with high wages during periods of intense demand and with reduced wages during periods when demand was less. The company increased its revenue with dynamic pricing.

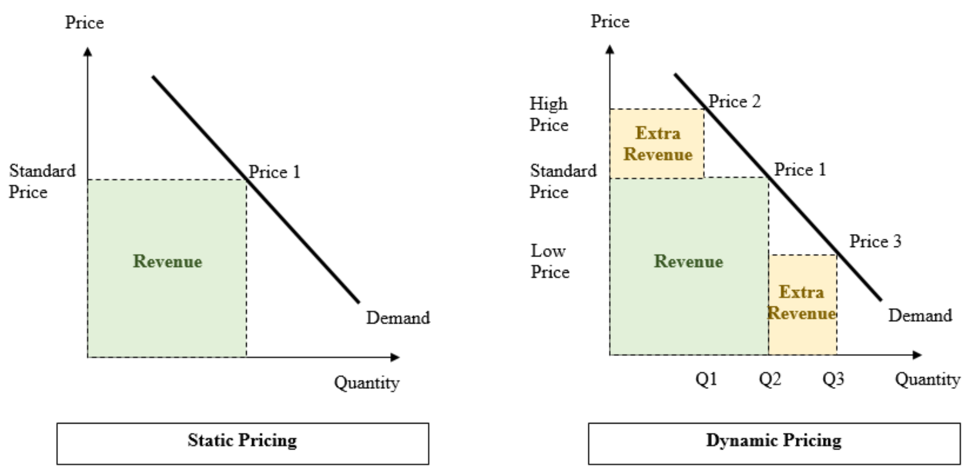


Figure 7.1: The Price, Quantity and Demand Charts for Static and Dynamic Pricing

In passenger business, real-time models are used for years. Despite the passenger side, electronic booking and dynamic pricing is slowly coming into existence and relatively new subject for cargo side against the passenger side.

In the air cargo sector, price differentiation can be applied due to the structure of the sector. In order to maximize revenues from their limited capacities, carriers apply variable price levels by considering different criterias.

Air freight shipment's price is negotiable and variable. Many factors can be affecting to shipment price, in addition, the relationship between the forwarder/shipper and carrier is also included. These relations should be among the factors to be considered in designing the dynamic pricing process.

Dynamic pricing is not only ensuring benefit to air freight carrier but also the customer. Customers who don't mind waiting a few days extra for delivery will find that standard shipping rates are lower than hurry rates and end up costing less (Medium, 2023).

Air freight companies become flexible with dynamic pricing via adjusting rates according to a variety of factors. These factors can be summarized as below;

•Buying Power: Price increases are possible when demand rises.

•Market Trends: Pricing will be influenced by overall industry fluctuations, such as surges in demand or oil price fluctuations.

•Seasonal Variations: Fluctuations in demand arising from various seasonal variations, such as around the festivals, national holidays, harvesting periods will influence pricing.

•Historic Demand: Historical data are used for determining the current price via forecasting algorithms.

Variable costs and fixed costs in air freight industry all influence dynamic pricing. On the other hand, variable costs change based on the amount of cargo. As cargo volume increases, so too do variable costs. There are many factors such as, fuel surcharges, labor costs, truck cost, warehousing costs etc. that increase the variable costs.

When creating the dynamic pricing model, air freight carriers need to care all these factors together.
Dynamic pricing promotes to full capacity usage, with consider the supply and demand fluctuation in market conditions. So, dynamic pricing optimizes capacity and price.

The problem of dynamic pricing for Air Freight can be defined as the dynamic adjustment of sales prices that will maximize the expected revenue stream while a predetermined capacity is exhausted in a given planning period. First, in the fifth part of the study, it was decided how much of the capacity would be allocated for allocation and how much for free sale. Then, by applying dynamic pricing for the part allocated as free sale, the sales price will be adjusted dynamically to maximize revenue.

