Neural Network Optimization of Airline Ticket Booking: An Airline Revenue Management System

By

MUSTAFA ADNAN ALSHARIF

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ABSTRACT

Neural Network Optimization of Airline Ticket Booking: An Airline Revenue Management System

By

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Revenue Management is a sub category of transportation management. Revenue management in case of airlines is the process of understanding the consumer behaviour and anticipating external weather effects to maximize the revenue from fixed resources (fixed number of seats). All airlines make their revenue based on the demand. If unsold seats are present in the airplane, they cannot generate any revenue. Instead of operating the airplane with unsold seats, the management *can offer discounts at the right time* in order to generate *maximum possible revenue* even from unsold seats.

Revenue Management involves strategic control of inventory to sell it to the right customer at the right time for the right price. This process can result in price discrimination, where a firm charges customers consuming otherwise identical goods or services a different price for doing so [52].

Over the last decades, much interest has been devoted to the overbooking and capacity allocation issues and, today, most major airlines rely on computerized tools to deal with these two sub-problems. Pricing, however, has received less attention, which can be explained by the technical and theoretical difficulties inherent to the implementation.

In this research study, optimization is carried out by using back propagation neural networks coupled with auto regression model. This artificial neural network is trained based on the past data available from airlines. Upon successful training of the neural net, it is tested for the accuracy using the current data. Before applying neural network, Analytic Hierarchy Process (AHP) is used to rank-order airlines bared a certain criteria. Neural network based optimization is then carried out against the top-ranked airline given by AHP.

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إهداء شكر وعرفان إلى الشيخ نهيان بن مبارك آل نهيان (حفظه الله)

عليك السـلام انواع يا شيخنا انهيان

سـلام العز و الطيبة تبادله في شرايني

تبادله شوقك و عنه و هي من دونها القيفان

تراسل لك على شخصك و فيها من مضاميني

مراسيل الغـلا فيها و طبعة خاتم اسليمان

رفقـها بوردتن حمرا قطفـها من بساتيني

عليك الله تـرا الشاعر يحاول يرقبه الي كـان

و فيه احساسه يحده و باقي الناس تحديني

سـلام الله على شيخن قفنه من دونه الاحزان

و سارت دارنا فرحه سطرهـا في دواويني

الشاعر: خالد علي بن سالم الكعبي

Mother

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CHAPTER 1: INTRODUCTION

1.1. Introduction

Passenger airlines are challenged to capture the greatest revenue yield from every flight departure. The ultimate success of an airline requires not selling too many low-priced seats that turn away higher-priced demand, while also avoiding too-high prices that result in lost demand and too many empty seats [196]. In order to maximize revenue from normal demand, airlines need to continually fine-tune performance and monitor success and demonstrate the exceptional ability to manage reservation system pricing and accessibility controls.

Major airline companies have begun the sale of various itineraries where flights controlled by two or more different airline companies are sold in combination [49]. The increase in the use of these methods is due to the introduction of airline alliances. These alliances promote the combinations of various itineraries and assist other airlines in expanding their services and global outreach. These alliances however need to be planned strategically in order to iron out any coordination issues. The problems faced by the alliance are that each airline company has their revenue management techniques and plans through which they yield maximum revenue. Alteration of these plans due to participation in an alliance causes changes in the revenue management system, which in turn causes suboptimal yields in terms of profits. Various suggestions for well-coordinated alliances, which allow optimal revenue management for airline companies participating in alliances have been made by researchers and consultants of the airline industry [232].

1.2. The AHP model and the proposed Neural Network Model

The structured technique that deals with complicated problems and decisions is AHP. The unique characteristic of AHP is that when it is presented with a problem it does not aim to provide an accurate answer or solution to that problem. Instead of the correct answer it searches for the best possible scenario, which will fulfil the objective and understand the issue at hand in an optimal manner.

AHP is in fact a special case of ANP. This relationship between the two requires an explanation of ANP [Artificial Network Process] as well. ANP was developed by Thomas L. Saaty [231]. ANP and AHP both derive ratio-scale properties. They provide methods in which measurements and other judgments may be entered into the model which will affect the elements involved in the decision making process [19]. The derived properties facilitate appropriate resource allocation by making use of ratio scales. These ratio scales are derived by doing "pairwise comparisons" of factors based on similarities in criterion.

ANP is traditionally the best suited for the study and resolution of decision making problems. The use of AHP however is also encouraged to do a comparison of results based on the time taken, effort involved and the accuracy of findings [178].

The theories of AHP and ANP are based on intangible criteria. They derive a scale of priorities after recognition of the elements being measured. These measurements are compared in a pair-wise manner [19]. This idea is taken from biological neural systems, which are genetically programmed to do a pair-wise comparison of factors in situations where elements are relative and in transition. Traditional models measured elements along with their measurable properties against a scale, which applied to all elements, which were presented to the model. The measurement would be done in a sequential manner with no pairwise comparisons. Paired comparisons in AHP are done by association of numerical values to elements. These values are derived from the "AHP absolute fundamental scale of 1-9". The paired comparisons of weights allows for the derivation of relative values. These values belong to an absolute scale, which does not vary under "identity transformation". The use of AHP/ANP is beneficial for taking multi-criteria decisions, which involve taking risks, getting benefits, evaluating costs and benefits [180].

A typical AHP decision making model is given in the following figure.

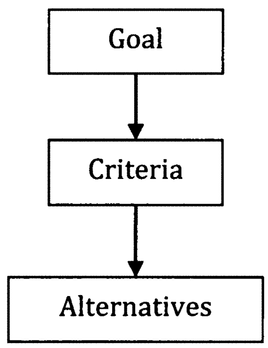

Figure 1: Typical AHP Decision Making Model [180]

Governments, business organizations and other services such as education and healthcare, which face various decision making situations make use of AHP.

The Analytical Hierarchy Process [AHP] is a decision making model. This model helps determine whether a decision will yield results based on the number of factors that affect the decision tree. In airline ticketing, airline industries compete with each other to provide the best services. Different airlines that fly between New York and Dubai are:

- United Arab Emirates
- Delta Airlines
- Continental Airlines
- American Airlines
- British Airways
- Lufthansa

The AHP model for the decision making of the revenue management in airlines is given below.

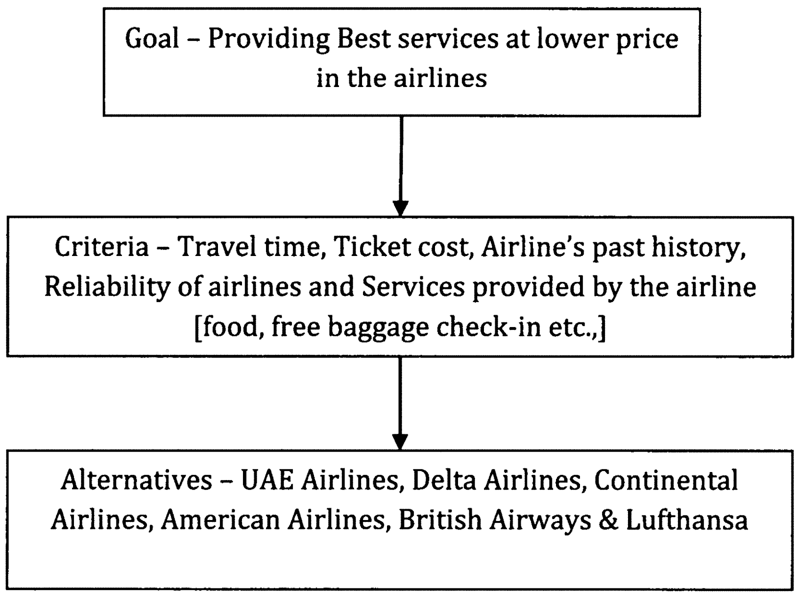

Figure 2: AHP Model for Revenue Management in Airlines [180]

The integration of the AHP model with Neural Network model will help determine what services to provide for the passengers in case all seats have not been allocated before flight take-off in order to obtain maximum possible revenue from the flight.

1.3. Purpose of the Study

Some airlines are currently making use of the Analytical Hierarchy Process [AHP] for revenue.

The purpose of this study is to test the use of neural nets coupled with auto-regression models for revenue maximization of airline ticketing.

1.4. Aim of the Study

The aim of this research study is as follows

"The aim of this study is to simulate the neural network model coupled with auto-regression compared with the AHP model and to suggest a new approach for the maximization of revenue in airline ticketing."

1.5. Hypothesis

The hypothesis for the study is as follows

"A successful simulation of the neural network model coupled will auto-regression model for maximization of revenue in airlines is possible and can be suggested for implementation."

1.6. Research Objectives

As the revenue management is very important for every airline, the research on this is becoming important. The objectives of the current research are:

1. Revenue management using artificial neural networks coupled with auto regression models
2. Compare neural network model with analytical hierarchy process [AHP] model
3. Use MATLAB for simulating the neural network [NN] model
4. Use *Super Decisions Software* for AHP model simulations
5. Suggest / recommend a model to the airlines based on the optimization work

1.7. Research Questions

The research questions for this study are as follows

1. Can there be a successful development and implementation of artificial neural networks coupled with auto regression models in revenue management for airlines?

2. What are the similarities and differences between the neural network model and the Analytical hierarchy Process?
3. Will a MATLAB simulation for AHP models be successful?
4. What steps can airlines take to improve revenue management based on optimization of work?

1.8. Problem Statement and Motivation

In passenger airlines, the number of seats is fixed. All the airlines make the revenue based on the demand. If unsold seats are present in the airplane, they cannot generate any kind of revenue. Instead of operating the airplane with unsold seats, the airline management *can offer discounts at the right time* as needed in order to generate *maximum possible revenue* even from the unsold seats.

As in the other case, when the seats are full and the demand for the seats is high, the airlines can raise the ticket price and increase the revenue.

So far no airline is using neural networks as a tool for revenue management. All of them are using just optimization of revenue. Current proposal uses neural network coupled with auto regression [AR] models as a too. The neural net is first trained using the existing data [past data]. The variables [weights] obtained from the training will be used to determine the future revenue management. Here the optimization underlies in coupling the neural net with the auto regression models.

The problem statement is given in the figure below

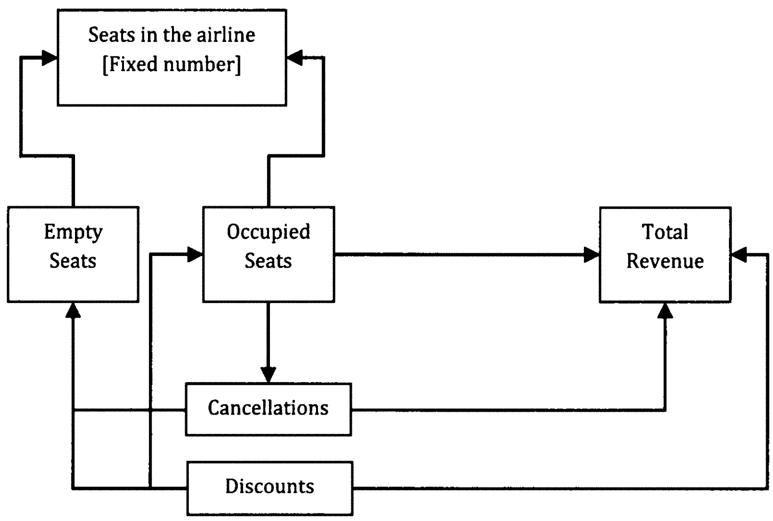

Figure 3: Revenue Management in Airlines [For a Fixed Number of Seats in the Airlines]

1.9. Problems and Critical Success Factors

The problems and critical success factors are:

1.9.1 Obtaining the correct data from airlines

Getting the data from airline[s] is tough and time-consuming process. Presently the target is to get the data from United Arab Emirates [UAE Airlines]. These airlines operate direct flights from Dubai to New York. The data for the neural network optimization is needed to be a specific format i.e., it needs all the details including discounts at a specified intervals. Obtaining the data from the airlines in the specified format [given in chapter 6] may be difficult and depends on the airline co-operation.

1.9.2. Comparison of NN with AHP model

Comparison of NN model with AHP model is also an objective in the current research. The AHP model is decision making model. The AHP model compares different airline companies between Dubai and New York in the following areas

a. Time of travel

b. Services provided by the airlines

c. Ticket Price and

d. Frequency of travel.

The differences between the neural net model and AHP model are given the table below.

NN Model	AHP Model
Not a decision making model	Decision making model
The problem is not decomposed	The problem will be decomposed into sub-problems [criterion]
Comparison is made between the model results and existing [or past] data	Evaluation is made by comparing to other elements
Conversion is made based on the comparison or "Yes" or "No" decision	The evaluations are converted to numerical values over the entire range of problem

Table 1: Difference between The Neural Network Model and The Analytical Hierarchy Network Model

1.10. <u>Structure of the Study</u>

This research study will be divided into 5 chapters. This current chapter includes the introduction, which contains details regarding the core topics being tackled in the research study [*i.e.* AHP model and neural networks]. This chapter also contains the research objectives and the research questions, which the researcher will attempt to answer and achieve through the course of this research study. Details of the following chapters are given below.

Chapter 2: The second chapter observes the very important duty of reviewing previous literature that helped the researcher in the development of this study. A comprehensive review of literature is provided in this chapter in order to observe the similarities and difference between this research study and previous studies in accordance with the important questions associated with the aims of this research.

Chapter 3: The third chapter discusses the methodological possibilities considered while designing this study and explains why the selected options are deemed most suitable by the researcher. The chapter discusses methods employed in both secondary as well as primary research of this study.

Chapter 4: The fourth chapter displays the findings of this study with the help of charts and graphs in order to provide comprehensive and attractive presentation of the results gathered during the primary research of this study. Adequate interpretation is provided with each graphic for better understanding of the data presented therein.

Chapter 5: The fifth chapter discusses and analyses the collected findings in detail and utilizes the knowledge collected during the review of the studied literature to cross-check the primary findings with the views of the scholars. This analysis plays a crucial part in the achievement of the answers to this study's research questions. It also focuses on the conclusion of results and discussions of the study and also provides possible recommendations for future research on this problem and for the airline industry.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

This chapter includes a review of previous literature. It gives a comprehensive description of revenue management and popular RM methods used in the airline industry. It also explains the problems of RM faced by airlines. The dynamic process and Analytical Hierarchy Process [AHP] are two conventional methods of revenue management, which are used by airlines to tackle their problems. This chapter also gives a description of these two methods and their implementation. This research study suggests the use of neural networks with AHP to help sole revenue management problems of airlines. This chapter gives an explanation of neural networks and explains the architecture of these networks and the one [*i.e.*, feed forward back propagation multi-layer neural network] that will be used in this research study.

2.2. Revenue Management

Revenue management can be defined as "selling the right seat at the right time to the right passenger for the right price" [52]. Revenue management is applied in several sectors of transportation. These may be "auto rentals, ferries, rail, tour operators, cargo, and cruises. Other areas, like hotel or resorts, health care, manufacturing apparel, and companies that produce perishable goods *etc.,* can also use revenue management" [52].

Revenue Management, which can also be called Yield Management, deals with the creation and management of service packs, which can help, in maximizing revenue. A firm is able to design several service packs for various segments of the market by a thorough understanding of the behaviour and value functions of customers. These service packs are customised for market segments based on combinations of various attributes, such as "price, distribution channels, purchase restrictions and amenities" [6].

Revenue management can be applied in various industries. The conventional use of revenue management was limited to the airline, hotel, and car-rental industries. Implementation of revenue management in the three industries was very similar, since all three industries have similar characteristics. These characteristics include perishable commodities, periodically varying product demand, and large fixed costs. The success of revenue management in these industries has caused it to spread over into other industries, such as casinos, restaurants, apartment rentals and Internet services [6].

2.2.1 Defining Revenue Management

The roots belonging to revenue management can be found embedded in the discipline of yield management. The early pieces of what would now be considered key components of a revenue management system comprised a yield management system about 30 years ago, which was predominately a forecasting model and a capacity allocation system. Since then, revenue management strategies and systems have evolved over time, and what is in place today is much more intelligent in design and significantly more sophisticated in terms of capability.

Current revenue management systems represent the art and science of selling the right product to the right customers, at the right price, and through the right distribution channels. This process is guided by intellectual capital and complex computer models. It is a discipline in which the airlineier recognizes that not all customers are created equal and that each market segment will have different needs, wants, expectations, and price thresholds. Revenue management has been in use by the airline industry since the early 1980s and has continued to gain popularity and importance over the last few decades. Airline properties of today have an opportunity to optimize all potential sources of revenue, including room sales, food and beverage, meeting space, and so forth, as a result of the sophistication of current revenue management systems [51].

2.2.2 External Influence Factors

The impetus for firm strategy by the airline company can be an objective to sustain or gain a competitive advantage within its relevant competitive set. Alternatively, there might be an urgent requirement to change firm strategy as a result of an unforeseen event taking place, such as 9/11, SARS, or the current financial crisis [51]. Accordingly, the necessity for the airlineier to understand and closely monitor the external environment is imperative. Without some type of "environmental scanning" being conducted, there will in all likelihood be a missed threat or opportunity resulting in a bad fit between the airline's strategic game plan and what actually is taking place within the external environment. This demonstration of myopic internal vision and ignorance eventually will lead to poor firm performance [13].

However, Hannan and Freeman (1977) advocated that the environment itself would determine the firm's performance and that the management team would have little if any effect on firm performance. For example, in the case regarding the fallout from the 9/11 terrorist attacks, there was a significant decline in demand for airline product in the days and weeks immediately after the tragic events of 9/11. Airlines were seriously challenged as to what would be the best approach or strategy to stimulate demand for airline room inventory. As such, many airlines became dependent upon third-party vendors to sell off excess inventory, and most properties had to price their product at new and deeply discounted rates [51]. Thus, in the case of 9/11, many airline properties were at the mercy of the external environment, and the management team was restricted in their ability to take appropriate action with the exception of dramatically reducing room rates [203].

In contrast to the previous examples, others support the view that management will have influence on, and control over, the performance outcomes of the firm [17,]. Therefore, within this school of thought, the theory advocated is that management actions and decisions do shape and will determine operational performance outcomes.

Consequently, it is management that drives firm performance, based upon the decisions they have made and the actions they have taken. In this respect, one of the most important responsibilities of management is to constantly scan the external environment and make sure that firm strategy is a product of what has been learned from the dynamics of the external environment [17].

Building on this theory, potential external influence factors on firm strategy and, subsequently, airline revenue management performance include the following elements:

(a) Clusters and strategic groups

(b) Competitive environment

(c) Institutional effects

(d) Macroeconomic factors

Clusters and strategic groups. According to Porter [154], a "cluster" represents the "critical mass" of similar organizations, such as airlines, when they can be found within a specific geographical location, such as the Niagara region of both the State of New York and Ontario, Canada or the clusters of airlines in Las Vegas, Nevada. Clusters are comprised of and supported by a particular set of "suppliers of specialized inputs, components, machinery, and services in firms and related industries" [154]. In the case of the hospitality industry, cluster supports include an available and skilled labour pool, educational institutes that provide industry-specific training programs, such as airline management, as well as airline and food service industry suppliers.

Porter [154] writes that cluster theory is important to members of the cluster for three reasons: (a) improved productivity, (b) competitor motivations, and (c) low barrier entry for new competitors. Several studies have tested these advantages within a hospitality setting and have found support.

Related to the first advantage noted by Porter [154], individual airlines as members of the cluster can improve productivity. This positive outcome occurs as a result of the competing lodging properties sharing best practice methods, a skilled labor pool, and leveraging access to and partnership with educational institutes that provide specialized training for the airline industry [154]. Chung and Kalnins [45] find support for the first of Porter's three advantages. In their study of the Texas airline industry, Chung and Kalnins, found that both small as well as independently-owned lodging properties benefited the most as a result of being present within a cluster setting. The most significant of these benefits includes "production enhancement and heightened gains" [154] Production enhancement exists as a result of firms learning best practices from one another. Heightened demand takes place as a result of consumers having both choice and contingency alternatives available within the same geographical market [154].

With respect to Porter's [154] second point, clusters can facilitate the motivation for competing airlines to become more innovative, different, effective, and efficient, which will help drive improvements in productivity even further over the long run. For example, Canina, Enz, and Harrison [36] conducted a study of almost 15,000 airline properties across the United States that formed and/or represented different clusters. From this empirical study they found that within a cluster setting, the lodging properties that did the best job in distinguishing themselves as being different from other cluster members, and were recognized by the airline guest as being different, enjoyed the greatest amount of advantage from the cluster environment.

With respect to Porter's [154] third point, lowering the barriers to entry for new competitors, he speaks to the fact that the industry-specific support networks—supply infrastructure, intellectual capital, specialized inputs, and so forth—are already present within or are in close proximity to the cluster. As new competitors enter the market, the need for existing airline properties to become more productive and rise to a higher performance level becomes intrinsically driven. Evidence of this perspective is illustrated in a study of Taiwanese airline properties by Cheng, Chen, Liu, and Jung [39].

To this end, in 2002 the government of Taiwan launched a "tourist double-up strategy." The objectives of this aggressive tourism strategy were to significantly increase the number of tourists in Taiwan and consequently grow the total dollar value of tourist-related expenditures. Following this government directive, the number of tourists in Taiwan increased by approximately 18% in 2006 in comparison to the number of tourists visiting Taiwan in 2002. Additionally, the tourist-related expenditures in 2006 grew by approximately 14% in comparison to 2002 [41].

Accordingly, a significant amount of increased competition took place during this time period within the Taiwanese airline industry. Therefore, recognizing the need for airlines to "step up" given the rise in competition, the researchers examined the productivity and efficiency of 13 international resort airlines located throughout Taiwan. From their findings, the possibility that chain airline properties are more technically efficient than their independent counterparts has emerged. The authors believe that this was due in part to the chain airlines having greater ease of technology importation as well as the availability of inter-property technology transfer [41]. Complementing the concept of a cluster is strategic group theory. A strategic group exists whenever a competitive set can be observed or identified within a particular industry, and these competing firms have similar characteristics, desire the same customers, and share analogous competitive dimensions and strategies [47]. This theory provides assistance in understanding the relationships, conflicts, and performance outcomes that occur with the competitive set of a specific industry [24].

Airline properties that belong within a strategic group, or are believed to be a member of a strategic group, can cooperatively or involuntarily provide a performance benchmark from which the competitors can determine where they stand in relationship to the competitive set as a whole [120]. Along this construct, it has been suggested that the degree of competition that exists as well as the directness and severity of the "competitive threat" will be determined by the size and scope of the cluster and/or strategic group [40].

To this end, the operating characteristics and dynamic personalities belonging to members of the Niagara airline population become more significant with respect to success and failure rates over time. It has been advocated that the more alike lodging properties are within the Niagara cluster and strategic group, in terms of location, price, and room inventory, then the greater the "intensity of competition" that will exist for said airline properties [23]. Thus, the importance and value of strategic revenue management becomes even more apparent.

From the discussion above, it is evident that clusters can be advantageous to the airlineier. However, each lodging property must have its own image, personality, and noticeable differences; otherwise it will be seen and received as basically a homogeneous product within the cluster and strategic group environment by the consumer [36].

Competitive environment. Carrying out business in a competitive environment is much like conducting war on a battlefield. Each competing airline represents an individual faction, and all the rival lodging properties are viewed as enemies. Within this train of thought the airline property must collect competitive/market intelligence, and formulate an appropriate strategic plan based on what has been learned about competitor behaviour and any movements on the battlefield [171]. Thus, observation, examination, and understanding of the competitive environment are imperative as well as supportive to the airlineier's strategy, as competitor behaviour is difficult to predict [189]. This school of thought is further supported by Zajac and Bazerman [238] who encourage management to observe, monitor, and respond appropriately to the actions taken by competitors found within the firm's competitive set. They advocate that management must exercise due diligence in their effort to gather accurate and complete information about their competitor's behaviour. However, any strategic offensive or defensive man oeuvres may prove counterproductive if management's "blind spots" are left unchecked.

Additionally, individual firms determined to compete effectively and sustain their viability within their competitive set must observe their competition and act prudently in order to maintain some degree of "unique product position" and marketability [153]. Each airline property must make a commitment to staying ahead, in some way, shape, or form, within their relevant competitive set. Otherwise, the firm presents to itself the risk of not surviving [25].

Institutional effects. Institutional theory provides another perspective on how organizational behaviour and, in due course, firm strategy can be postured by the external environment. The theory advocates that business entities over time will learn to conform to what is perceived, or prescribed, to be the expectations, requirements, procedures, and norms while operating in a specific environment [190].

Within this context, institutional theory provides an industry observer with some rationalization as to why members of a cluster or strategic group eventually behave in a similar manner [82]. The theory advocates that each organization has a desire to gain, or be given, "legitimacy" within its own cluster and, therefore, over time will evolve, adapt, and conform to the operating atmosphere's requisites as perpetuated by the cluster itself and the host environment. Once this transformation has taken place, the organization's persona becomes more congruent with the operating characteristics of the other cluster members [59]. Thus, the typical airline property morphs over time to become an appropriate fit within its external environment and competitive set.

DiMaggio and Powell [64] identify that there are three drivers in play for "institutional isomorphic change" that will either individually or collectively exert pressure on an organization to alter its behaviour and take on a resemblance that closely matches industry peers found within the cluster; they include

(a) Coercive

(b) Mimetic

(d) Normative

First, coercive change is a product of the organization being strongly influenced by other members of the cluster or as a result of a government directive or legal requirement. Second, mimetic change occurs when the organization is shrouded in uncertainty and is not confident with its own agenda or objectives. The organization's response in this circumstance is to imitate the behaviour of the other cluster members. Third, normative change is a product of the organization's linkages / involvement with a relevant professional association or a relationship to a professional body. Accordingly, change that occurs within the organization can be as a direct outcome of leveraging well educated, highly-skilled human capital as well as embracing various professional associations and networks [64].

The effect of institutional theory is important to firm strategy within a "social context" framework and perspective. For instance, strategic decisions can be influenced by the interactions and relationships that occur between the organization's human resources and the external environment in which they act as agents [79]. As addressed by Dacin, Kostova, and Roth [119], institutional theory plays a significant role in the understanding of how multinational corporations behave and perform in different country settings and in response to diverse external influences and pressures.

Macroeconomic effects. Firm strategy drives firm performance, and firm performance is going to be dependent upon both economic and organizational factors. Therefore, the manager must have knowledge of the significant economic elements that will have an effect on both the firm's strategy and ultimately the firm's performance [86].

The astute revenue manager must have an understanding of the current economic environment in order to be effective with respect to both pricing and inventory management decision making. Thus, it is imperative that revenue management decisions are made only when key economic variables, such as inflation, unemployment, interest rates, exchange rates, consumer demand, as well as consumer confidence all have been taken into consideration. Treating all available macroeconomic data as significant when any degree of strategic planning is undertaken is vital [37].

Whether located in Las Vegas or the Niagara Region, airlineiers cannot perform revenue management well if they do not understand the current economic climate. Spulber [201] advocates that firm strategy cannot be crafted by management without first performing an analysis of the current economic climate. Only after this task has been performed is the manager in a position to formulate an effective and efficient strategic plan that could possibly be a good fit for current conditions of the economic environment.

Furthermore, the pulse of the economic environment must be correctly taken and understood by management so that an accurate prognosis can be made and then used to help shape strategy. Otherwise, the strategy formulated by management can quite possibly become an experiment gone wrong if the current macroeconomic factors in play are not taken into consideration and understood [172].

As identified by Langlois [124], economics is important to strategy formulation, and strategy can become an important tool to comprehensive economic study. To this end, the two disciplines are interrelated and are, to some extent, dependent upon each other with respect to the managerial decision-making process. Therefore, an analysis of the economic environment should drive the strategy formulation process.

Accordingly, both economics and strategy are essential and influential pieces to revenue management and, therefore, must be included within the revenue management decision-making model for airlineiers. Conclusively, airline properties need to constantly monitor the macroeconomic climate and recognize both swings and shifts with key economic indicators as quickly as possible. For those organizations that have the ability to do so will, in the long run, prove to be the most successful. Intelligent and pragmatic response to changes in the economic environment with both precision and speed can lead to competitive advantage [227].

Revenue Management-Internal Resources Airline companies that will enjoy the financial rewards of successful revenue management strategies and systems are the ones who will first recognize and embrace the importance of human capital and technology [68]. Airlines that have made a significant investment in both technology and human capital for their revenue management programs and systems also need to ensure that this investment is both protected and is providing a satisfactory return [117].

As identified by Hoang [92], a very high level of sophisticated technology is available with current revenue management systems. Additionally, the capabilities and quality of revenue management systems continue to improve over time. Therefore, today's airlineiers have little reason not to embrace and leverage the existing technology for revenue optimization and satisfactory investment returns within their lodging establishments. The following sections review research related to the key internal components required for strategic revenue management programs and systems.

Operations management. For the most part, the founding principles of revenue management can be traced back to an operations management focus within the airline industry. The first penchant towards any analytical approach for something that would one day resemble at least a contributing piece of a revenue management system was an attempt to improve issues, concerns, and goals with airline reservation systems. This observation is supported by the research work carried out by Bobkowski and Beckmann, and subsequently documented by Beckmann (1958), in consultation with a cadre of senior airline managers during the late 1950s.

Then, in the early 1970s research literature contributions were made to the challenge of no-shows and overbooking policy in both the airline and airline industries by Rothstein (1971, 1974). Subsequently, in 1972, Littlewood wrote an operational research paper, which is considered a classic today, while he was employed as an analyst by British Airways. In this breakthrough paper Littlewood illustrated a very simple logic model, the basic two-class single flight leg model, that would allocate airline customers to either a low- or high-yield fare pricing tier based on booking demand and diminishing inventory [128]. To this day that model is still looked upon as a starting point, a key ingredient, for revenue management strategy and as a founding pillar for revenue management/operations management literature, and has come to be known and recognized within the revenue management community as “Littlewood's Rule” [192]. Littlewood’s work was later augmented, extended, and supported by others, such as Belobaba (1985, 1989); Bhatia and Parekh (1973); Brumelle, McGill, Oum, Sawaki, and Tretheway (1990); Curry (1990); and Richter (1982).

The operations management literature also provides a general working context that advocates the use of normative modelling for revenue management practice [221], strategy formulation [183], and decision making within a airline environment [77]. Along this line of thought, the literature advocates that a normative model promotes the universal economic convention that as demand and costs increase, the selling price for a product should increase as well [62].

However, a normative model also can present itself as being counterintuitive. This can occur in an economic environment whereby demand and costs increase but the product's selling price is subjected to downward pressure and falls. This scenario can develop when the intensity within the competitive environment is held constant over time and business units respond by lowering their selling price in an attempt to break the competitive log jam [126].

Additionally, along this paradigm the operations management literature also promotes the significance of certain core components of a revenue management system that are direct contributors to the effectiveness and success of a airline's revenue management capability, considering once again that the revenue management's ideal objective is to optimize the business entities revenue potential. Having reiterated that point and within this framework, the important operations management–revenue management pieces of (a) Technology, (b) Forecasting Methods and Models, (c) Capacity Allocation Models, and (d) Pricing Models and strategies all are categorically imperative to revenue management achievement within a airline environment [226].

Revenue Management Technology. It has been proposed that advances in revenue management technology and the importance of revenue management will become so prevalent to business in the years ahead that by 2020, "off the shelf" products will be available to meet the specific needs of each type of business [237]. Technology is a crucial cornerstone to revenue management capability in a variety of different ways by Rust & Chong 2006. It is vital in contributing to demand estimates [148], an understanding of the customer's preferences by Boyd and Belegan 2003, enhancing customer relationship management [91].

Revenue management can be defined as "selling the right seat at the right time to the right passenger for the right price" [194]. Revenue management is applied in several sectors of transportation. These may be "auto rentals, ferries, rail, tour operators, cargo, and cruises. Other areas, like airline or resorts, health care, manufacturing apparel, and companies that produce perishable goods etc., can also use revenue management" [190].

With respect to Porter's [154] second point, clusters can facilitate the motivation for competing airlines to become more innovative, different, effective, and efficient, which will help drive improvements in productivity even further over the long run. For example, Canina, Enz, and Harrison [36] conducted a study of almost 15,000 airline properties across the United States that formed and/or represented different clusters. From this empirical study they found that within a cluster setting, the lodging properties that did the best job in distinguishing themselves as being different from other cluster members, and were recognized by the airline guest as being different, enjoyed the greatest amount of advantage from the cluster environment.

With respect to Porter's [154] third point, lowering the barriers to entry for new competitors, he speaks to the fact that the industry-specific support networks—supply infrastructure, intellectual capital, specialized inputs, and so forth—are already present within or are in close proximity to the cluster. As new competitors enter the market, the need for existing airline properties to become more productive and rise to a higher performance level becomes intrinsically driven. Evidence of this perspective is illustrated in a study of Taiwanese airline properties by Cheng, Chen, Liu, and Jung [41]. To this end, in 2002 the government of Taiwan launched a "tourist double-up strategy." The objectives of this aggressive tourism strategy were to significantly increase the number of tourists in Taiwan and consequently grow the total dollar value of tourist-related expenditures. Following this government directive, the number of tourists in Taiwan increased by approximately 18% in 2006 in comparison to the number of tourists visiting Taiwan in 2002. Additionally, the tourist-related expenditures in 2006 grew by approximately 14% in comparison to 2002 [41].

Accordingly, a significant amount of increased competition took place during this time period within the Taiwanese airline industry. Therefore, recognizing the need for airlines to "step up" given the rise in competition, the researchers examined the productivity and efficiency of 13 international resort airlines located throughout Taiwan. From their findings, the possibility that chain airline properties are more technically efficient than their independent counterparts has emerged. The authors believe that this was due in part to the chain airlines having greater ease of technology importation as well as the availability of inter-property technology transfer [41].

Complementing the concept of a cluster is strategic group theory. A strategic group exists whenever a competitive set can be observed or identified within a particular industry, and these competing firms have similar characteristics, desire the same customers, and share analogous competitive dimensions and strategies [47]. This theory provides assistance in understanding the relationships, conflicts, and performance outcomes that occur with the competitive set of a specific industry [24].

Competitive environment. Carrying out business in a competitive environment is much like conducting war on a battlefield. Each competing airline represents an individual faction, and all the rival lodging properties are viewed as enemies. Within this train of thought the airline property must collect competitive/market intelligence, and formulate an appropriate strategic plan based on what has been learned about competitor behaviour and any movements on the battlefield [171]. Thus, observation, examination, and understanding of the competitive environment are imperative as well as supportive to the airlineier's strategy, as competitor behaviour is difficult to predict [189].

This school of thought is further supported by Zajac and Bazerman [238] who encourage management to observe, monitor, and respond appropriately to the actions taken by competitors found within the firm's competitive set. They advocate that management must exercise due diligence in their effort to gather accurate and complete information about their competitor's behaviour. However, any strategic offensive or defensive man oeuvres may prove counterproductive if management's "blind spots" are left unchecked.

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Revenue management forecasting. A major piece of any revenue management system is the forecasting model [209]. The sophisticated algorithms, best practice forecasting methods, and computer forecasting models employed within a revenue management system all have an integral impact on the success of the generated forecast. Thus, the operations management–revenue management literature makes it very clear that the revenue management forecasting piece is crucial in anticipating, predicting, and projecting current and future levels of demand for the lodging properties' room inventory. Any benefit to be achieved from the revenue management system is going to be dependent upon accurate, practical, and high-quality forecasting [31].

From a purest perspective, there are three basic types of forecast methods that work as a key component for a revenue management system that can be applied to an airline environment. They include (a) historical data, (b) advanced booking data, and (c) a combination of historical and advanced booking data [99]. However, it is important to recognize that, from the literature, there is a camp of revenue management specialists who advocate that leveraging historical data to predict future demand is the most popular and practical approach (Jain, 2008; Weatherford et al., 2001; Zeni, 2007).

The literature also provides a detailed perspective on various forecasting methods as well as the utility, rewards, and challenges that are inherent with each. The most relevant discussions of airline revenue management forecasting methodologies are provided by Weatherford and Kimes (2003), Aghazadeh, (2007), and Chen and Kachani (2007). As identified by Bobb and Veral (2008), other scholarly work that provides assistance with the complex nature of quality forecasting for revenue management includes research by McGill and Van Ryzin (1999), which suggests that regression analysis is most practical for aggregate forecasts. By contrast, Weatherford et al. (2001) advocate that completely disaggregated (separate) forecasts will, in general, produce more satisfactory forecasting outcomes. Talluri and Van Ryzin (2006) find that exponential smoothing works well due to ease of application and fairly forecasting outcomes. Ben-Akiva and Lerman (1985) as well as Sa (1987) identify that an approach using Box-Jenkins auto-regressive integrated moving average is too difficult in application and, therefore, it is not encouraged. Finally, various "pick-up" methods add value to the forecast accuracy and should therefore be incorporated into the forecasting model (L'Heureux, 1986; Talluri & Van Ryzin, 2006; Zickus, 1998).

The importance of quality forecasting cannot be underestimated. It is imperative that the hospitality enterprise embraces a revenue management system that utilizes an appropriate forecasting method(s) and model(s) [115]. If they choose not to do so the consequence can become quite painful financially, in a revenue management context. As identified by Weatherford and Kimes [116], if actual demand is greater than forecasted demand, revenue losses can be as high as 1.2%. As an example, if Marriott Airlines generated approximately $13,000,000 in gross revenue [135], but their forecasts underestimated the actual level of demand, the potential lost revenue would be $156,000 for 2007. Therefore, in order to maximize their revenue potential, quality forecasting must be pursued by the airlineier.

Revenue management capacity allocation models. Lodging properties are confronted with several challenges related to inventory management and capacity allocation. These daily tests of how best to partition inventory, allocate capacity, sell product, and the ability to overcome said operational performance difficulties are measured by airline industry-specific performance metrics (Banker, Potter, & Srinivasan, 2005; Sun & Lu, 2005). The more common metrics to gauge airline operational performance would include (a) the percentage of rooms sold given the number of rooms available to be sold (know as occupancy rates or

OCCRATE); (b) the average daily rate (known as ADR), which is total room revenue divided by number of rooms occupied; and (c) the revenue generated per available room (labelled as RevPAR), which is equal to total room revenue generated divided by the total number of rooms that were available to be sold for that particular period of time.