## 7.1. Dynamic Pricing Model Description for Air Cargo

The final issue to be addressed in the study is the determination of the unit price to be applied to customers in the air cargo industry. In this problem, the outputs of the capacity allocation problem in chapter 5 and the output of the demand forecasting model in chapter 6 are utilized as inputs to the model.

The comprehension of dynamic pricing necessitates the response to a series of inquiries. What factors influence the fluctuation in price over time? Does the data set include information on these variables? What are the means by which the available data can be employed to influence prices? Finally, it is necessary to determine how a streamlined process can be implemented that incorporates the aforementioned considerations. In the context of dynamic pricing, each booking request is evaluated in consideration of all the price influencers at that specific point in time (Medium, 2023).

In addition to a comprehensive literature review, the in-situ perspectives of employees across various roles within the air cargo sector were also incorporated into the process of determining the parameters affecting the price.

The origin-destination pair represents the most significant input in determining the price. In addition to the aforementioned factors, flight distance, air cargo demand between the relevant flight pairs, and market conditions also influence the price. The aircraft type utilized in the flight also affects the price, as it determines the available capacity. Although there is a general increase in demand for air cargo during certain periods, there is also a decrease in demand during other periods. Furthermore, the seasonality of the sector also affects the price, as it alters the balance between supply and demand. In light of these circumstances, the flight date has been incorporated into the model. It is observed that sales made at an a priori date, which is a considerable period before the flight, are typically less expensive. However, as the flight date approaches, the price may increase. Consequently, an input indicating the remaining time until the flight has been incorporated into the model. The tonnage of the product to be transported also affects the price, and this has been included in the model as an input.

The following assumptions are made regarding the model data set:

- No-shows, overbookings, and cancellations are not considered.
- We do not consider discounts.
- It is assumed that the planned flight will take place on the specified date and route with the specified type of aircraft.
- A two-year period of data was analyzed for four different destinations.
- The pricing structure is designed for the transportation of general cargo.
- It should be noted that additional services, such as those pertaining to security, are not included in the aforementioned services.
- The assumption is that market conditions will remain stable, with the exception of any unforeseen circumstances that may affect air cargo prices, such as the impact of the ongoing pandemic, trade wars, congestion in other modes of transportation, fluctuations in oil prices, and other extraordinary movements.
- For reservations made up to 30 days before the scheduled flight, the dynamic pricing model will be applied.

The inputs for the model are determined as follows:

- Origin: The city where the sale was made.
- Destination: the destination city of the sold cargo.
- Flight Type: The type of airplane will take the flight. Two types of aircraft are specified, fre or pax.
- Flight Month: The month in which the flight will take place.
- Time to Flight: The number of days remaining until the flight. It varies between 0 and 30. 0 indicates a sale made on the day of the flight.

- Tonnage: The weight of awb sold. It shows the weight in kg.
- Revenue: Revenue generated per awb. Used to train the model.
- Capacity: The weight capacity of the aircraft.
- Flight Total Tonnage: It is the weight sum of all awbs in the flight.
- Total LF: is the total occupancy of the aircraft. It is a two-precision decimal value after the comma. It takes a value ranging from 0 to 1.
- Real-time Tonnage: This indicates the total tonnage of the aircraft at the time of sale.
- Real-time LF is the instantaneous occupancy rate of the aircraft when sales are made. It is expressed as a percentage.
- Minimum price: This is the minimum price offered for a given origin and destination pair during a specific time period. This price is in USD.
- Maximum price: the maximum price to be offered for the origin and destination pair selected in the relevant period. It is the price value in USD.

## 7.2. Solution Algorithm

SARSA Algorithm is used to dynamic pricing offers. The rest of the section will discuss this model and its results in detail.