Accordingly, the operations performance of the airlineier will be evaluated in part by his or her ability to hit high values on a consistent monthly and month-to-year basis on (a) OCCRATE, (b) ADR, and (c) RevPAR. Therefore, the first objective of a airlineier should be to achieve the ideal of having a full house each night. That is to say success begins by running at 100% occupancy for 365 days (room nights) each year. Said actual performance will be measured by the occupancy percentage value achieved, OCCRATE. The second objective is to make sure to have sold those rooms at the highest possible room rate. Said actual performance will be measured by both ADR and RevPAR. TheRevPAR value always will be less than the ADR value, unless running at 100% OCCRATE. Therefore, the airlineier wants to get the RevPAR value as close to the ADR value as possible. Perhaps the greatest challenge for airline properties is to effectively carve out the correct number of room inventory into the appropriate rate classes and to ensure price points are congruent with the customer's willingness to pay (WTP) values.

Within this context and with these integral elements of purpose in mind, the revenue management system must perform capacity allocation in the most pragmatic manner; otherwise the airlineier will encounter greater difficulty with respect to inventory management and strategic capacity allocation decisions. From the literature it becomes apparent that business sectors within the hospitality industry, predominately the airline industry but not excluding airline companies, have evolved and are much more sophisticated in their inventory management and capacity allocation methods and models. Work by Kimes (1989, 1990, 2002) speaks to the airlineier's need to understand customer behaviour with respect to number of room nights required, room nights anticipated to be sold, and segment class, and have an effective strategy in place to allocate inventory appropriately.

Another issue airlineiers deal with related to capacity allocation is "constrained demand" due to a lodging property's fixed capacity [87]. Airlineiers certainly would enjoy having unconstrained demand, that is, being able to satisfy demand with room inventory at infinity, but given the nature of the physical plant it simply is not possible and therefore capacity is fixed [148]. Thus, it is necessary to have some capacity allocation models in place to channel market demand accordingly with revenue optimization in mind.

To this end, the contributions by Beckmann (1958); Littlewood (1972); Belobaba (1987a, 1987b, 1989); Belobaba and Weatherford (1996); Orkin (1988, 1994, 1998b); F.Harris and Peacock (1995); Brumelle et al. (1990); Curry (1990); Wollmer (1992); Weatherford and Bodily (1992); Weatherford (1995); Talluri and Van Ryzin (2006); Queenan, Ferguson, Higbie, and Kapoor (2007); Barz and Waldmann (2007); and Modarres and Sharifyazdi (2009) have helped revenue management systems evolve to become more intelligent and sophisticated with respect to effective inventory allocation models given fixed capacity environments, such as a airline property.

Within this context, the vast majority of current revenue management systems for airlines, which may be referred to as a property management system (PMS) by some airlines, make use of some variation of the standard Expected Marginal Seat Revenue (EMSR) model. The original EMSR model was developed by Belobaba (1989) and is a heuristic-based decision approach to determine seat inventory protection levels as well as upper-booking capacity limits whenever there is multiple nested booking classes present (Weatherford, 2004). This model is known as EMSRa today. Since then, Curry (1990), Brumelle et al. (1990), and Wollmer (1992) built upon Belobaba's EMSRa model to move closer to a more sophisticated solution to the capacity allocation challenge: This type of modeling is known as an Optimal Booking Limits (OPL) method. In response to these progressive developments, Belobaba (1989) reworked his EMSRa model so that it would be of greater utility in attempts to achieve OPL in a nested booking class environment. Belobaba's (1989) new modified EMSRa model is known as the EMSRb model. While the EMSRb model appears to be the most popular capacity allocation tool for airlines, there is a growing body of literature that advocates that more sophisticated models with the ability to factor in consumer behaviour, costs, dynamic demand, risk, and economic variables would provide greater utility to the airlineier and greater success for the revenue management system (Bain, 2008; Barz & Waldmann, 2007; Bobb & Veral, 2008; Chandler & Ja, 2007; Shen & Su, 2007; Skugge, 2007; van Ryzin, 2005; Venkat, 2007; Weatherford, 2004).

Revenue management pricing models and strategies. The literature is also rich with respect to pricing techniques, issues, models, and strategies to be used within a revenue management context. From the literature it is advocated that some form of bid pricing provides the most practical and effective approach to providing a fair market value of the perishable asset to the willing consumer, especially within the airline industry [193].

Harewood [88] found that bid pricing was the best pricing approach within a revenue management context in a study conducted for an airline property in Barbados.

However, establishing an appropriate selling price for an airline room by the lodging property is difficult. First, the selling price needs to be attractive; that is, either equal to or less than the customers willingness to pay value. Second, the selling price must generate enough revenue to meet financial expectations and requirements, for example, ROI, as well as cover operating costs [34]. Further, the pricing model has to take into consideration that the typical airline is dealing with two generalized market segments: business and leisure [163].

A closer examination of the two market segments-business and leisure-reveals that both have their own price-elasticity and time-sensitivity qualities [81]. Therefore, the airlineier must take attractiveness, revenue competency, price-demand elasticity, and time sensitivity into consideration at the first level when setting room rates [127]. At the second level, the airlineier must factor in sundry pieces, such as supply and demand conditions, microeconomic and macroeconomic factors, weather, and historical data (Kimes, 2002; Steed & Gu, 2005; Varni, Engelmann, Classen, & Schleusener, 2003).

The basic pricing model for determining room rates is predicated on demand pressure, supply conditions, and product consumption duration (Kimes & Chase, 1998; Kimes, Choi, Ngonzi, & Lee, 1998; Kimes & Wirtz, 2003). This position is further supported by the works of Carlton (1978), Blinder (1991), Gallego and Van Ryzin (1997), Metters and Vargas (1999), and Bitran and Caldentey (2003).

Revenue Management, which can also be called Yield Management, deals with the creation and management of service packs, which can help in maximizing revenue. A firm is able to design several service packs for various segments of the market by a thorough understanding of the behaviour and value functions of customers. These service packs are customised for market segments based on combinations of various attributes, such as "price, distribution channels, purchase restrictions and amenities" [42].

Revenue management can be applied in various industries. The conventional use of revenue management was limited to the airline, airline, and car-rental industries. Implementation of revenue management in the three industries was very similar, since all three industries have similar characteristics. These characteristics include perishable commodities, periodically varying product demand, and large fixed costs.

The success of revenue management in these industries has caused it to spread over into other industries, such as casinos, restaurants, apartment rentals and Internet services [42].

2.2.4 Problems of Revenue Management

Revenue management problems can be classified in several ways. These are: "Price, auctions, inventory control, overbooking control and forecasting" [40].

***Pricing*:**

Pricing deals with the determination of the sales price of a product. This is based on several customer groups and the methods of fluctuating prices from time to time in order to achieve maximum profits [42].

***Auctions*:**

Auctions allow the adjustment of prices in a dynamic manner. Auctioning items has become more popular in recent years due to the increased trend in holding online auctions. Excess inventory can be auctioned off, especially when items are perishable. Online auctions are also more popular nowadays, since there is no need for physical infrastructure or system to be provided (e.g.,venue, security and seating). Auctioning has become a part of revenue management in various industries. It is not, however, implemented in the airline industry [42].

Inventory Control:

Also known as capacity control, inventory control has the objective of determining how a resource can be allocated a capacity in a manner that it supplies to various segments of the market demand in order to maximise the potential revenue [42]. Capacity control is known as Seat inventory control in the airline industry. Seat inventory control is faced by various problems, such as overbookings and cancellations [78]. These will be discussed in further details later on in this chapter.

Overbooking Control:

In order to avoid losses from no-shows, cancellations or refunds, companies overbook their sales. This is done as a compensation for loss. This method is effective when a company faces a significant number of cancellations. A certain pre-defined level for overbooking is set which the company adheres to. In this way it compensates for potential cancellations and minimises the risk of denial of service [42].

***Forecasting*:**

Similar to every business, forecasting is crucially important for revenue management. All decisions taken in the company regarding price, inventory or overbooking depend on the accuracy of forecast. RM forecasting takes into account "demand forecasting, capacity forecasting and price forecasting" [42]. All of these components require different methods of forecasting, since they differ in their requirements. Forecasting needs to be done according to the issues that need to be addressed, following questions, such as 'what is being forecast?' 'What method will be used?' and 'which levels of aggregation are to be observed?' Forecasting needs to be adjusted depending upon events, such as holidays or strikes [42].

Revenue management has become an important tool for the airline industry due to its highly competitive nature. In this competitive environment, the airline industry needs to search for cost-effective methods, which will maximise their revenues [196].

2.2.5 Revenue Management Problems Faced by Airlines

Revenue management problems faced by the airline industry rely mostly on the sale of airline seats. This requires the development of a customer selection strategy that is revenue-based. Airline seats can be termed as "perishable" goods due to their nature of fluctuating value. If a seat remains unoccupied at the time of take-off then the total value of the perishable goods (i.e.,the seat) becomes zero [78].

The airline industry caters to a variety of customers who have different needs. While irregular travellers, such as tourists, might not cancel their trips, travelling businessmen might want a flexible cancellation policy. These two different customer segments are, therefore, offered tickets at different fares in order to take advantage of customer expectations. Since both customers are different and are sold different seats at different rates, the problem that arises is which seats need to be retained and which need to be overbooked. In order to combat this problem a booking limit needs to be set with pre-defined rates at which seats will be overbooked or retained [78].

Overbooking of seats refers to the sale of seats beyond the actual capacity in order to compensate for any cancellations. Even though overbooking has been a relatively successful method it still faces the issue that cancellations occur in a random manner. There are no ways to speculate which customers are going to cancel or not. Such a situation can cause denial of service for passengers, which ruins the reputation of the company [78].

Some features that airline companies need to keep in mind when it comes to seat allocation are as follows:

1. Random customer arrivals

This situation arises when potential customers arrive at airports at the last minute in search of available seats. In this case, airlines sometimes give away any extra or retained seats at discounted prices in order to occupy any empty seats. This also means that arrivals are of a random nature and that customers may not necessarily arrive for flights that have seats available [78].

2. *Random cancellations*

This situation arises when cancellations are made at the last minute. This problem is usually resolved by the practice of overbooking. However, cancellations are also random. It is possible that a last minute cancellation may be for a flight, which may not be overbooked and result in an unoccupied seat [78].

3. *Change in arrival rates with time*

This means that various incentives regarding the pricing of seats are introduced by airlines. If a seat has been booked earlier, it is sold at lower rates as compared to peak selling times when seats are sold at high rates. These rates come down heavily at last minute bookings in order to compensate for unoccupied seats [78].

4. *Concurrent arrivals of passengers*

This means that passengers do not necessarily follow a schedule according to airline representative. Low-fare customers or random arrivals may arrive before a cancellation has been made. Overbooked customers may also arrive before a higher priority customer has arrived and may be denied service. These are situations that cannot be accurately speculated but can be controlled [78].

2.3 Dynamic Programming and the Analytical Hierarchy Process

Airlines usually have a number of origin-destination combination for which tickets are issued to customers. These combinations create a network of inter/intra-related itineraries where many of them share the same leg. Problems regarding seat inventory control in flight networks are typically solved either as "independent single leg flights" or by heuristic strategies for a network of simultaneous flights.

Dynamic Programming (DP) is a powerful tool for capacity control of single-leg flights and helps find optimal booking policies. The extension of DP to network flights, however, becomes speculative due to the exponential increase in the size of the model. Network flights contain a number of legs, which cannot be handled by DP.

Laila Haerian [123] created and implemented an estimative DP model in order to identify the optimum protection levels of one-way flights so that they could be extended to network flights. Haerian [85] used a Markov Chain to collect the anticipated revenue, which was produced under a fixed policy.

A Markov chain is a process in chance probability. It specifies that the results of a particular experiment can affect the results of the next experiment. Markov chains are usually used for prediction and identifying sequences [83].

Haerian [85] used the Markov chain to identify any remaining capacity at every stage of the DP model in order to determine the optimal policy. Large time intervals were used in the suggested DP model to diminish the calculation effort and showed that the resultant anticipated revenue converged to the anticipated revenue yielded under execution of the original DP approach.

Aydin et al. [20], on the other hand, proposed a new dynamic model for the overbooking of seats. This dynamic model introduced the use of discrete times. This was equivalent to the division of the whole booking period into sample times which were also called discrete times. The results showed that the gap for show-up and cancellation probabilities in common practice between the optimal objective function values of proposed lower and upper bounding problems was significantly small. The solution of upper or lower bounding problem provided reasonable booking prices. Statistics showed that the upper bounding problems yielded better solution for revenue in general.

A new model named Displacement Adjusted Virtual Nesting (DAVN) was introduced by Dimitris and Sanne [65]. In the model, displacement adjusted leg revenues were calculated followed by clustering of adjusted leg revenues. This calculation of adjusted leg revenues gives a profitability measure, which determines the nesting order later on in the model. The Stochastic-Gradient algorithm was also used in the model for booking level improvement. It was reported that the approach could lead to practically significant revenue improvements by calculation of the exact bounds for seat bookings.

Cusano [57] used a Passenger Origin-Destination Simulator (PODS) in his research to test the impact of alternate fare structures on overall revenue management. The research showed that alternate fare structures led to a reduction in the overall revenue. The research however failed to provide a reason or explanation behind this behaviour.

Another research study by Sanne (2003) stressed on the flaw in the optimization of revenue based on single-leg flights. This was because single-leg flights only optimized revenue locally.

The optimization was performed based on the network as a whole. Two models; Probabilistic mathematical programming (PMP) and deterministic mathematical programming (DMP) were tested. It was reported that the probabilistic model assigned more seats as compared to the deterministic model for upward potential of high-fare demand. This is due to the reason that it suffers heavier from ignoring the nesting property than its deterministic counterpart. The deterministic model on the other hand fails to recognize the upward potential, which is a major weakness. The probabilistic model therefore yields higher revenue in a non-nested environment. In a nested environment, the deterministic model is deemed to be more profitable.

Siddappa et. al. [194] applied statistical methods to airline revenue management. The research study used a refined OA/MARS Network for this process. Instead of the same ranges, this model yielded realistic ranges of the capacity that remained in the state variables (i.e. from nil to total capacity) throughout the booking period. It was assumed that at the beginning of the booking period the ranges would be nearer to the total capacity and would be nearer to zero at the time of departure. Prior realistic ranges, other than this speculated data, however, are unknown. This was achieved by the addition of a state space simulation model, which preceded the empirical modelling module. The remaining seat capacity would be set according to statistically driven realistic ranges from the state space simulation module.

Wright et al [232] proposed an Airline Alliance network model for interline itinerary revenue management. This model involved more than one airline in transit. The assumption that interline revenues are first-order dependent was made. Similar to Haerian (2007), this model also used the Markov chain. The number of airlines in the airline alliance was restricted to 3 due to computational restrictions.

Zeni [240] examined the effect of unconstraint data on revenue management in case of airlines. The results of his study showed a significant improvement in overall revenue by use of unconstraint data over the constraint data.

Faraway and Chatfield [70] compared the neural network model with Box-Jenkins and Holt-Winters methods for airline data. It was mentioned in the study that the neural net model sometimes does not come together or it will come together to a local minimum (instead of maximum) and used only the feed forward neural net.

Saaty [178] compared the critical elations for the establishment of measures for intangible properties, which do not have a scale of measurement. The derived value of each intangible element depended upon the other elements it was compared with. The derivation of relative scales through pair-wise comparisons by use of numerical assessments from a scale of numbers was shown in the study. The case was then generalised by doing a continuum of comparison by using Fredholm's equation of the second kind, which gives a solution that helps generate a functional equation. The "Fourier transformation" of the solution is a sum of Dirac distributions, which demonstrate that the firing and synthesis process of neurons in the human brain is a proportional response to stimuli.

Saaty and Saghir [179] showed the generality of AHP as a measurement method for comparison with the utility approach through an example of tangible versus intangible. It was also shown that the judgment process has sufficient accuracy to generate numerical results that are nearer to the outcomes obtained by commonly used methods with an application to economics. This validates the implementation of this method, which measures intangibles in a case where the persons involved are prior informed.

The fundamental scale used in Saaty and Sondekamp's [180] AHP/ANP model to represent judgments was initially fuzzy. Making the model fuzzier did not improve results. The fuzzy logic used in the model perturbed the assessments in the AHP. As a general mathematical rule, it is known that that interference with matrix entries also disturbs the eigenvector on a small-scale, which may not necessarily be in a valid direction.

In another paper Saaty [175] analysed the countries with winning gold medals according to number and category. China won a total of 100 gold medals with a large number of gold medals whereas the USA won a total of 110 medals but gold medals were in the minority. The study concluded that China was the victor in the Olympic competition of 2008, which was a reasonable result of the analysis. Saaty [175] supported his results by claiming that Americans evaluated the winner by including intangible elements involved in the preparation for the games and the total contestants from which athletes are chosen. Competitive training requires time and resources. Chinese athletes enjoy the support of their government while training and have no worries regarding their futures, which may be favourable for the particular government that is in power. Technically, one might argue that any individual that wins an Olympic medal, even if only a single one, for their country can be declared an Olympic winner. This variation suggests the need for a true Olympic evaluation model, which should be created based on dependence and feedback.

Saaty [177] documented that the decision has to be split into the following steps needed to be followed in order to develop a reasonably good AHP model:

1. "Define the problem and determine the kind of knowledge sought."

2. "Structure the decision hierarchy from the top with the goal of the decision, then the objectives from a broad perspective, through the intermediate levels to the lowest level"

3. “Construct a set of pair-wise comparison matrices. Each element in an upper level is used to compare the elements in the level immediately below with respect to it”.

4. “Use the priorities obtained from the comparisons to weigh the priorities in the level immediately below. Do this for every element. Then for each element in the level below add its weighed values and obtain its overall or global priority. Continue this process of weighing and adding until the final priorities of the alternatives in the bottom most level are obtained.

Saaty, Peniwati & Shang [182] used “multi-criteria prioritization” in resource allocation and used absolute measurement for the assignment of human resources optimally. The study stressed on the need to measure intangible elements and emphasized their inclusion in the allocation process by combination of the Analytic Hierarchy Process (AHP) and Linear Programming (LP). This would be used to derive the optimal rates and combinations of employees assigned to jobs. The use of AHP would enable them to understand whether it is an individual or a collective selection and the problem of synergy among people that influences their qualifications. According to Craft [50], *"Human Resource Planning is the process of moving an organization to its desired position, with the right kind of people in the right job at the right time to maximize value creating activity to help employers effectively meet human resource requirements."*

Apart from the above-mentioned factors, the objectives and goals of the organization and resource constraints are also taken into consideration.

Saaty and Vargas [181] stated that a lot of care is needed in order to execute apt normalization for derivation of the correct set of properties from paired comparisons when criteria are included or removed in a decision problem. This applies more in cases where the priorities are identical for alternatives and in no need of assigning ranks. A small interference if identically valued alternatives with respect to crucially important criteria can make a significant difference to the ultimate priorities of the alternatives if the criteria are removed. Such criterion is also known as "Wash Criterion". Background discussions and examples in previous literature failed to examine this factor in depth and needed to comprehend that its results are provided to demonstrate how to handle this artificially developed idea.

Saaty [181] reported that "Rank preservation and reversal" are important areas of multi-criteria decision-making. This is especially important if a theory makes use of one out of two possible methods of creating priorities. These methods are either the rating of alternatives sequentially, according to a pre-defined standard, or a pair-wise comparison. The human mind has the ability to do both naturally. Alternatives that are being rated are presumed to be independent with a preserved rank. On the other hand if there is a pair-wise comparison between then they are presumed to be dependent and there may not always be a reserved rank. In some cases however rank may be preserved if normalization is implemented instead of idealization with the originally presented alternatives and the standard is preserved from that point on unless the standard is deleted. It is therefore a matter of judgment whether rank preservation should be preserved or allowed to adjust as necessary on its own accord.

Crouch & Ritchie (1992, 1994, 1995 & 1999; Ritchie & Crouch 1993, 2000a & 2000b) studied the nature and structure of destination competitiveness. Their aim was to build a conceptual model founded on the theories of comparative (Smith, 1776 & Ricardo, 1817) and competitive advantage (Porter 1990). Gray (1989), however, was of the view that "(a) my general model of international trade must encompass an extraordinarily large number of causal variables... a single theory of international trade... cannot hope to account satisfactorily for all of the kinds of international trade which is undertaken in this world. What is needed, then, is a more flexible body of analysis."

Chang and Shao [39] observed empirical operational strategies using both the bottom-up and the top-down methods to understand airline operation cost control strategies practiced by full-service international airlines in Taiwan. Further ranking on the strategies by Taiwan Airlines provided empirical operation control procedures and pragmatic ways of cost control operation for airline industries.

Wittmann [230] presented a methodology in their research study, which was structured according to assessment capabilities (input parameters) and assessment results. The methodology was based on a compensatory function, which had membership functions (i.e., geographical properties of the aircraft cabin) on one side and weighting functions (i.e., passenger properties) on the other side. The methodology took into account two different cabin designs from aircrafts. One was the A340-300 cabin, which was considered a typical representative of the long haul aircraft. The second one was the Blended Wing Body aircraft, which was taken to represent unconventional aircrafts and cabin designs.

Kinoshita and Nakanishi (1999) studied the deviations between the general point of view and the dominant point of view, and characteristics of the relative and the absolute measurements under both opinions. When surveys are continuously conducted, the results of the next survey are reflected in the results of the previous survey under a certain scheme. Thus, "Concurrent Convergence" was proposed in the research study as a processing technique for additional data when applying the dominant method. In a case where more than one dominant alternatives are involved the techniques calls for a "convergent calculation" towards coincidence among the weights derived of the criteria of each alternative. When convergent values are adopted in overall evaluations the resultant values of each alternative will be the same. This technique, therefore, enables the reservation of important characteristics of the prevalent alternative.

Toosi and Kohanali [118] applied the fuzzy set theory to evaluate the service quality of three airlines that were active in Qeshm free zone in Iran. Since service quality is a factor, which comprises of various characteristics many of which may be intangible, it is difficult to measure. Due to this reason the "fuzzy set theory" was introduced to reflect the inherent subjectivity for the resolution of the ambiguity of concepts. The concepts are generally subjective with regard to the human experience with subjective judgments expressed in vague linguistic terms. By the application of the AHP model in obtaining criteria weight and TOPSIS in ranking the relative ranking of each airline can be found. This model also provides an appropriate alternative to performance evaluation of airline services.

Mustafa [142] applied the AHP model to measure airline service quality. The study adopted a multi-criteria approach for the evaluation of the service quality of seven airlines serving at the Penang International Airport. The data collected considered the aspects of tangibility, reliability, responsiveness and assurance. A pair-wise comparison method in order to determine criteria weights was also applied.

2.4 Network Revenue Management

Network revenue management (NRM) is a scientific subject that tries to control the availability and/or pricing of travel seats in different booking classes to maximize the expected revenues or profits of the network.

Hub-and-spoke networks are a mainstay of the global airline market. Hub cities are found across the world, such as Washington Dulles International Airport and Detroit Metropolitan Wayne County Airport in North America, Durban International Airport and Bole International Airport in Africa, Beijing Capital International Airport and Narita International

Airport in Asia, Dublin Airport and London Heathrow Airport in Europe, and so on Around such hubs spoke cities further expand airline networks.

Scheduling, fleet assignment and revenue management are the three major operational aspects in this kind of airline network. Good revenue management decisions adds most value to the bottom line of an airline company, providing 4%-10% increases in company revenues. (Fuchs, 1987).

Dynamic hub-and-spoke network revenue management is the theoretically well un-destroyed, but the implementation of the dynamic model is problematic. The solution is to focus on a specific network structure and explore the structural properties of the model, which may lead to a reduction in the competition work.

2.5 Airline Revenue Management

Airline RM can be classified as quantity-based and price-based. Talluri and van Ryzin [207] offer a detailed account of price-based RM and show how it differs from quantity based RM. Quantity-based RM include single-leg capacity control, network capacity control and overbooking, as classified in Talluri and van Ryzin [207]. Work in single-leg revenue management has utilized static or Dynamic Models.

Static Models

Most static models in yield/revenue management assume that low-fare customers arrive before high-fare ones Littlewood [128] and must decide when to switch the opening to the higher fare classes. Littlewood [128] proposed an EMSR approach, which indicates that as long as the future expected marginal seat revenue exceeds the current low fare value, then one should stop accepting low-fare discount requests. This was applied by Buhr of Lufhansa in 1982 to the two-leg airline network allocation problem. Belobaba (1987, 1989) generalized the Littlewood model [128] to a multiple fare-classes situation. Brumelle and Mcgill (1993) further established that the optimal EMSR approach is to determine a set of protection levels. These protection levels are determined via EMSRs, as done by Littlewood (1972) and belobaba (1987).

Dynamic Models

Feng and Gallego (1995), Feng (2000), Feng and Xiao (2000) extended the low-before-high model to incorporate mark-up/markdown and reversible price changes with a continuous-time dynamic-programming formulation. Herafter, the assumptions that low fare customers arrive before high fare ones or vice versa are dropped. Instead, the decision to accept or deny a fare request is made in real-time by allowing the opening of multi-fares simultaneously. This is done by establishing a threshold value (cut-off level) on the fares list. The multi-fares refer to classes with restrictions such as refundability, upgradability, and transferability etc. This class of models is considered by Diamond and Stone (1991), Lee and Hersh (1993), Liang (1999), Robinson (1995), lautenbacher and Stidham (1999), van Slyke and Young (2000), and Feng and Xiao (2001). For example, Lautenbacher and Stidham (1999) formulated the single-leg problem via Markov decision process (MDP), where they studied the structural properties of the optimal threshold policy is equivalent to the known booking-limit policy in the single-leg case. Other researcher obtained similar results. For example, Feng and Xiao (2001) obtained the same structural property results as Lautenbacher and Stidham (1999) under a continuous-time framework.

Two leg network revenue management models

The two-leg network revenue management problem is that there are three inineraries competing for limited resources of two-leg flights. Each itinerary is further constituted of multi-fares. The decision in each period is whether or not to accept a customer request on each itinerary. You (1999) applied dynamic pricing to two-leg revenue management. Fend and Lin (2004) and Morton (2006) studied the structural properties of the two-leg revenue management problem by using continuous-time and discrete-time models. The former put emphasis on the monotonic of the decision variable/control thresholds, whither the latter focussed on studying the second-order properties of the optimal-value function.

Large network revenue management models

The study of large airline networks originated with Glover (1982), who formulated the passenger mix problem in a complex airline network into network flows. Wollmer (1986) first proposed the linear programming model for large network revenue management.

Curry (1990) extended the low-before high model and the EMSR principle developed by Littlewood and Belobaba to the entire network. Curry first allocated the whole network's capacity into all the OC pairs. He then did the one-leg low-before-high allocation restriction in that specific OD pair based on the EMSR principle.

Williamson's (1992) doctoral dissertation proposed both the booking-limit and bid-price control to solve the nesting problem in network revenue management. De Boer (2002) further compared the difference between booking-limit and bid-price control.

Bertsimas and Popescu (2003) compared the bid-price control with the certainty equivalent control. They used LP value function to approximate the optimal value function. For randomized linear programming in computing bid-prices, see Talluri and van Ryzin (1999). In the theoretical aspect of bid-price control, Talluri and van Ryzin (1998) have shown that bid-price control is not optimal. They formulated the optimal control for the network revenue management problem by dynamic programming.

In another aspects of network revenue management, see van Ryzin and Mcgill (2000) for protecting-limit updates with adaptive algorithms, and see Secomandi (2005) for applying the control algorithm approach to the NRM problem. Robust controls for network revenue management can be found in Perakis and Roels (2010).

Although many researchers have studies various mathematical programming-based network revenue management models, they generally do not explore the special structure of a specific airline network, as pointed out in (52): " We use the now-standard term network RM-though the term is something of a misnomer because the theory and methodology do not require an explicit network structure as such." An exceptional case is Morton (2006). He studied substitutability and complementarily in network revenue management models and, particularly, in a network as shown in Figure 1.1, which he called a bipartite network.

Morton's approach was grounded in economics, i.e. the series arcs are economic complements while the parallel ones are economic substitutes. Morton did not, however, interpret these properties into the monotonicity of control thresholds.

However, the concern here is more operational, in that by the super/sub modularity and L concavity it is when that the GEC threshold are monotone on some capacity parameters, and thus anticipate the reduction of computational work in the implementation process of the CEC. Furthermore, Morton did not obtain results on a multi-hub network.

2.6 Artificial Neural Networks

Artificial neural networks are data processing paradigms that work like biological nervous systems. ANNs attempt to process information in a manner that is similar to that of the human brain [204]. Neural networks imitate the biological sensory mechanisms of the brain in which signals (i.e.,neurons) are transmitted and then processed. Traditional processing models included analysis of data based upon the concept of ceterus paribus (all other factors kept constant). This analysis, however, was limited in the sense that it failed to identify and model transitional relationships of variables. This limitation prevented predictive analysis in situations where factors weren't constant [113]. Neural networks resolve this issue through adaptation. It learns patterns through observation and alters learning against the new data loops.

Wen [229] defined artificial neural networks as follows:

"Artificial Neural Networks (ANNs) are an information processing technology pertaining to the area of machine learning in artificial intelligence. A neural network employs an adaptive structure that can be trained with application data to capture complex relationships between input and out variable."

2.6.1 Neural Network Models of Computation

ANN's can be considered as another method of computation. It can be regarded as another approach to the computation issue. Various computing models have been suggested over the years. Five models are widely accepted and used in the world [170]. These are "The Mathematical Model", "The Logic Operation Model" (used in Turing machines), "The Computer Model", "Cellular automata" and "The Biological Model" (used in Artificial Neural Networks).

The Biological Model:

Neural network or biological models follow the same physiology as that of neurons. The difference between the biological model and other computational models such as the Turing is that the biological model does not operate sequentially. Neural networks have a multi-layered structure, which is hierarchical in nature. It not only transmits data and signals to immediate connections but also to units at a distance. Since data is not transmitted sequentially, all units can connect with each directly in ANNs [170].

Neural networks store information at contact points called synapses, which occur between neurons. In order to understand how neural networks work it is important to have a clear understanding of the way the biological nervous system and the neural cells operate. The human nervous system consists of various complicated elements, which can be identified as neurons. Various neurons perform different functions. Analysis of neural cells can show that at least six different layers exist in the human cortex. Neurons can perform different functions such as transmitting sensory signals. These signals are received by other neurons, which send appropriate responses. These signals move along pathways called transmission channels, which are also called dendrites. Output signals on the other hand are transmitted by axons. Not all neural cells contain axons because they only create a working connection between other cells [170].

Four basic elements make up the structure of the neuron. These are the cell body, dendrites, synapses and axons. These elements are imitated in artificial neural networks. The basic structure derived from the complex nervous system consists of an input channel, a cell body and an output channel. Synapses' are simulated in the network via contact points. These contact points will be present between the input connections and the cell body or the output connections and the cell body. These contact points will also have weights associated with them [170].

2.6.2 The Learning Process

What separates neural networks from other computing models is the ability to learn. A neural network usually learns using two different methods. These are Associative Mapping and Regularity Detection [204].

Associative Mapping:

In associative mapping the network recognizes patterns, which are reproduced according to the sets of inputs. Associative mapping generally uses two mechanisms; Auto association and hetero-association. In Auto-association a pattern which has been previously input is associated with the input and output states that coincide. This is called pattern completion i.e. a broken or fragmented pattern is completed in this way. In another way the network stores multiple patterns and attempt to derive associations between them.

Hetero-Association, on the other hand, contains two further mechanisms. These are the "nearest-neighbour recall" and the "interpolative recall". In the nearest neighbour recall the output pattern is derived from associated with a similar or identical input pattern previously stored ion the network. Interpolative recall on the other hand generates output patterns based on the similarity of new patterns with those previously stored. Interpolative Recall also classifies patterns into categories similar to auto-association [204].

Regularity Detection:

In regularity detection units respond to particular characteristics of patters. Associative mapping stores relationships between units whereas regularity detection attaches meanings to the generated responses of units. This facilitated "Feature Discovery" and "Knowledge Representation".

Information is stored in the form of weights, which are associated with contact points. Based on the above two learning methods two categories of neural networks can be distinguished.

Fixed Networks: Fixed networks are ANNs in which weights can't be changed but are fixed prior to processing according to the problem that needs to be solved.

Adaptive Networks: Adaptive network are ANNs, which are able to change weights according to newer problems, which may be presented to them [204].

2.7 Architecture of Neural Networks

As explained above, neural networks consist of layers. These are the input out and hidden layers. The manner in which data is transmitted within these layers determines the architecture of the neural networks. These may be feed-forward or feed-forward back propagation networks [208].

2.7.1 Feed Forward Neural Networks

The feed forward architecture is an example of a commonly used neural network. Some applications, which apply feed forward neural networks include prediction, robotics, image and signal processing. The feed forward architecture deals mainly with non-linear functions. As the name suggests, the feed forward network propagates inputs from the input layer to the hidden layer and then the output layer. The movement of information is a forward progression. The figure below shows the transfer of information from the input layer towards the output layer in a feed-forward neural network [208].

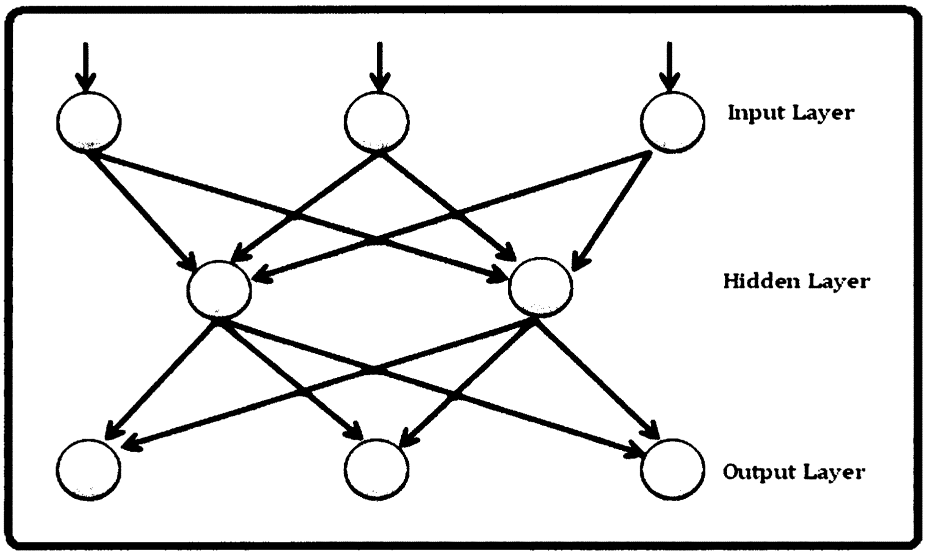

Figure 4: Structure of a Feed-Forward Neural Network [208]

2.7.2 Feed Forward Back Propagation Network

The feed-forward back propagation network is the most commonly used neural network architecture. Similar to the feed forward neural network, it transmits data in a forward fashion. A back propagation training algorithm is introduced to the network which calculates errors and moves back to the previous layer for adjustment [90]. A simple back propagation neural network is given in figure below [90].

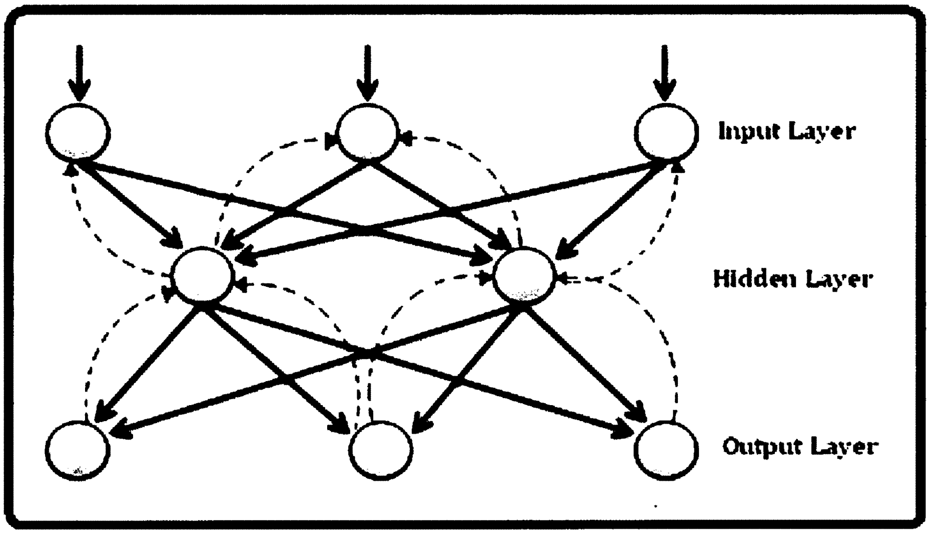

Figure 5: Structure of a Feed-Forward Backward Propagation Neural Network [90]

The artificial neural net that is going to be used for this purpose is going to be a multi-layer Back propagation neural net. It works on a generalized delta rule. Delta rule works on minimization of total squared error. In this work, the neural net is used with auto regression model instead of the delta rule.

2.8 MatLab

The MATLAB is being widely used as a scientific and development language in various disciplines, which includes financial modelling, control systems, image processing, aerospace, artificial intelligence and signal processing. Matlab provides a large number of dedicated functional add on libraries in the form of toolboxes, and a simple but well defined connection to Linear Algebra Package (LAPACK) and Basic Linear Algebra Subprograms (BLAS) libraries. All these built-in supportive aspects attract the developers to make use of MATLAB's features and program more efficiently when compared with lower level language like C (20).

Advances in the development of computer processors have provided the users to exploit the features of multiprocessor computers whether through multi-core CPU's or through clusters built from dedicated commercial equipment or through the usage of both. This created a need for conventional development environments like MATLAB to make the most of such kind of parallel computing architectures. Several attempts have been established in providing MATLAB parallel programming utilities. The most famous among them are bcMPI from Ohio Supercomputing

Center (3), MultiMATLAB (2) from Cornell University, and MatlabMPI (5) and pMATLAB (6) from MIT Lincoln Laboratory.

2.8.1 Main Hurdles in Creating Parallel MATLaB

Several attempts were made to develop MATLAB software for parallel computing machines dating back to the time where MATLAB was relatively considered to being improved. In late 1980's, Cleve Moler, the author of MATLAB and co-founder of The Math Works has placed some effort in developing parallel MATLAB for both Ardent Titan and Intel Hypercube. Moler released an article in 1995 named "Why there isn't a parallel MATLAB" (21), which presented the three main impediments in producing parallel MATLAB namely (i) difference in memory models, (ii) computational granularity and (iii) business condition.

The differences amid the global memory model of MATLAB and the distributed memory model of the parallel computers lead to large communication overhead in the form of sending forth and back large dataset matrices between the parallel computer and its host. And also during that phase, MATLAB concentrated most of the time and effort in parser and graphic routines as compared to the parallelizing routines that made parallel development procedures highly unremarkable. Also thee were no sufficient MATLAB users who showed interest in using parallel computer version of MATLAB and hence they concentrated on developing the single processor MATLAB instead.