### 7.2.1 SARSA Algorithm

Reinforcement learning represents a machine learning method that is designed to map environmental states to actions. The objective of reinforcement learning is to enable autonomous decision-making based on interactions with the environment, with the aim of maximizing the expected cumulative return (Zhang et al, 2024). Reinforcement learning represents an approach to understanding and automating goal-directed learning and decisions. Unlike other machine learning techniques, this approach does not require supervision or complete models of the world around it. Reinforcement learning can also be used in situations with insufficient training data (Mutsaers, 2020).

The model represents the way the environment behaves. Building an accurate model often requires knowing and understanding much about the behavior of the environment. The advantage of model free reinforcement learning algorithms lies in the absence of models. The agent relies on trial and error to update its knowledge in a model-free reinforcement learning algorithm. A policy is a map from all condition-action pairs in an environment to an action to perform when in that state. In this context, a state is the current situation and can be very different depending on the goal of the reinforcement learning algorithm. The state may be the location of the agent itself and the last known location of the avoidant for this experiment, or the position of the legs of the walking robots. The action is what the agent is able to do in a particular state (Mutsaers, 2020). A typical reinforcement learning model can thus be represented as in Figure 7.2 (Spiceworks, 2022).

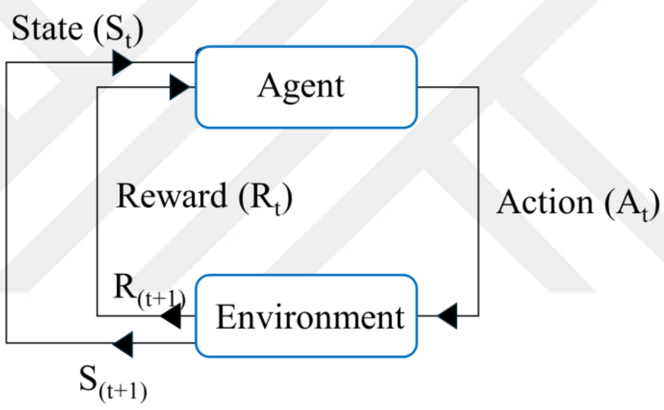


Figure 7.2: Dynamic Pricing Model Input & Output Parameters

Among the numerous reinforcements learning algorithms, the SARSA algorithm serves as a paradigmatic illustration of an online learning algorithm. The fundamental principle underlying this algorithm is the updating of the value associated with each state in accordance with the current action and the action to be taken (Zhang et al, 2024).

SARSA can be defined as an on-policy temporal difference learning algorithm. The SARSA algorithm is based on the sequence of events represented by the acronym 'SARSA' itself. State, Action, Reward, State, Action. In SARSA, an agent begins in a given state and then performs an action. Following the action, the agent receives a reward, which results in the agent being transitioned into a new state. The state in reinforcement learning represents a set of discrete values representing the current state of the world (Tokarchuk et al, 2004). As a model free reinforcement learning algorithm SARSA is a type of temporal-difference control method that operates on a specific policy. This method aims to estimate the action-value function for the behavior policy that is defined by a variant of "ε-greedy" (Eubel, 2020)

An intelligent agent engages in an ongoing iterative process of interacting with its surrounding environment, continually updating values within a Q table. This allows the agent to make action decisions. The decisions are based on an ε-greedy strategy. This is a probability-weighted combination of the agent's current Q-table values. It is also based on the agent's previous experience. The decisions are also based on the agent's current state (Zhang et al, 2024).

#### 7.2.2.1 Core Components of the SARSA Algorithm

There are some core components of the SARSA algorithm as agents, state, action, reward, policies, next state, and next action. (Tutorialspoint, n.d; Medium, 2024)

**Agents:** Agents are defined as decision-makers that interact with their environment. These agents can be conceptualized as analogous to a robot or a game character.

**State (S):** A state is defined as a reflection of the environment, encompassing all details pertaining to the agent's current situation.

**Action (A):** An action signifies the decision made by the agent contingent upon its present condition. The action selected from the repository initiates a transition from the current state to the subsequent state. This change is how the agent interacts with its environment to achieve the desired results.

**Reward (R):** A variable provided by the environment in response to the agent's action within a specific state, reward serves as a feedback signal that instantaneously demonstrates the outcome of the agent's choice. By indicating which actions are desirable in certain situations, rewards facilitate the agent's learning process.

**Next state (S'):** the state to which the agent shifts following its action, serves as the agent's updated environment upon acting in a specific state, otherwise known as state s'.

**Next Action (A'):** Subsequently, the agent determines the subsequent action to be executed from the current state.

**Policies:** Policies can be considered as strategies, delineating the course of action that the agent should pursue at any given state.

The SARSA algorithm consists of the following steps:

**Initialization:** An initial state is typically selected at random, and the action is determined.

**Action Implementation:** The environment is advanced by implementing the selected action, resulting in a new state and reward.

**New Action Selection:** A new action is selected based on the current policies.

**Learning:** Q-values are updated based on information from past actions and the new action.

The SARSA algorithm updates the Q-value using the following formula (Liao, 2020):

$$\underbrace{Q\,(s,a)}_{\text{Updated Q-value}} = \underbrace{Q\,(s,a)}_{\text{Current Q-value}} + \underbrace{\alpha\,[r + \gamma Q\,(s',a')}_{\text{Target Q-value}} - \underbrace{Q\,(s,a)]}_{\text{Current Q-value}} \qquad (7.1)$$

In the equation, s represents the current state, a represents the current action, s' represents the new state, a' represents the new action, r represents the reward, α represents the learning rate, and γ represents the discount factor of future rewards.

**Repetition:** The latest status and activity are revised as the present status and activity in the following stage, and the policy development cycle is reiterated.

The primary characteristic of SARSA is that the Q-values revised at each stage in the learning process also incorporate the action options. This results in a learning process characterized by increased consistency and reliability. However, the update's basis on the selected action could lead to a less optimistic outcome.

The SARSA algorithm finds application in scenarios necessitating a balanced consideration of exploration and exploitation (EITCA, 2024). Within the domain of machine learning, particularly in the context of reinforcement learning, the SARSA algorithm finds utilization in fields such as natural language processing, image processing, and recommendation systems (Builtin, 2024). The SARSA algorithm employs an exploration and exploitation policy during interaction with the environment and finds application in various domains, including decision-making in robotics, path planning, and video games (DataScientest, 2024).

#### 7.2.2.2 Solving the Air Cargo Dynamic Pricing Problem with SARSA Algorithm

SARSA algorithm was used for dynamic pricing. Figure 7.3 shows the input and output parameters of the model.