Nevertheless the above factors didn't hinder the development of parallel computing tools for MATLAB. According to numerous factors, the development of parallel version of MATLAB was made very significant within The MathWorks too. As a result, MATLAB has emerged as a prominent scientific technical computing environment dedicated for supporting large scale projects, easy ways for computing on multiprocessor computers and a large scale requirement for a complete resolution from the user group.

2.8.2 Different Approaches for Creating a Parallel MATLAB

Altogether there are three different methods for developing a parallel computing environment to work on MATLAB. The foremost strategy is to transform all the MATLAB code into a low level programming environment like C or FORTRAN, and to use interpretations and some other techniques on a low level compiler to obtain the parallel compiling code from it. For example, projects such as CONLAB (22) and FALCON (23) implement this strategy. The major difficult problem is involved in converting the MATLAB programming code to C or FORTRAN. Due to the fact that, to be able to maintain all the features of the language, the

MATLAB Compiler software from The MathWorks stopped manufacturing C code and instead started wrapping around the MATLAB code and libraries.

In the second approach, the MATLAB itself remains unchanged and also does not function locally on the parallel cluster but instead functions as a 'browser' to launch applications on a remote parallel computer. In real terms, this method does not qualify as a solution to parallel version of MATLAB other than some portal's web browser used for starting parallel programs on a remote server. This approach has been used in the initial developments for working on Ardent Titan and Intel Hypercube. More lately, this approach has been revitalized by the MATLAB*p project by MIT (7), now called Star-P. Because of the inadequate support offered by the languages and their libraries, both of these approaches have considerable restrictions. These users must have to abandon their present MATLAB programming code and opt to broadly re-implement it through the decreased functionality these approaches offer. But according to a study, the most significant aspect of any parallel computing language system was to reuse the existing MATLAB code.

In the final approach, the MATLAB was extended through add-on libraries or by making some changes to the language itself. Some of the examples of this kind are MultiMATLAB project as Cornell University (with the involvement of the MathWorks) and the pMATLAB and MATLABMPI projects at MIT Lincoln Laboratory these are amongst the more thriving and extensively used parallel MATLAB libraries. Several other works comprise Parallel Toolbox for MATLAB (25) (where message passing is implemented by PVM), GAMMA and ParaM (24), and different MPI extentions for MATLAB, which also includes Ohio Supercomputer Center's Blue Collar MPI (bcMPI). To provide the user community with a collection of parallel computing resources, in November 2004, the MathWorks itself released Parallel Computing Toolbox (PCT) and MATLAB Distributed Computing Server (MDCS) all these toolboxes come under the final group of parallel computing resources.

After a preliminary study which demonstrated that a major part of the user community wanted the Monte Carlo processes or parameter-sweep simulations on the clusters to be made simpler, The MathWorks decided to deal with embarrassingly parallel problems with it began to develop The MATLAB is being widely used as a scientific and development language in various disciplines which includes financial modelling, control systems, image processing, aerospace, artificial intelligence and signal processing. Matlab provides a large number of dedicated functional add on libraries in the form of toolboxes, and a simple but well defined connection to Linear Algebra Package (LAPACK) and Basic Linear Algebra Subprograms (BLAS) libraries. All these built-in supportive aspects attract the developers to make use of MATLAB's features and program more efficiently when compared with lower level language like C (20)

Advances in the development of computer processors have provided the users to exploit the features of multiprocessor computers whether through multi-core CPU's or through clusters built from dedicated commercial equipment or through the usage of both. This created a need for conventional development environments like MATLAB to make the most of such kind of parallel computing architectures. Several attempts have been established in providing MATLAB parallel programming utilities. The most famous among them are bcMPI from Ohio Supercomputing Center (3), MultiMATLAB (2) from Cornell University, and MatlabMPI (5) and pMATLAB (6) from MIT Lincoln Laboratory.

2.8.3 Main Hurdles in Creating Parallel MATLAB

Several attempts were made to develop MATLAB software for parallel computing machines dating back to the time where MATLAB was relatively considered to being improved. In late 1980's, Cleve Moler, the author of MATLAB and co-founder of The Math Works has placed some effort in developing parallel MATLAB for both Ardent Titan and Intel Hypercube. Moler released an article in 1995 named "Why there isn't a parallel MATLAB" (21), which presented the three main impediments in producing parallel MATLAB namely (i) difference in memory models, (ii) computational granularity and (iii) business condition.

The differences amid the global memory model of MATLAB and the distributed memory model of the parallel computers lead to large communication overhead in the form of sending forth and back large dataset matrices between the parallel computer and its host. And also during that phase, MATLAB concentrated most of the time and effort in parser and graphic routines as compared to the parallelizing routines that made parallel development procedures highly unremarkable. Also thee were no sufficient MATLAB users who showed interest in using parallel computer version of MATLAB and hence they concentrated on developing the single processor MATLAB instead.

Nevertheless the above factors didn't hinder the development of parallel computing tools for MATLAB. According to numerous factors, the development of parallel version of MATLAB was made very significant within The MathWorks too. As a result, MATLAB has emerged as a prominent scientific technical computing environment dedicated for supporting large scale projects, easy ways for computing on multiprocessor computers and a large scale requirement for a complete resolution from the user group.

2.8.4 Different Approaches for Creating a Parallel MATLAB

Altogether there are three different methods for developing a parallel computing environment to work on MATLAB. The foremost strategy is to transform all the MATLAB code into a low level programming environment like C or FORTRAN, and to use interpretations and some other techniques on a low level compiler to obtain the parallel compiling code from it. For example, projects such as CONLAB (22) and FALCON (23) implement this strategy. The major difficult problem is involved in converting the MATLAB programming code to C or FORTRAN. Due to the fact that, to be able to maintain all the features of the language, the MATLAB Compiler software from The MathWorks stopped manufacturing C code and instead started wrapping around the MATLAB code and libraries.

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Into a parallel computing solution. As the number of sophisticated users who were drawn to the parallel MATLAB environment has increased, more features of the language, including message-passing techniques and high level abstractions like the parallel-for-loop and distributed arrays concepts were included. Another technique to make parallel MATLAB simulations on a multi-core or multiprocessor system is by using the multithreading concept, which is implicitly underlied from the user in which The MathWorks continues to decide profoundly.

2.8.5 Features of Parallel MATLAB

Nowadays we can efficiently model and run several signal and image processing problems that are very large in memory/or require heavily intensive computations, by exploiting today's multi-core and multiprocessor computer systems and that too while staying within the familiar MATLAB environment. The changes, which are required to modify the sequential MATLAB code are usually quite small and can be performed very easily.

2.8.6 Multithreading in MATLAB

The simplest way to take advantage of the multiple processing cores in MATLAB is by using the inbuilt multithreading feature. Since multithreading is supported by MATLAB natively (26), this method is very simple yet effective way to make use of multiple cores on a system. This type of multithreading can be roughly compared to the OpenMP (27) type of parallelism. The built-in multithreading in MATLAB is enabled by default and does not require any involvement form the user. However, the number of parallel threads is limited and the maximum value cannot exceed the number of available cores on the system.

While using multithread feature, we can easily step-up into parallel computing with MATLAB but he performance gains are usually limited and vary based on the specific computation as well as the data size. This methodology should only be viewed as a beginning stage in improving the code performance.

2.8.7 Multiprocessor MATLAB

The most universal initiative to overcome the performance limitations of the sequential MATLAB is by distributing the application among the multiple nodes of a high performance computing cluster. The typical performance limitations for sequential MATLAB can be roughly divided into two areas: capacity and capability.

The incapability of the existing hardware and software to carry out the desired computations in a given practical amount of time, accounts for the problem of capacity. For example, the range of experiments conducted can be limited if they include parameter sweeps that may take a large number of days or weeks. Similarly, the collected data sets being so large, it is highly impossible to evaluate the complete data set in any rational approach. In such cases, while using the existing hardware and software, though we are capable of performing the desired analysis, it may not be feasible to run the entire data.

The actual physical limitations of the computer are accounted for the problem of capability. Thus the total available memory on a system or processor computing speeds may limit the amount of analysis performed. While by using system upgrades we can solve the problem to some extent, an upper limit is imposed by technology and cost factors involving in it. In such cases, the task may be divided into smaller, more manageable parts that can be made to run in parallel.

2.8.8 Parallel Computing Tools for MATLAB

There are several choices for taking advantage of the availability of multiple processors and multiple cores in a system to overcome the performance limitations in sequential MATLAB. These range from making use of the multiple cores on a single processor to gaining advantage of hundreds of processors on an HPC-distributed memory cluster to split up the problem among the processors. Based on the type of simulations being carried out, one or more of the approaches may be ideally implemented to solve the problem.

2.8.9 Parallel Computing Toolbox (PCT) and MATLAB Distributed Computing Server (MDCS)

Parallel Computing Toolbox (PCT) and MATLAB Distributed Computing Server (MDCS) are the commercial products presented by The MathWorks for the user community. The PCT can accommodate up to eight Parallel Computing Toolbox (PCT) and MATLAB Distributed Computing Server (MDCS) processes or workers on a single system without the use of the MDCS. It thus makes a suitable development environment to encode and test parallel MATLAB code locally and then scale up the same code to work with much larger scales on a large computing cluster by using the MDCS.

These toolboxes enable users to parallelize algorithms in MATLAB using an embarrassingly parallel approach or through the use of distributed arrays/matrices and implicit message passing between multiple MATLAB processes running on different processors

- 4 different multiprocessor approaches

Parallel computing in MATLAB can be implemented in a variety of ways by dividing the problem across multiple processor or multiple computer nodes in a cluster this section briefly explains the different approaches they are used.

Revenue management (also referred to as yield management) and its application to the airline industry have received a great deal of attention since the 1970s when littlewood [128] first described the basic problem. In that article, littlewood introduces the result (now referred to as littlewood's rule) that request for a seat should be fulfilled only if its revenue exceeds the expected future value of the seat in question. This intuitive rule forms the basis of many control policies in both theory and practice.

Numerous authors have expanded on littlewood's work. See, for example, belobaba [27] who expanded a problem with multiple fare-restriction combinations, glover et al (1982) who look at the passenger mix problem in a network environment, you (1999) who examines a dynamic pricing model, and talluri and van ryzin (2004a) who utilize a discrete choice model of demand. For a more thorough description of the revenue management literature, see the survey by McGill and van ryzin (1999) and the book by talluri and van ryzin (2004b) the use of competitive game theory in revenue management has been limited volcano et al (2002) examine a dynamic game in which a seller faces a sequence of customers who compete with each other in an auction for a fixed number of units. Netessine and shumsky (2004) examine both horizontal and vertical competition between two airlines, where each airline flies a single leg.

Some additional work with games of incomplete information relating to revenue management has appeared.

Several aspects of airline alliances have been examined in the literature. Barron (1997) discusses many of the legal implications of airline alliances, focusing on code-sharing agreements used widely in the industry. Park (1997) and Brueckner (2001) examine the economic effects of alliances on fares, traffic levels, profits and market welfare. Bruckner and Whalen (2000) provide an empirical analysis of the effects of international alliances on fares, showing that interline fares charged by alliances are approximately 25% lower than those charged by non-allied carriers. ITO and Lee (2006) examine the impact of domestic alliances on airfares.

Little attention, however, has been given to how revenue management should be implemented by an airline alliance. Wynne (1995) describes transfer price schemes based on the value of local fares. Boyd (1998a) discusses the methodological and technical challenges of the alliance revenue management problem. He also refers to a more formal analysis in an unpublished working paper (Boyd 1998b) in which he formulates a static linear program to describe the alliance revenue management problem. Boyd then derives conditions under which the seat allocation between the two airlines maximizes alliance-wide revenue under this model. Vinod (2005) describes many of the alliance coordination mechanisms now being considered by the airlines, but provides no formal analysis of their advantages and disadvantages. Shumsky (2006) argues that low-cost competitors are driving the network airlines to rely on alliances for an increasing proportion of their traffic. Both Shumsky (2006) and Fernandez de la Torre (1999) discuss the need for more research on the effectiveness of alliance agreements. In their paper on revenue management games, Netessine and Shumsky (2004) describe and analyze a static alliance revenue-sharing mechanism for a two leg network based on the expected flow of passengers. Most recently, Graf and Kimms (2009) present an option-based approach to sharing revenue within an alliance.

Ongoing research by Houghtalen (2007) and Agarwal and Ergun (2007) looks at various aspects of alliances, focusing specifically on cargo carriers. In addition to the inherent difference between the cargo and passenger revenue management problems (Kasilingam, 1996)

The flow of products in the traditional supply chain literature moves in one direction, from raw materials to the consumer. Therefore the unused product does not move' sideways' within a level. Second, in the supply chain literature, production of a product begins at one level with one set of firms (supplies 0 and demand is fulfilled at another level by another set of firms (retailers). Considering supply chain systems we find that in the traditional supply chain literature, an assembler receives components from several suppliers that are combined to create a new product to sell (e.g, Nagarajan and Bassok 2008 and Granot and Yin, 2008).

In addition, the traditional research on supply chain coordination focuses on either single-period newsvendor problems (e.g., Lariviere and Porteus 2001) or repeated games in which inventory is replenished between each repetition of the game (e.g., Cachon and Zipkin, 1999). The characteristics of such problems are quite different from ours, a finite, multi-period problem with fixed capacity allocated to a stochastic arrival stream.

The use of stochastic approximation methods is a popular choice for simulation-based optimization of functions that cannot be practically evaluated in their exact forms. A wide variety of options exist and the reader is directed to texts such as Kushner and Clark (1978), and Wasan (2004) for more detailed.

CHAPTER 3: METHODOLOGY

3.1. Introduction

This chapter outlines the methodological route that was taken by the research study. This chapter defines the approaches, philosophy and the methods used in this research. It also includes details regarding the data collection methods and the kind of data being collected. It suggests ways in which the data will be processed and pre-processed. The flowchart containing the solution methodology also provides the various steps taken during the data processing stage. It also describes the normalization of data, which is required in order to obtain reliable results. The chapter also includes technical details regarding the pseudo-code used for this research study followed by the activation function and the auto-regression model.

3.2. Research Philosophy

The research philosophy that is chosen is dependent upon the researcher's perception of knowledge development. The inherent nature of the researcher subconsciously affects the choice of philosophy even if much thought is not given to the actual process [188]. A researcher may choose between two philosophies; either positivist or phenomenological. The philosophy in which the researcher takes an objective stance and independently analyses data free of bias in a quantitative manner is the positivist philosophy [147]. The aim of positivism is to understand situations in a "value-free" manner draw assumptions from these situations and make resultant generalizations [46]. Neuman [147] defined positivism as follows

> *"Positivist Social Science is an organized method for combining deductive logic with precise empirical observations of individual behaviour in order to discover and confirm a set of probabilistic casual laws that can be used to predict general patterns of human activity."*

In contrast to the positivist philosophy, the phenomenological approach deals with the observation and measurement of "meaningful social action" [147]. Phenomenology measures the reactions of individuals to their social situations and the manner in which they attach significance to their natural environment. The aim of phenomenology is to qualitatively assess situations and make unique observations, which are not generalizable [12]. The belief of the phenomenological philosophy is that every individual is inherently different and reacts differently to different social situations based on their diverse internal nature and perceptions [188]. Neuman [147] defined phenomenology as follows

"The phenomenological or interpretive approach is the systematic analysis of socially meaningful action through the direct detailed observation of people in natural settings in order to arrive at understandings and interpretations of how people create and maintain their social worlds."

The choice of philosophy in this research study is positivist. The reason behind this choice is the nature of the study. Since the study asks for an empirical analysis and applies numerical models [*i.e.* Analytical Hierarchy Process & Neural Network Model]. The application of these mathematical and computational methods requires the use of a positivist philosophy.

	Positivism	Phenomenology
	External and Objective world	Socially constructive and subjective world
Basic beliefs	Independent role of observer	Role of researcher as part of what is observed
		Human interests and motives as drivers of science
Research	Value-free science	Focus on meanings

Method	Focus on facts	
	Look for causality and fundamental laws	Understanding of what is happening
	Phenomena is reduced to simplest possible elements	Situation looked at as a whole
	Hypothesis generation and testing	Induction used to develop ideas from data
Research design	Structured, formal and specific detailed plan	Evolving and flexible
Researcher Involvement	Research material and researcher maintain distance	Researcher involved with phenomena being observed
	Short-term contact	Long term contact; emphasis on trust and empathy
Preferred method	Concepts are operationalized to facilitate measurement	Different views on phenomena established by using multiple methods
Sampling	Large samples	Small samples investigated in depth or over time
Data collection	Experiments, survey,	Observation,

methods	structured interviews and observation	documentation, open-ended and semi-structured interviews
Research Instrument	Questionnaires, scales, test scores and experimentation	Researcher
Strengths	Wide coverage of scope of the situation	Observation of process development and change on a long-term basis
	Researcher in control of research process	Greater understanding of people's meanings
	Fast and economic data collection due to clarity of objective	Adjustment to new issues and ideas as they emerge
	Helps to generalize previous research results and test previously developed hypotheses	Contributes to the evolution of new theories
		Natural data collection process
Weaknesses	Inflexible and artificial	Time taking and resource

	methods	hungry data collection
	Ineffective understanding of processes and human attachment to situations	Difficulty of analysis of data
	Unhelpful in theory generation	Difficult to control the research process
		Reliability problem with results
	(Amaratunga, Baldry, Sarshar & Newton,2002,p.19-20)	

3.3. Research Approach

The research approach refers to the process that is used in order to arrive at the end result. A research approach may either be inductive or deductive. In The inductive approach, results are obtained through careful observation of events, which are generalizable [197]. According to Neuman [147], the inductive approach includes observing data, analysing the reasons behind the observations and moving towards a theory, which may be generalized. The deductive approach on the other hand begins with a theory, which is the probable outcome and forms the basis of the research. Numerical evidence is generated from an in-depth study of the theory [130]. Skinner [174] defined the inductive approach as a "bottom-up" approach whereas the deductive approach was defined as a "top-down" approach. Two models defining the steps in the two approaches are shown below.

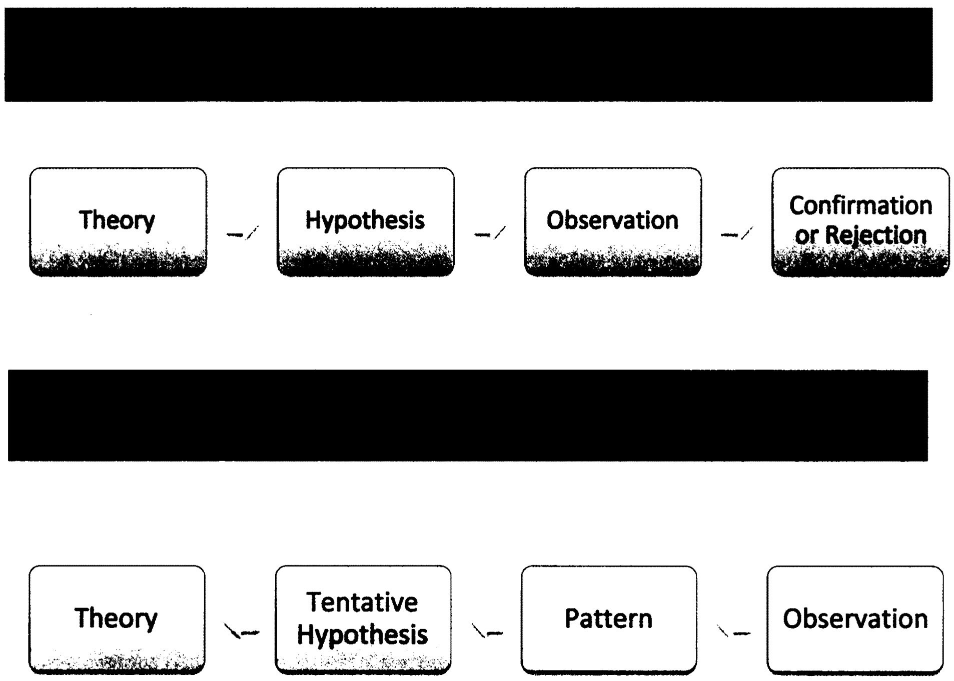


Figure 6: The Deductive and The Inductive Approach

The research approach being used in this research study is deductive. The research study is based on the hypothesis that a successful implementation of neural network coupled with an auto-regression model for revenue management in the airline industry is possible.

3.4. Research Method

Research methods may be quantitative or qualitative. The qualitative method of research observes individuals in their natural environments and the ways in which they attach significance to the social situations that they face. In contrast the quantitative method deals with a numerical analysis of data. The assumption made by the quantitative method is that all phenomena can be empirically rationalised. It deals with the association of numerical values to natural events, which result in "social facts" [12]. The choice of method for this research study is quantitative. This is due to the nature of the study, which requires an empirical analysis of revenue management and seat allocation models. This is also in accordance with the choice of philosophy and approach [*i.e.* positivist and deductive].

3.5. Data Collection and Screening

Time series forecasting deals with current and future values, which are estimations based on past or available data. Prediction is an important aspect for a company, which makes the collection and screening of data an equally important task [70].

Collection of reliable and sufficient data is a task in need of careful planning and execution. Lack of planning in this regard may lead to misleading and incomplete results, which would not serve their purpose [195].

Statistical data may be collected in the form of a survey or an experiment. Data collected by observing various individuals or items, included in a survey, are affected by many external factors beyond the control of the company. For example, the wages of workers in a nation may be influenced by various factors like abilities, academic qualifications, gender of worker; training and experience and even the racial background of workers in some places [195].

The data being collected in this research study can be classified into 3 categories. Technical data, Fundamental data, and Derived data.

Technical Data

Technical data represents all data that are referred to the predictor [the time series for which are going to predict the future values] only. In this case, the technical data will include price of the airline ticket at various time frames [one week interval] starting from booking open date, Price variation with number of bookings per day / time interval. Engineering, evaluation, and research and development information associated with design, production, operation, use, and/or maintenance of an equipment, machine, process, or system.

Fundamental Data

Fundamental data is all data related to the good will of the airline industry, services provided by the airlines to the passenger's, weather conditions, airlines past history, net profit margin per booking and future plans of the airlines.

Derived Data

These data can be obtained by the combination and transformation of the technical and/or fundamental data. Derived data are used to calculate effect of unexpected incidents on ticket bookings.

3.6. Data Collection

Historical data representing the airline booking price will be obtained from air lines considering various basic institutions. The available data should have the following independent variable effects on the ticket price.

1. Time between booking open and journey
2. Discounts availability
3. No. of seats in the fleet
4. Length of journey in a single stretch
5. Weather Conditions
6. Special Events [e g. Sports meets]

3.7. Data Pre-processing

Before an algorithm uses data, it will go through several transformations in order to prepare the raw data. The success of an algorithm greatly depends on the quality of input data. As different methods can handle only different samples, it is recommended to exploit certain data features with the purpose of finding out which pre-processing transformation works best.

Data Processing refers to any actions performed or work done on raw data. Data processing is done through programs, which manipulate and organize data, which is usually numeric in nature. Data processing applications are usually accounting programmes, which require organization of numerical data. Word Processors on the other hand which deal with text rather than numeric data aren't referred to as Data Processing Applications [48].

Normalization

Due to the chaotic nature of the data, the values of a time series can vary between wide ranges within a very short period of time, depending on the market volatility and airlines reputation. This can cause a great difficulty to neural networks, which can get disturbed by large fluctuations in prices.

Normalization is a method of data organization, which is aimed at the minimization of data redundancy. The process identifies the anomalies in larger datasets and breaks them down in order to form relationships between them. This makes the dataset smaller and structured and allows data isolation, which helps in future deletions, additions or alterations. For example in a normalized database, modification of data in one field will be made on the single table but will then be propagated throughout the database. This will be done though the previously defined relationships between the tables.

All the activation functions that are used in NN so far are bounded. The special activation function that is going to be used is not bounded. This avoids the pitfalls from the data.

3.8. Solution Methodology for Airline revenue Management

The solution methodology is presented below in the form of a flowchart, which outlines the steps, which will be taken on the raw data.

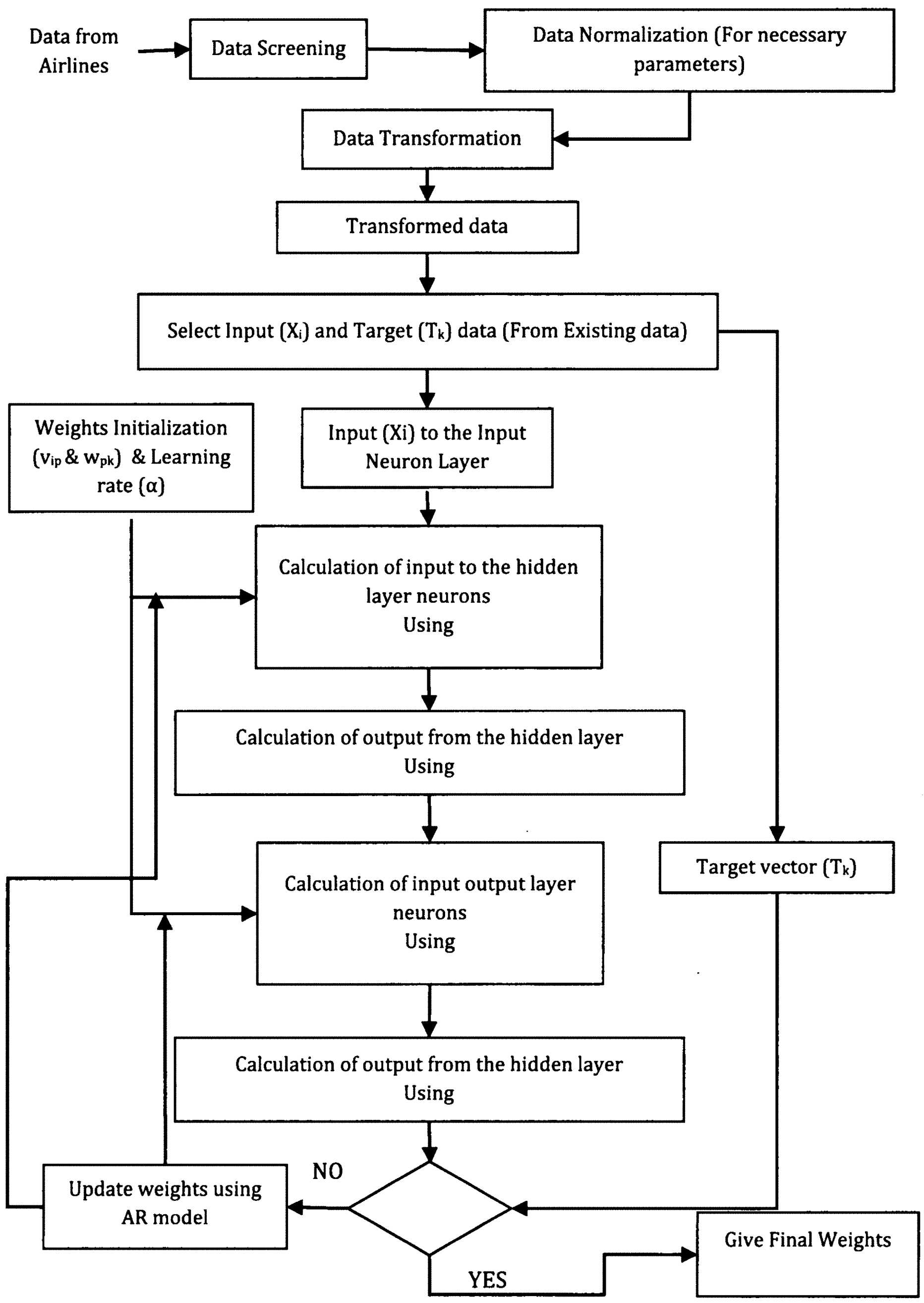


Figure 7: Solution Methodology for Airline Revenue Management Using Neural Networks

3.9. Pseudo-Code for Solution Methodology

The pseudo code for the solution methodology is given below

3.10 Sanitize the series data

Series data can be sanitized by transformation of "non-stationary airline tickets and time series data" into stationary data using a method for transformation which is based on behavioural analysis of raw data.

Selection of input variables

In order to select the input variables the time lags or periods in waveforms will need to be measured the time lags are those gaps that appear between two simultaneous peaks or troughs. All periods occurring during the observation period will have to be measured and the weighted average of each recent period that carries more weight than previous will be calculated. The most recent past values for the current values will be selected from the total derived series.

Create the Auto regression (AR) ensemble

To create the "Auto Regression Ensemble", each auto regression will be connected to a singular input node. The variables that would be input in the nodes will be different for each network.

Train each member Auto Regression model

Each element of the auto regression model will be trained using past values of the "stationary time series" data against the values being targeted.

Estimate weights of each member AR Model

Each auto regression model will be presented with different training patterns for which weights will be calculated for hidden neurons. These patterns will be identified and memorized by the model for forecasting purposes.

This process will be repeated until the calculated value is equal to the targeted value.

3.11 Neural network revenue maximization of airline industry

The data collected contains the following input-target pairs.

Input:

a) Number of seats available in each class – (Input type - number)
b) Discounts available for each class – (Input type - number)
c) Price @ booking date – (Input type - number)

d) Weather forecast for the source and destination (Input type – quality – Good (1)/ bad (0)
e) Any festivals / occasions on the date of journey (Input type – quality – Yes (1)/ No (0)
f) No. of cancellations in each class – (Input type – number)
g) Total revenue generated from cancellations (Input type number)

Target:

Total revenue (Output type - number)

The neural network designed for this purpose will have 7 input neurons in the input layer, 7 neurons in the intermediate / hidden layer and only one neuron in the output layer.

Once the inputs as described above are supplied to the neural net input layer, the sum of the product of weights (vij) and input values (xi), z_inj will decide the activation of the neurons in the intermediate layer. The activation function will give the output (zj) of the intermediate/hidden layer.

The sum of product of output from the hidden layer neurons and weights (wij) will be calculated and passed through the activation function to find the status / output of the neuron(s) in the output layer. This is the final output of the neural network as whole.

This final output is compared against the target (i.e., the total revenue) existing / previous data. If the output is not matched, the weights are adjusted using the auto-regression algorithm, which is presented later in this chapter.

This process is repeated until the output of the neural net matches with the target (with a specified tolerance).

3.12 The Activation Function

The activation function that is being used is very special, unique and nobody has used so far. The activation function is given by

$$f(x) = \begin{cases} 1 + \dfrac{1}{1 + e^{-x}} x \leq 0 \\ \\ \dfrac{x}{1 + e^{-x}} x > 0 \end{cases}$$

The provided activation function contained a function within itself consisting of the term; $\frac{1}{1+e^{-x}}$ which is also known as the Log-Sigmoid Function (also known as the logistic function in terms of regression analysis). The function also has a continuous derivative, which allows it to be effectively used in back propagation making it optimal for use in AHP.

The range provided in the function is x > 0. This means that the output would have been normally generated by assuming the value to lie between 1 to x. The activation function however also contains the sigmoid function; the range for which is generally defined as lying between 0 to 1 dependent on the real numbers. The output layers and the hidden layers of the neurons were defined using this activation function.

The input is calculated by using

$$y_{in(k)} = w_{ok} + \sum_{j=1}^{j} z_j w_{jk}$$

The output from each neuron will be computed according to the activation function given above

$$y(k) = f(y_{in(k)})$$

This will compare against the target value. The error between the calculated output and the targeted value will be used in the Auto regression models for error back propagation instead of delta rule (As in the original back propagation algorithm)

3.13 Auto regression model

Auto regression models are linear models based on time series. They are generally applicable in parameterization and optimization problems. Auto regression (AR) models are similar to rational polynomials as an approximation for general non-linear and exponential functions.

There is a lot of literature available for auto regression models. But, only limited research has been conducted in the area of using auto regressive model coupled with artificial neural networks.

An auto regression model of order "n" can be written as

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_n X_{t-n} + Z_t$$

Where,

Z_t Pure random process

α_n AR coefficients

X_t Present Values

CHAPTER 4: RESULTS AND FINDINGS

4.1. Introduction

This chapter includes results of the analysis done on the data according to the methodology provided in the previous chapter. The analysis was done using the "Super Decisions Software" which is explained in detail in this chapter. This is followed by a narration of results and detailed discussion on the narrations.

4.2. Super Decision Software

The analysis of the preferred airline hierarchy of the AHP model was done using the "Super Decision Software". The "Super Decisions Software" [6] is used for decision making purposes based on feedback and dependence. SDS is implemented in situations where it can face and understand 'real-life' decisions. SDS is an extension of AHP, which makes use of a similar process of prioritization by making pair-wise comparisons and judgments based on the comparisons. Elements in the AHP model are set in a hierarchal fashion whereas the decision structure in the ANP comprises of flat networks with elements in clusters. In decision making methods it is usually assumed that decision criteria are independent of each another. The alternatives of the decision and even the criteria of the alternative among themselves are also assumed to be independent [6].

Decision making is a fundamental and permeating human activity which is inherent in the nature and the biological make-up of the human mind. Decision making plays a crucial part of human life and shapes the events in their lives. The human mind does not only select alternatives that are the best possible solutions for a particular scenario. It prioritizes alternatives, according to allocation of resources or the preferences of the individual, in order to devise a decision based on the collective preference of the individual [6].

The application of mathematical equations to decision making requires ways in which personal or collective judgments and preferences may be quantified in a subjective and intangible manner. When comparing two elements the preferences are decomposed into various properties or characteristics of the elements. The importance of these characteristics is comparatively analyzed allowing the generation of a relative preference based on these divided characteristics, which are synthesized to determine the overall importance of the element to the individual [6].

The comprehensive way of viewing a problem mathematically is by the breaking down of a problem into components in the form of a hierarchal framework or a feed forward back propagation network and by the establishment of weights or priorities which define the ranks of the alternatives. This method is known as "Multi-Criteria Decision Making" (Super Decisions Software Guide, 2003 and Saaty & Sodenkamp, 2010).

Decision making in operations research and management science is mainly considered with goals and associated criteria and the ways in which they are measured and ranked. Majority of the models observed in previous literature only focused on single-criteria decision making. This singular criterion also known as an objective function in optimization is a quantity that is measurable.

The data collected from the questionnaires filled out by nearly 50 passengers was analysed using the "Super Decision Software". The data was initially entered on a 1 to 10 scale based on the alternatives provided.

4.3. Results of Analysis

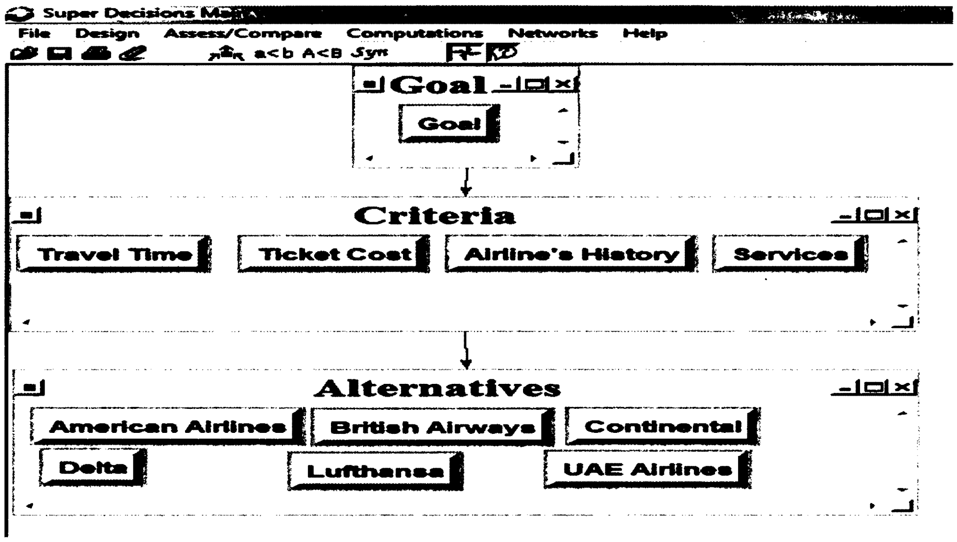


Fig 8: Preferred Airline AHP model in Super Decisions

The snapshots in figure 8 show the various results derived from the analysis.

The criteria for evaluation in the analysis were:

1. Travel time
2. Ticket cost
3. Airlines history and
4. Services provided by the airlines

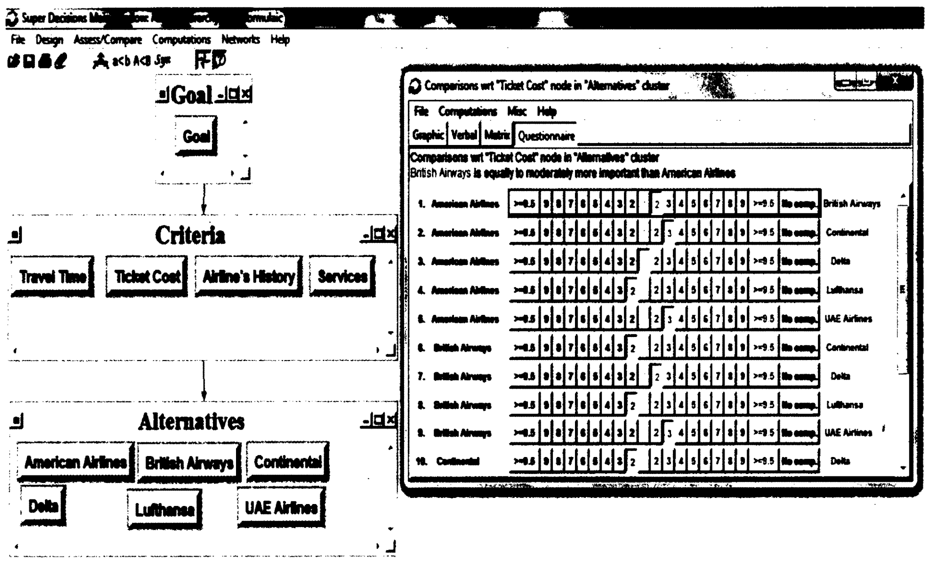


Figure 9: Data Entering Form in Super Decisions (Questionnaire Tab) for Ticket Cost Among The Alternatives

The data was entered in the form of a matrix for each of the criterion. The form where the data was entered is shown in the figure above. After entering the data in the questionnaire tab, the Matrix button was clicked to know which one was preferred over the other.