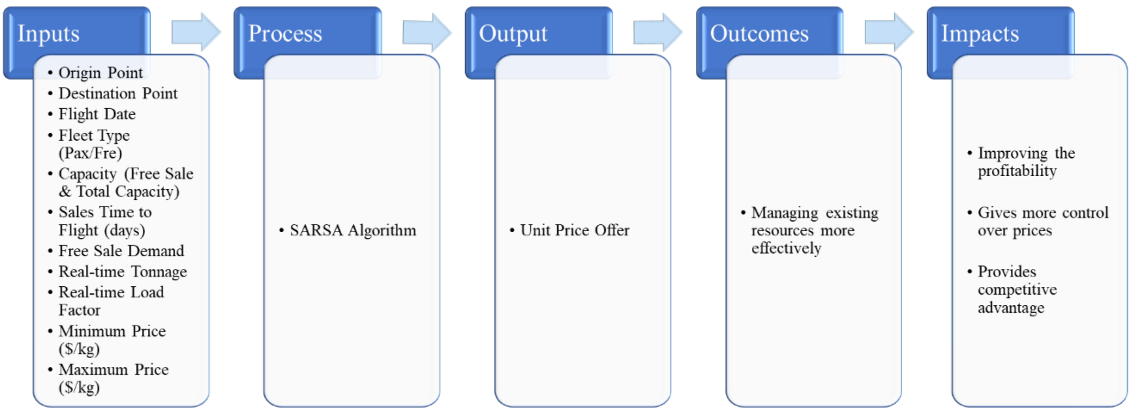


Figure 7.3: Dynamic Pricing Model Input & Output Parameters

In the model, we defined the state space as the origin and destination, the real-time and total load factors, the maximum and minimum prices, the flight date, the capacity, the time to flight, the demand, and the tonnage. The action space was defined as the price range between the minimum and maximum prices, as well as tonnage less than the aircraft capacity. Our objective in the model was to optimize the aggregate revenue per flight, and we finalized the model by establishing this objective as the reward function. Using a reinforcement learning algorithm, we trained the model to learn through experiments instead of relying on pre-labeled data, and to provide the most appropriate price recommendation. We trained the model using real data. The dataset encompasses four destinations and ten origin points. We conducted a comprehensive analysis of sales to each destination. Consequently, there are 40 origin and destination pairs in total. Incorporating additional inputs, such as flight date and fleet type, generated 25,203 rows of data. We used Python to model the data, dividing it into two parts: 80% for training and 20% for testing.

In this study, hyperparameter optimization is used to optimize the performance of a model. The objective of hyperparameter optimization is to identify the optimal combination of hyperparameters, with the goal of maximizing the performance of a model. In this study, we optimized these hyperparameters: alpha ($\alpha$), gamma ($\gamma$), epsilon ($\epsilon$) and number of episodes (num_episodes). These hyperparameters directly influence the learning process and the behavior of the model. The grid search method was used.

Grid search is a widely used method in hyperparameter optimization. This method tries all possible combinations using the Cartesian product of defined value ranges for specific hyperparameters. The model's performance is evaluated after it has been trained with a given combination of hyperparameters. In this study, a performance metric that give the maximum cumulative reward is used to evaluate the performance of the model. A detailed description of the model's training and evaluation is provided below.

Python code is used to implement the grid search algorithm. The code evaluates the performance of the model for different combinations of hyperparameters and determines the set of hyperparameters that gives the best performance.

In this study, the performance of the model is optimized for four different hyperparameter combinations using the grid search method. The highest total reward was used as a performance measure to evaluate the optimization model. The results show that one particular set of hyperparameters performs better than the others. The best performing hyperparameter set is shown in Table 7.1.

Table 7.1: Best Hyperparameter Set and Performance

| **Hyperparameters** | **Value** |
|---|---|
| $\alpha$ | 0,1 |
| $\gamma$ | 0,9 |
| $\epsilon$ | 0,1 |
| *episodes* | 25.000 |

These results underscore the importance of selecting the right hyperparameters to optimize model performance. Future work should investigate wider ranges of hyperparameters and different optimization techniques, such as random search and Bayesian optimization.

The results obtained when the results of the SARSA model are compared with the data allocated for the test on a destination basis are shown in Table 7.2. For the fourth destination, the model's price recommendations are most aligned with the actual prices. Using the model to determine pricing will allow the company to reduce labor costs, have more control over prices, and generate more revenue. Evaluating the model's results shows that it is suitable for providing dynamic price recommendations in the air cargo sector. However, the long training time required for the model may pose a problem for its real-life application.

Table 7.2: Best Hyperparameter Set and Performance

| **Destination** | **MAD Value** |
|---|---|
| 1 | 1,15 |
| 2 | 0,8 |
| 3 | 0,94 |
| 4 | 0,61 |

# CONCLUSION

Air cargo management represents a pivotal element of contemporary global logistics and supply chain operations. However, the management of air freight may be a complex and challenging undertaking that necessitates meticulous planning and coordination across a multitude of domains.

One critical issue which air freight firms faced is the sales the ability to regulate the limited cargo space. The sale of air freight capacity is subject to a number of conditions, including the necessity for the capacity to be sold before the flight departure. Air freight capacity is a prime candidate for revenue management strategies, according to Amaruchkul and Lorchirachoonkul (2011).