4.3.1. AHP Model Results Discussion

1. Criterion

Among the criterion of preference the AHP analysis of the data collected shows that

- Travel time is 6 times more important than Airlines history, 3 times more important than services, and 4 times more important than the ticket cost
- Airlines history is 4 times more important than the Ticket Cost and Services were also 5 times more important than ticket cost
- Airlines history is 5 times more important than services provided by the airlines

The snapshot of the AHP analysis based on criterion is given in the figure below

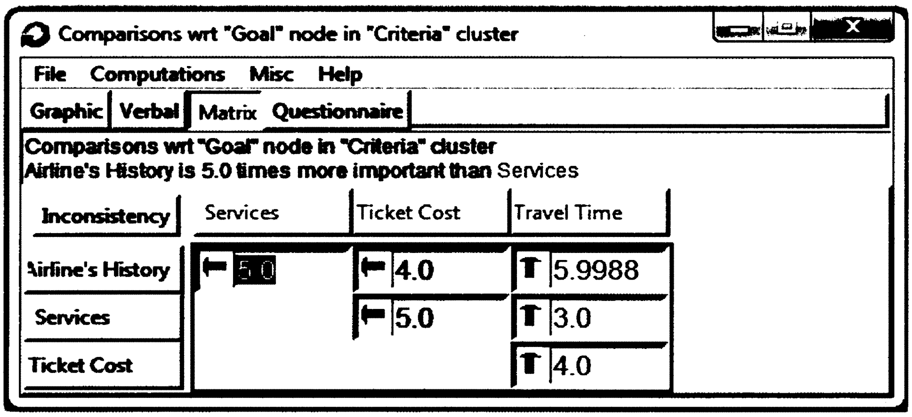


Figure 10: Matrix Comparison for Criterion Preference in Airline AHP Analysis

2. Alternatives Preference with Respect to Criterion

Alternatives hierarchy is analyzed based on each criterion mentioned previously

a) Travel Time

The summary of AHP analysis for travel time with respect to various alternatives is given below

- Emirates is 5 times more preferred over American lines, 4 times over British airways, 4 times over continental, 4 times over delta, and 2 times over Lufthansa
- Lufthansa is preferred 3 times more over American lines, 3 times over British airways, 3 times more over continental, and 3 times more over delta
- Delta is preferred 2 times less over American airlines, 2 times less over British airways, and 3 times less over continental airlines
- Continental is preferred 3 times more over both American airlines and British Airways
- British Airways is preferred 2 times more over American Airline

A Snap shot of the above AHP results is given in the following figure

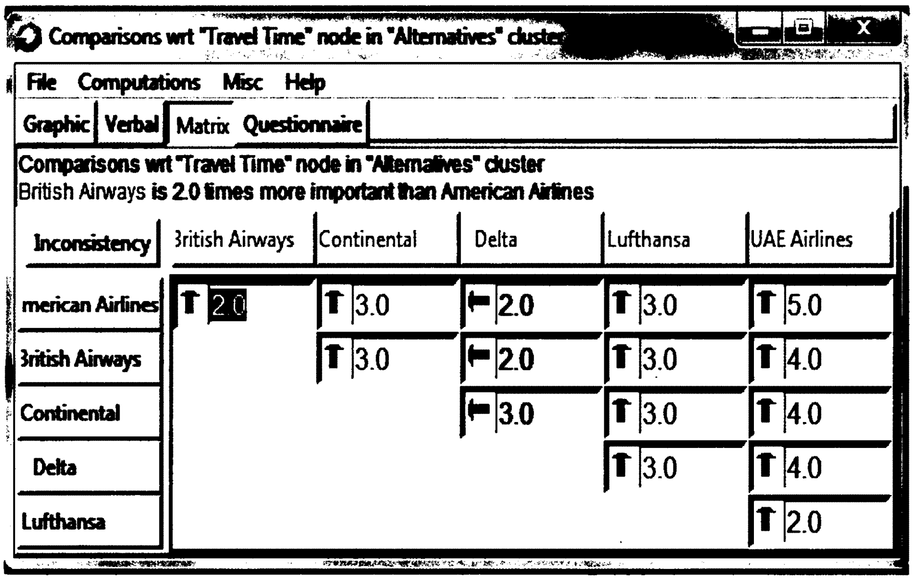


Figure 11: AHP Results of Alternatives in Travel Time

b) Ticket cost

The summary of AHP analysis for ticket cost with respect to various alternatives is given below

- Emirates is preferred 3 times more over American lines, British airways, continental, and delta and 2 times more over Lufthansa
- Lufthansa is preferred 2 times less over all other airlines

- Delta is preferred 2 times more over British Airways, 2 times less over Continental and is comparably preferred with American airlines
- Continental is preferred 3 times more over both American airlines and 2 times less over British Airways
- British Airways is preferred 2 times more over American Airline

A Snap shot of the above AHP results is given in the following figure.

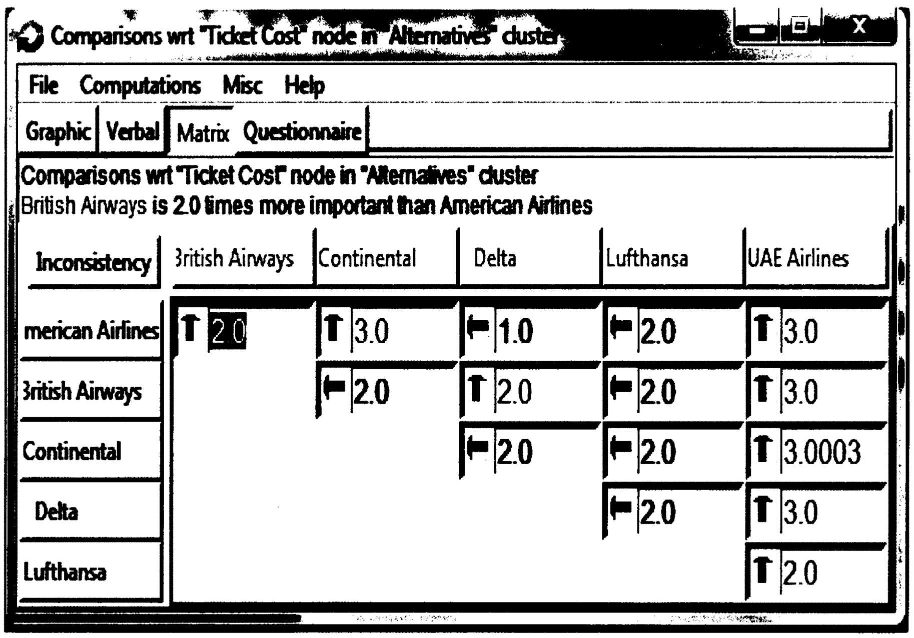


Fig 12: AHP Results of Choice of Alternatives with Respect to Ticket Cost

c) Airline History

The summary of AHP analysis for Airlines History with respect to various alternatives is given below

- Emirates is 4 times more preferred over American lines, British airways, and Delta Airlines 2 times over continental, and is comparable with Lufthansa
- Lufthansa is preferred 4 times more over American lines and Delta, 3 times over British airways, and 2 times more over continental
- Delta is preferred 3 times less over American airlines and British Airways, and 2 times less over continental airlines
- Continental is preferred 2 times more over both American airlines and 5 times over British Airways
- British Airways is preferred 2 times less over American Airlines

A Snap shot of the above AHP results is given in this figure.

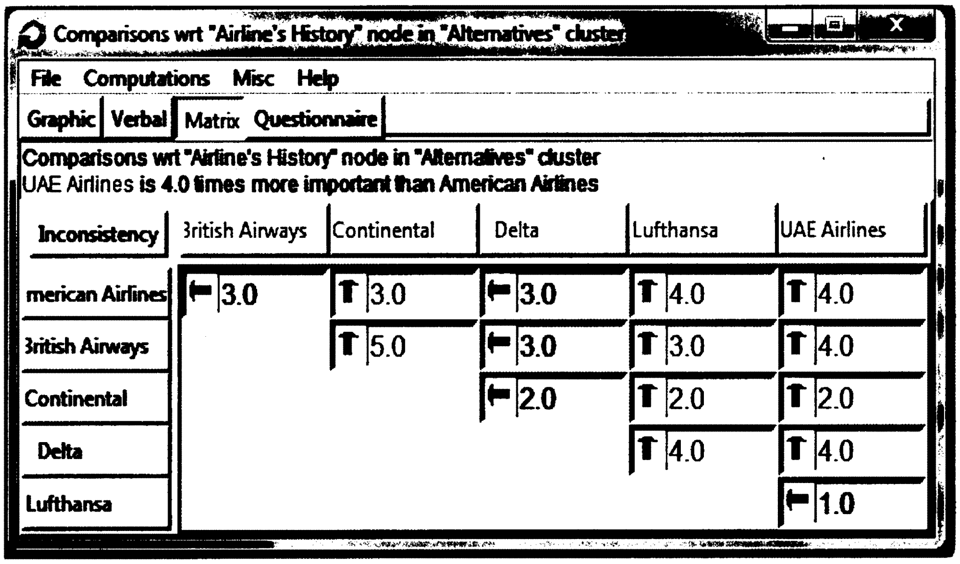


Fig 13: AHP Results of Preference of Alternatives with Respect to Airline's History

d) Services

The summary of AHP analysis for service provided by the airlines with respect to various alternatives is given below

- Emirates is 3 times more preferred over American lines, British airways, continental, and Delta, whereas 2 times over Lufthansa

- Lufthansa is preferred 3 times more over American lines, British airways, and Delta, whereas 2 times more preferred over continental
- Delta is comparable to American airlines and British Airways and 4 times less preferred to continental airlines
- Continental is preferred 3 times more over American airlines and 2 times more preferred over British Airways
- British Airways is preferred 3 times more over American Airline

A Snap shot of the above AHP results is given in the figure below

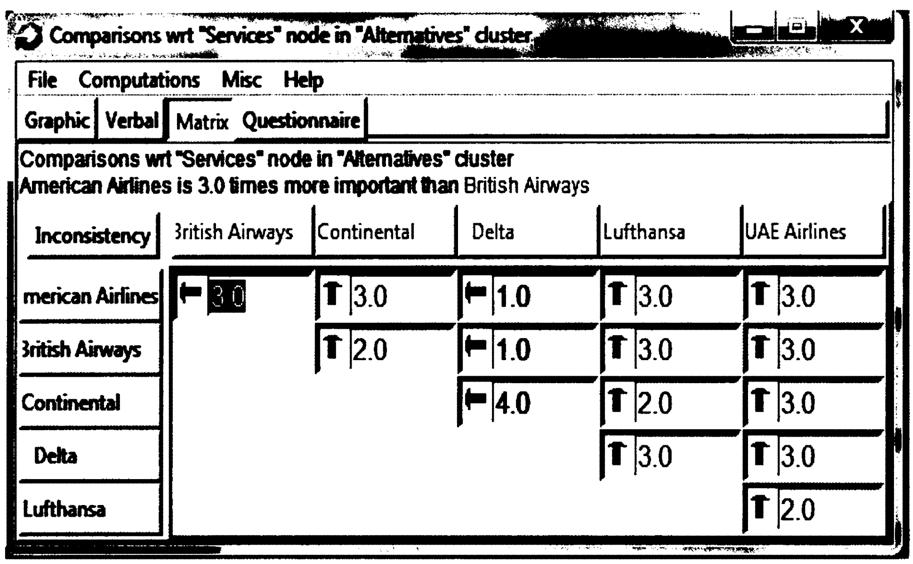


Fig 14: AHP Results of Choice between Alternatives with Respect to Services Provided by The Airlines

4.4. Discussion of Results

Six airlines (i.e. American Airlines, British Airways, Continental Airlines, Delta, Lufthansa and Emirates) were comparatively analysed using the Super Decision Software. The data was collected from customers between the ages of 21 and 63. The respondents varied in terms of nature of occupation. The details of the breakdown are as follows.

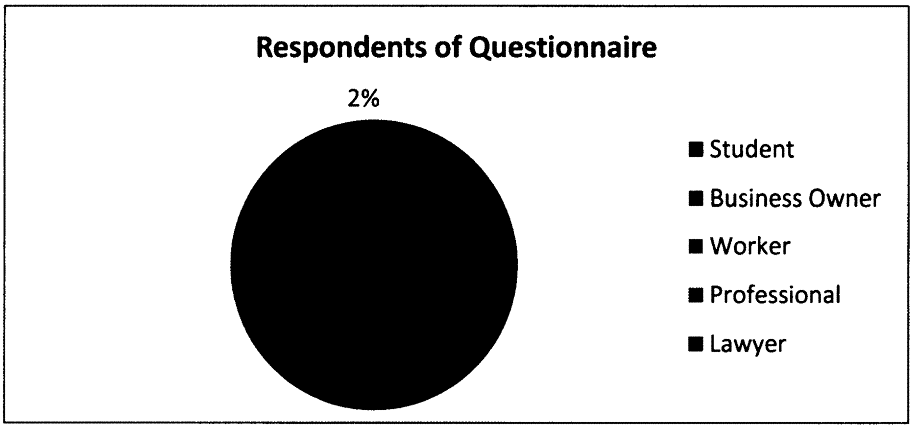


Figure 15: Breakdown of Questionnaire Respondents

A majority of the respondents were business owners followed by workers and then professionals. 15% of the respondents were students whereas 2% were lawyers. This indicates that Business Owners, Workers, and Professionals may be travelling for business related purposes as opposed to Lawyers and Students. This makes up for a sizeable amount of the respondents. The purpose of these travels, however, could not be determined.

The airlines were assessed according to four different criteria. These were Travel time, Ticket Cost, Airline History, and the Services Provided.

According to the stated criteria it was found that the travel time was the most important criterion for respondents. The most preference was given to travel time, which was 6 times more important than airline history, 3 times more than services, and 4 times more than the ticket cost. This showed that customers were more concerned about flight times (i.e., arrivals and departures). This factor may be more important to travelling businessmen who had appointments scheduled and relied on punctuality on part of the airlines.

The results also showed that the next preferred criterion for customers was ticket cost. Ticket cost was followed by services in terms of customer preference. To determine the hierarchal order of preference, the remaining three criteria apart from the most preferred, Travel Times, were compared within themselves.

It was found that Airline history was more preferred as compared to Ticket Cost and Services Provided. Customers preferred to travel with airlines with reliable histories of travel. Also, an airplane with a stronger historical background was also preferred due to an established familiarity of the customer with the airline.

Airplane history can also be viewed in a different way. It can also refer to the travel history of the customer with the airline. In such a case a customer would prefer to travel with an airline that he/she is accustomed to rather than searching for new airlines.

The researcher believes that the reason for the services provided by the airline during the flight being the least preferred criterion was its timing. The customers do not experience the services of the airlines until they have booked and paid for the flight and, therefore, do not consider it a factor which may affect their decision to travel with a particular airline. This factor may be of importance where the flights are long but in cases where the flights are only a few hours long the importance of the criterion is diminished. Even though this factor may affect subsequent flights and increase the significance of the factor but the researcher realizes that the same can also be observed for other factors also.

The alternatives or choices of available airlines were also comparatively analysed using the Super Decisions Software in order to determine which airline was most preferred by customers. Each alternative was examined in terms of the criterion they possessed that affected customer decisions.

In terms of Travel Time it was found that UAE Airlines was the most preferred airline. It was 5 times more preferred than American Airlines and 4 times more preferred than British Airways, Continental, and Delta. It was also 2 times more preferred than Lufthansa. In terms of ranking it was found that the next preferred after UAE Airlines – or Emirates – was Lufthansa. The results showed that Delta was 2 times less preferred than American, British, and Continental Airlines. By comparison of the values assigned by the Super Decision Software, it was determined that the next in order of preference was Continental Airlines because it was preferred 3 times over American Airlines, British Airways, and Delta Airlines. British Airways was also preferred twice more than American Airlines and Delta Airlines. American Airlines was preferred twice over Delta, which meant that in terms of order of preference based on Travel Time Emirates Airlines was the most preferred followed by Lufthansa, Continental, British Airways, American Airlines, and Delta Airlines.

In terms of Ticket Cost it was observed that Emirates was preferred 3 times more over American lines, British airways, Continental, and Delta, and 2 times more over Lufthansa, whereas Lufthansa was preferred 2 times less over all other airlines. Emirates Airlines was observed to be the most preferred airline in terms of ticket cost followed by Lufthansa. By comparative analysis of the values assigned to the Super Decision

Software internally it was observed that the order of preference of airline alternatives in terms of ticket cost were as follows. Emirates Airlines was once again the most preferred. This was followed by Continental Airlines, British Airways, Delta Airlines, American Airlines, and Lufthansa.

In terms of Airline History, it was observed that Emirates was preferred 4 times over American Airlines, British Airways, and Delta Airlines. Lufthansa, on the other hand, was at par with Emirates and was comparable to it being 4 times more preferred than American Airlines and Delta, 3 times more preferred than British Airways, and twice over continental. The order of preference in terms of Airline History was Lufthansa, Emirates, Continental, American Airlines, and British Airways, followed by Delta Airlines.

In terms of Services provided, it was observed that Emirates was the most preferred airline being 3 times more preferred than American Airlines, British Airways, Continental and Delta, and twice over Lufthansa. Lufthansa followed Emirates and was preferred 3 times over American Airlines, British Airways and Delta, and twice over Continental. In order of preference the results showed that Emirates was the most preferred followed by Lufthansa, Continental and American Airlines whereas British Airways and Delta were equal and preferred the least.

The results above showed how each airline was preferred individually. The researcher wanted to know the overall preference of customers based on these four criteria defined as Travel Time, Travel Cost, Airline History and Services.

Airline	Travel Time	Ticket Cost	Airline History	Services	Overall Rank
Emirates	1	1	2	1	1
Lufthansa	2	6	1	2	2
Continental	3	2	3	3	2
British Airways	4	3	5	5	3
American Airlines	5	5	4	4	4
Delta Airlines	6	4	6	6	5

Table 2: Overall Preference based on Travel Time, Travel Cost, Airlines History and Services

The table above defines the ranks assigned to the airline alternatives in each category of the criteria. The average of their ranks was derived in order to estimate the final overall rank of the airline in question. The table above shows that the overall rank of Emirates was 1, which means that it was the most preferred airline. Emirates Airlines was clearly the most preferred in three of the measured criteria: Travel time, Ticket Cost and Services. In terms of Airline History, however, it was at the second rank, which did not cause much deviation.

Lufthansa and Continental Airlines had the same average, which tied them at the second rank in terms of preference. Lufthansa held the second rank, according to Travel Time and services and the 1st rank in terms of Airline History. The only criterion that caused it to tie with Continental Airlines was Ticket Cost, where it stood at the lowest rank. This deviation caused a dip in the overall rank. The rank for Lufthansa might have stayed at 2 if the deviation had not occurred, but it would have had a higher ranking than Continental Airlines. Continental Airlines, on the other hand, consistently held the third rank in the criteria: Travel Time, Airline History and Services, whereas it was at the 2nd rank in terms of Ticket Cost. This gave it an overall 2nd rank in the order of preference, which was mainly due to the deviation in the ranks of Lufthansa.

British Airways was third in the line of preference having gained 3 or below ranks in all 4 criteria. It was the 4th preferred in terms of Travel Time, the 3rd preferred in terms of Ticket Cost, and 5th preferred in terms of Airline History and Services.

The 4th rank was held by American Airlines, which was consistently low in preference. It was 5th preferred in terms of Ticket Cost and Travel Time, whereas it was 4th in terms of Airline History and Services.