Two bases are provided for the sale of the cargo capacity: contract sale and free sale.

1. A guaranteed capacity contract is an agreement. It is between a carrier and a customer. The agreement guarantees a specific flight. The flight will have a certain capacity. Air freight carriers may sell a portion of their capacity to forwarders. This is done under the terms of a contract. The contract specifies the allotments.
2. Free sale: there is no capacity guarantee.

In comparison with the number of articles about revenue management on passenger side, air freight has much less articles on revenue management. Demand forecasting, pricing and overbooking are some of the important revenue management research areas.

Revenue management for air freight industry is different than from passenger side. The main difference between these two industries is about capacity. There is two-dimensional capacity as weight and volume in air freight industry.  The capacity for air freight is not fixed, unlike the passenger side. The number of passengers and the total weight of baggage can affect the capacity for air freight. Another distinctive feature of cargo revenue management is the consideration of demand, which is an important aspect of the process. The pattern of passenger demand is characterized by seasonal fluctuations, whereas the demand for cargo is more closely aligned with the specific requirements of individual services and therefore more challenging to predict. The capacity which occurs after the allotments is a free sale. There is no capacity guaranteed and capacity sold at standard rate.

Our first aim is determining the correct ratio of contract sale and free sale. We will create a model for this aim. When creating this model, historic data will guide us at this stage. After determining capacity that will sold as free sale, we will create a dynamic pricing model to increase the revenue from the free sale. We will implement our model to an air freight company.

In today's rapidly developing and changing world, making accurate predictions for the future is critical. At this stage, managing the available resources more effectively is closely related to making correct predictions. Capacity management is critical in the air cargo industry, posing the important question of how much capacity should be allocated to allotment sales versus free sales. By correctly allocating the capacity, the rate of capacity utilization can be increased, thereby increasing the revenue to be obtained.

It is almost impossible to obtain perfect estimation results due to the fact that not all factors affecting the parameter to be estimated can be reflected in the model. However, it is extremely important to use the model that gives the most realistic results for estimation.

In the first stage of the study, it is aimed to make capacity allocation correctly. For this purpose, CVaR and ANN models were employed, and the models' outcomes were compared with the actual data. By comparing the obtained model results and realized allotment ratios, it was decided whether it would be meaningful to use the models for the prediction of allotment ratio.

Firstly, CVaR model were used for the first stage of the study. This model is based on the 2017 study by Wada et al. regarding the capacity allocation problem in the air cargo industry. In order to make this model more compatible with real life, an additional penalty cost for soft allotment contracts has been added to the model. Using GAMS, the model has been implemented for cargo and passenger aircraft across four different destinations. The estimated results are subsequently evaluated against the actual values. Statistical data obtained as a result of comparison are interpreted. When the results obtained from the CVaR model were compared with the allotment rates realized, the $R^2$ value obtained was found to be 0.4598.

ANNs were used secondly. First of all, the factors affecting the allotment rate were determined by the expert opinion. Factors that affect the rate of allotment most after the meeting with experts were determined as, destination, month, fleet type, capacity, allotment type, allotment demand, allotment unit revenue, free sale unit revenue. MATLAB was used in the application of ANNs. D_Min_Max normalization was performed to bring the variables to be added to the MATLAB into the range [0, 1]. As the output values were also in the [0, 1] range, the output values were not normalized. Models for many different networks and different neuron numbers have been created and the results have been evaluated in MATLAB. As a result of the experiment, it was determined that the NARX model with 7 hidden layers produced the best outcome. When comparing the results from the best model to the actual allotment rates, the $R^2$ value was found to be 0.9335. Given the superior performance of the NARX network, it will be used for allotment prediction.

When the CVaR and ANN model results are compared, we can see that the ANN model gives better results. It can be stated that ANN model has high validity for capacity allocation model. It can be stated that ANN model produces highly similar results to actual results for capacity allocation model.

In business economics, dynamic pricing is defined as a strategy where the price of a product or service is adjusted in real-time based on various factors. These include market demand, competitive pressures, time of day and seasonality, as well as other external factors. The objective of dynamic pricing is to optimize revenue by establishing the highest price that customers are willing to pay, while concurrently achieving sales targets. This method uses variable pricing instead of fixed pricing, allowing numerous companies to generate profits and create offers based on ever-changing market conditions. In this context, accuracy is crucial, as poor-quality data leads to the generation of invalid offers. Dynamic pricing implementation in the freight industry holds the potential to advantage both carriers and shippers. For carriers, dynamic pricing enables them to optimize fleet and resource utilization by filling available capacity with profitable loads. For shippers, dynamic pricing provides a wider range of pricing options and flexibility in choosing the most cost-effective transportation solutions that meet their specific needs (FreightCenter, 2023).

The subsequent section of the study establishes a dynamic pricing model for air cargo. Initially, a forecasting model is developed for the demand data, which represents a crucial input for the pricing model. A variety of statistical techniques were applied in the forecasting of demand, including multiple linear regression, time series models (such as the winter model) and ANN models. The outputs of each model were evaluated by analyzing the ME, MAD and MPE values. The results demonstrate that the multiple linear regression model produces the most optimal outcome.

At last, a dynamic pricing model has been created in which the output of the capacity decomposition model and the output of the demand forecasting model are also used as inputs. Furthermore, in addition to the inputs of capacity and demand forecasting, the model incorporates inputs that reflect the seasonal fluctuations in price that are characteristic of the market. These include the time of the flight, the time before the flight, the point of sale, the weight of the cargo, and the type of aircraft. We applied the SARSA algorithm to the dynamic pricing model and implemented it using Python. We used 25.203 rows of data to examine the accuracy of the model. We used 20% of this data for testing and the remaining data to train the model. Finally, we created an integrated model by using the revenue output generated by the dynamic pricing model as input for the capacity allocation model in future periods.

The revenue generated by the dynamic pricing model is incorporated into the capacity allocation model as a variable input. Consequently, the three models are integrated with one another, resulting in the creation of an integrated model.

We have proposed a model for three of the most salient issues in air cargo revenue management: demand forecasting, capacity allocation, and pricing. Our model is distinct from other research in the field due to its integrated framework and breadth, as well as its employment of a reinforcement learning algorithm for dynamic pricing. Incorporating expert opinions enhances the model's ability to reflect real-life situations. The incorporation of expert opinions has enhanced the model's ability to reflect real-life situations. The implementation of the model using actual data from a major airline in the air cargo sector enabled the precise interpretation of the model's outputs. The implementation of our model will enhance the allocation of capacity, thereby increasing the overall load factor of the aircraft and the revenue of the company. In addition to dynamic pricing, demand forecasting will provide decision support for long-term strategies, including aircraft purchase decisions and personnel employment. The establishment of a dynamic pricing model enables the automated determination of prices by the system, thereby facilitating labor cost savings for the company, enhancing its pricing control, and contributing to revenue augmentation.

We also presented the models we proposed and the outputs obtained from the models to the airline management. The feedback we received from the management was very positive. Although the long time it took to train the dynamic pricing model negatively affects its use in real life, it can be used to help make decisions about how much capacity to allocation and how to forecast demand.

The suggestions for future studies are presented separately for the capacity allocation model and the dynamic pricing model. With regard to the capacity model, it is possible to consider overbooking, cancellation and no-show as model inputs. A hybrid model can be employed for the resolution of the aforementioned issues. With the dynamic pricing model, overbooking, cancellations, no-shows, and discounts can be incorporated as inputs. The input of product type data can be incorporated into the model for the purpose of pricing in other product types. To enhance the model's efficacy, a wider range of hyperparameters can be employed, and different hyperparameter optimization techniques can be experimented with, including Bayesian optimization.

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