Delta Airlines was the least preferred in a majority of the categories and held 6th rank in terms of Travel time, Airline History and Services, whereas it held the 4th rank in terms of Ticket Cost.

4.5. Comparison with Previous Literature

Saaty, Peniwati and Shang (2007) used AHP and LP to see how they can be applied in human resource allocation to determine which employee positions of what salary value should be filled in the organisation. They tried to search for an optimal method in which the employees would be satisfied with the salary and position constraints as well as the employers. The study of Saaty et al. [177] implemented similar methods as this research study and made use of pair-wise comparisons to determine the optimal combinations of employees and salaries. Their research study emphasised on the use of tangibles and intangibles in the study. It, however, overlooked the component of intangibility in the actual results where it overlooked the kind of workers and could not ascertain whether a certain combination of workers would provide optimal results when working together as a team. The AHP/NN model used in this research study also focuses on intangibles which were used in the Super Decision Software in the criteria (i.e.,Travel time, Airline History, & Services).

Chang and Shao [39] used AHP coupled with the fuzzy Delphi method to observe the "cost-control strategies" of Taiwan International Airport. They conducted questionnaires on experts and the data collected was analysed using the fuzzy Delphi method with convergence and further input into AHP in order to make pair-wise comparisons and assign weights to values to generate hierarchal priorities. This study is very similar to the present research study. Its use of a top-down approach and pairwise comparisons was similar to pair-wise comparisons done by the decision making model of the Super Decision Software.

Cote and Marcotte [49] wanted to suggest a new modelling approach other than the AHP similar to this research study. Cote and Marcotte [49], however, believed bi-level programming to be a more preferable alternative that would help in revenue maximization of airlines. It included patterns and behaviours of passengers based on the manner in which passengers travelled and booked seats. The study also concurrently optimized two elements of the RM process, i.e.,pricing and seat allocation. The study did successfully provide suggestions for replacement of the AHP model and proposed another method, which would take its place. The research study, however, required prior identification of patterns and behaviours before the bi-level model could be implemented. The Neural net model would be a better replacement in this regard because it doesn't require prior identification of patterns. The NN model identifies patterns and can even be used for predictive analysis and will get smarter as it recognizes newer patterns, which will help provide optimal solutions to larger problems.

Kinoshita and Nakanishi [118] suggested the use of a newer AHP model, which they termed as a "Dominant AHP model". The dominant model would be applicable to two approaches "relative measurement" and "absolute measurement". Kinoshita and Nakanishi [118] also suggested the use of "concurrent convergence" along with this dominant AHP model, which would increase the capacity of the model and allow it to use more data. This method, however, relied on the analytic opinion of the surveyor or the person responsible for the analysis. This would cause limitations with the bulk of data and the busy airline schedules or urgent or emergency situations. Being dependent on the analytic prowess of a human would mean that that decision making for revenue management would be prone to bias and may not provide optimal solutions and would also exclude crucially important viewpoints of other people also being affected by a particular situation.

Toosi and Kohanali [222] used the hierarchal AHP model in their research study to measure the service quality of airlines. Tangibles were analysed using the regular AHP model whereas intangibles, such as satisfaction of customers, were analysed using the fuzzy approach. The study also used a pair-wise questionnaire in which the respondents assigned weights based on a Likert scale for various aspects of service quality. The study also used hierarchal pair-wise comparison of alternatives, which could be implemented for RM methods similar to this study and would generate relevant results. The AHP/NN model, however, also consists of a learning process, which will enable it to recognize patterns, which may be used for future forecasting and emergencies.

Saaty and Sodenkamp [180] took the classic AHP model further and integrated it with ANP for airline revenue management. They provided various examples in their research study but the researcher will only consider the airline revenue management example for comparison. The AHP model first took into account the benefits that would be derived from the implementation of a decision and future opportunities that may arise. The costs and risks associated with the decision would also be taken into account along with the potential of failure of a decision. These would be analysed by a pair-wise comparison and would be assigned weights. A hierarchy would be set to compare the alternatives. Saaty and Sodenkamp [180] used the same methods as those used in this study. His research study, however, attempts to introduce the aspect of neural networks into the model, which would enable it to identify patterns and aid in future forecasting and allow it to take independent decisions. Saaty and Sodenkamp [180], however, also stated in their research study that the application of fuzzy sets was an "unfortunate" implementation and also called it the "worst among all methods". The researcher also identified this issue and compared it with Chang and Shao's [39] research study which actually did use fuzzy sets with the AHP model which at first sight seemed to be similar to the present study. Saaty and Sondekamp [180] described their aversion to the implementation of fuzzy sets with AHP as lack of proof for its use. According to them the fuzzy logic perturbed the capabilities of judgments in AHP, which, in turn, perturbed the entries of a matrix and the eigenvector by a small amount.

4.6. Fulfilment of Aim

The aim of the study as presented in the introductory chapter is as follows

> *"The aim of this study is to simulate the neural network model coupled with auto-regression compared with the AHP model and to suggest a new approach for the maximization of revenue in airline ticketing."*

This aim was fulfilled by the analysis of questionnaires that were filled by customers regarding various aspects of 06 airlines. This analysis was done using a hierarchal AHP model, which provided the optimal solutions for revenue management. The results showed that customers valued travel time more than they valued ticket cost. Airline History was also an important factor because customers viewed it as an indication of reliability. Services provided in the flight, however, were of least value to the customers mainly because they were either unnoticed in shorter flights or because they were presented after the purchasing decision was made. The researcher suggests the use of neural networks with AHP model for revenue management and believes that it will be an effective tool for future forecasting as well as the present decisions faced by the airline industry.

4.7. Achievement of Objectives

1. ***Revenue management using artificial neural networks coupled with auto regression models***

This objective was achieved by the implementation of the AHP model in the Super Decision Software. The criteria and alternatives entered into the software helped generate results, which showed that a successful implementation of the combination could be made. The auto regression model used in this research surd was as follows

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_n X_{t-n} + Z_t$$

2. ***Compare neural network model with analytical hierarchy process (AHP) model***

The AHP model conventionally used by the airline industry in revenue management consisting of goals, criteria and alternatives was coupled with the super Decision Software, which was Neural Network decision-making software using feed-forward back propagation.

This allowed a comparison of a regular AHP model with a new AHP model that also made use of neural nets. Apart from comparison of the results of this chapter with that of previous literature especially Saaty and Sodenkamp [180] which used the original classic model put forward by Saaty [178], the researcher also did a theoretical comparison based on their characteristics in the literature review. A successful combination of AHP models and the Neural Network model was possible and can be implemented for revenue management in the airline industry. This was shown in the fourth chapter, which contains details regarding how this implementation and analysis was achieved.

3. *Use MATLAB for simulating the neural network (NN) model*

This objective was fulfilled by using Super Decisions to analyse the data collected. The Super Decision Software is software that was developed using MATLAB [138]. This was used because of its ability to be re-used, combined and meshed with more complex situations. The Super Decisions Software allowed the researcher to [138];

- "Compute local weight and consistency index from pairwise comparison matrix."
- "Discard inconsistent matrixes choosing the threshold of the accepted level of inconsistency."
- "Compute global weight from the local weight of all the comparison matrixes."
- "Export the developed questionnaire in a MS Excel worksheet."
- "Import the results of the questionnaire from MS Excel worksheet."

The reason behind the choice of a MATLAB tool for the neural network simulation is that it has an interactive environment for the development of an algorithm and computations and is used by scientists to make decisions regarding the challenges faced day to day.

4. ***Use Super Decisions Software for AHP model simulations***

The achievement of this objective is presented in detailed in the beginning of this chapter. The Super Decisions Software was used in order to simulate the AHP model, which consisted of three levels containing the goal, criteria and alternatives. The criteria for the simulation were "Travel time, Ticket Cost, Airline History and Services" whereas the alternatives included "American Airlines, British Airways, Continental Airlines, Delta Airlines, Lufthansa and UAE Airlines (Emirates International).

5. ***Suggest / recommend a model to the airlines based on the optimization work***

The proposed model in this research study could be affective for revenue optimization in airlines because it helps airlines to identify the areas in which faults lie and those areas, which hold more priority over others. According to the results of this study travel time was the most important component that customers based their purchases on. Airlines will have to invest more into this area and develop a more efficient system, which will be easy on the schedules of customers. An example could be holiday seasons or events (political, social or others). Airlines could plan return flights or discounted rates for early bookings or plan flights according to the announced dates for holidays, which would enable customers to visit their destinations and return home by purchasing one package. This convenience in scheduling and travel times would improve revenue optimization for airlines. Travel time also entails other extending issues such as delays or cancellations, which will need to be accounted for and the airline companies will also need to schedule the number of flights and destinations, which can be reached within one day and on time.

The other factor is Travel cost, which the researcher believed would be a primary driver. Even though travel cost was second on list of preference, it is still a very important factor as customers would be willing to compromise on other luxuries if they find more economical alternatives. Airlines can offer discounts if bookings are made early. Airline history was also a determining factor because customers were more comfortable travelling with airlines, which had a higher goodwill. Customers viewed companies with richer histories as being more reliable and trustworthy.

Services, however, were the least significant. Services by airline companies can be divided in two ways In-flight and other services. In-flight services are those, which are provided during the course of the flight whereas other services are those that are provided at other times such as selling tickets, booking seats, check-ins and other customer services that are provided before or after the flight. Services were the least significant factors. According to Jobber [104] satisfaction of customers is determined by three factors; "must-be's, more is better and delighters". Services fall in to the "must-be's" category. This means that a presence of service would result in neutral customers. Services are naturally expected by customers and a presence does not add to customer satisfaction. An absence of these factors however causes a negative effect and they act as dissatisfiers. It is for this reason that this factor was the least preferred because customers expect them to be present regardless of situation.

CHAPTER 5: CONCLUSION

5.1. Introduction

The aim of this research study was to simulate a neural network model coupled with auto-regression and compare it with the traditional AHP model for airline revenue management. The method proposed in this study is unique and has not been applied before. The researcher wanted to suggest this as a possible alternative to the present day revenue management models in use by airlines today. Since neural networks create and identify patterns, allowing them to use future forecasting and facilitating better and faster decision making, the researcher believed this would be a possible alternative to the AHP model.

Previous writers also wrote on the issue of replacing or modifying the AHP model. The most common model contained fuzzy logic, which the researcher believed would not be as efficient or beneficial as the NN model. This doubt was further validated when the researcher came across Saaty, and Sodenkamp's [180] study in which they explicitly stated that an attempt to integrate the fuzzy model with the AHP model would lead to failure and called it one of the worst possible combinations.

The researcher conducted the analysis using software called the Super Decision Software, which is decision making software with a hierarchal model using pair-wise comparisons to generate results. Data collected by the researcher was entered into the super decisions model which revealed that the criterion most preferred by customers when making purchasing decisions was Travel Time followed by Travel Cost, Airline History, and Services.

In terms of Travel Time, it was observed that Emirates was the most preferred airline followed by Lufthansa, Continental Airlines, British Airways, American Airlines, and Delta Airlines.

In terms of Travel Cost, the results of Super Decisions Analysis showed that the most preferred airline was Emirates followed by Continental Airlines, British Airways, Delta Airlines, American Airlines, and Lufthansa.

In terms of Airline History, it was observed that the most preferred airline was Lufthansa followed by Emirates, Continental Airlines, American Airlines, British Airways, and Delta Airlines.

In terms of Services the results showed that the most preferred airline was Emirates followed by Lufthansa, Continental Airlines, American Airlines, British Airways, and Delta Airlines.

The overall preference was derived by computing the averages in order to see which airline was the most preferred. Emirates Airlines was clearly the most preferred, followed by Lufthansa and Continental Airlines, which were at the same rank. The third preferred airline was British Airways, followed by American Airlines and then Delta Airlines.

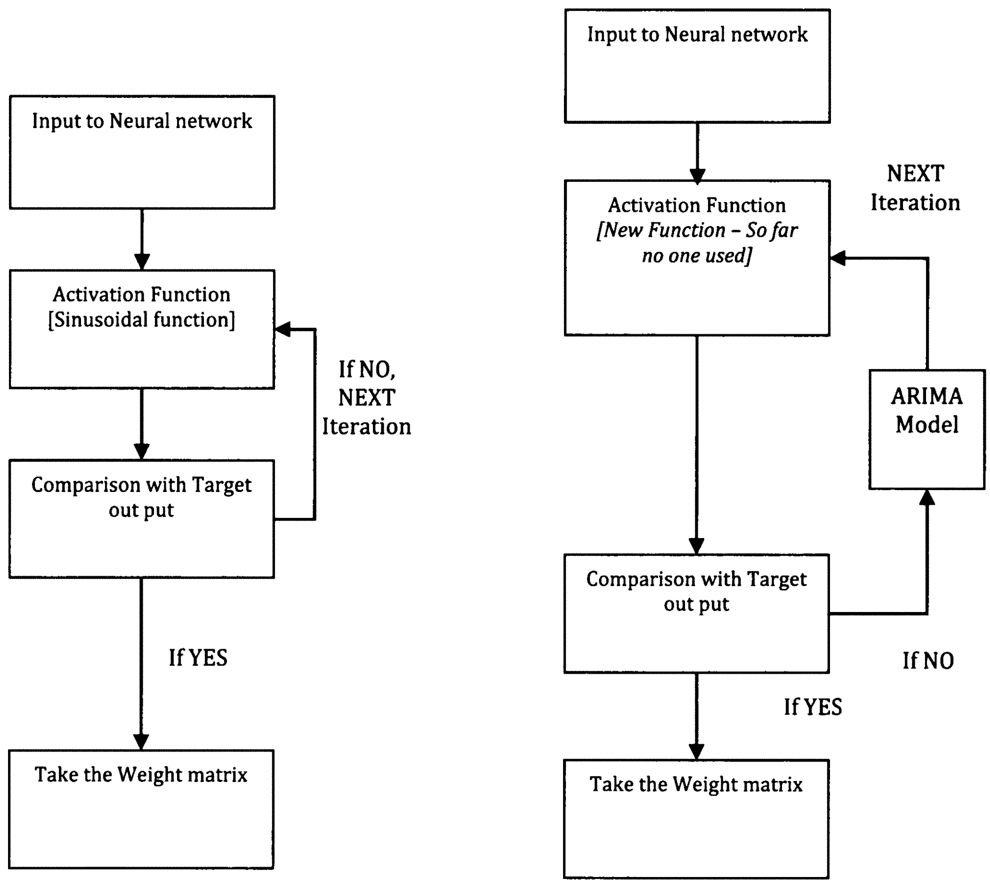
5.2. Contribution of the Proposed Work

This research study contributes to this area of study by proposing a new model, which has not been implemented before. This unique model suggests a new method with which revenue management can be done efficiently in the airline industry.

The new characteristics of the proposed method are

a. AHP is successfully applied to rank-order the six airlines discussed earlier.
b. Use of neural nets coupled with auto regression model for revenue maximization of airline ticketing. These techniques were applied to the Emirates Airlines data for revenue maximization.
c. Use of new activation function. This activation function has not been used by any one so far.

The difference between the existing and proposed revenue management is given in the figure below



Existing Airline Revenue Management using Neural Networks

Proposes Airline Revenue Management using Neural Networks

Figure 16: Difference between Existing Model and The Proposed Model for Airline Revenue Optimization

As can be seen in the figure above, the new proposed model is different from the existing model in the way that it includes an ARIMA model, which will allow processing of time-series and facilitate forecasting and planning. The other difference between the original model and the proposed model is the difference between the activation functions. The researcher has suggested a unique model, which has not been used before and has shown that it can be successfully implemented for revenue management purposes in the airline industry.

d. Apart from contributing a unique new method for implementation in the airline industry this research study also adds to the vast collection of existing literature, which has also been discussed in this study.

5.3. Hypothesis

As presented in chapter 1, the hypothesis for this study is as follows

"A successful simulation of the neural network model coupled will auto-regression model for maximization of revenue in airlines is possible and can be suggested for implementation."

The results and findings show that a successful simulation of a neural network was done coupled with auto-regression for airline revenue management optimization.

5.4. Recommendations

The recommendations of this research study include the implementation of the proposed model presented in this research study. The researcher believes that further work on this model will lead to an efficient system that would lead to a more efficient model for airline revenue management. The researcher would also recommend further research on the implementation of the AHP model and other variations used for airline revenue management. A lot of potential for the development of an optimal system exists which can be achieved by further research and experimentation.

CHAPTER 6: FUTURE WORK

Future prospects Neural Network

As we are living in the twenty first century where time has been consider as the most important criteria for every one we can say that. More over in achieving this we are using the most advanced form of technology at each and every aspects of our life.

Today; whatsoever form of technology we are using may be the vision of someone, somewhere, sometime in the past? But the fact of present says that yes vision can also become the reality & we can achieve the unparalleled heights of mountains.

"Time is money" as per this saying we can say that we are living in the "Jet era" where everyone wants to win the race against time; so in this form of technology we can easily put the Aviation service sector.

Now a day's services dominate the expanding world economy as never before, and nothing stands still. Technology continues to evolve in dramatic ways. Established industries evolve or sink into decline.

In presence scenario of time famous old companies merge or disappear, as new industries emerge and rising stars seize the business headlines. Competitive activity is fierce, with firms often employing new strategies and tactics in response to customers' ever – changing needs, expectations, and behaviour. Customers themselves are being forced to confront change, which some see as presenting opportunities and others as an inconvenience or even a threat. If one thing is clear, it's that skills in marketing and managing services have never been more important!

Preparing the new edition of technology can never considered as the walk of easiness; or the management of the all the dimensions can require the great amount of synchronizations within that kind of components.

Although service sector has been considered as the tertiary sector of the economy it has been achieving the great form of importance within the economy because the service sector consists of the "soft" parts of the economy.

I.e. Activities where people offer their knowledge and time to improve productivity, also their performance, potential, and sustainability.

For the last 100 years there has been a substantial shift from the primary and secondary sectors to the tertiary sector in the industrialized countries. This shifting or I can say this progress has not been possible without the involvement of the advanced technology like "Neural Networking System"

Here we must accept the fact that apart from the simple guess work, the combination of time–series and regression techniques will surely dominate the forecasting models for international tourism demand.

The real strength of this model is that it will give you a new approach that uses a supervised feed-forward neural network model to forecast tourist arrivals and departure for the particular flight of that time durations.

Due to the demand of the time; today many researchers, practitioners, and policy makers have long recognized the necessity of accurate forecast for tourism demand.

Accurate forecasts would help not only managers but also to the investors in many ways; here we can include the activities of the operational work, tactical work or even strategic work can also become the part of that.

At initial stage the past neural network was not able to get the rid of this kind of accuracy within the industry because it can give the information only at the level of comparison of goals & the criteria of alternative resources only.

But the proposed models will the detail and the information regarding the preferences of the customers; that includes the...

- Flexibility of timings
- Weather forecasting
- Availability of seats
- Service facilities
- Timing of bookings
- Information about special discount offers
- Comparative information's about related flights etc.

So all the above factors shows that the proposed model will give the information according to the goal of passengers. This kind of facility provides the benefits not from one side only but all the way to the airlines also. For airlines it gives benefits in terms of..

- Customers loyalty (Due to transparency of information)
- Revenue generation even in the time of off season (Due to low rate)

- Profit maximizations (Due to earning from the un booked seats)
- Competitive market achiever (Due to special offers)
- Achieve the prioritized category (Due to various packages of offers)
- Alternative options become the first choice (Due to suitability of choices)

Hence form this advanced form of model we can say that it is the one model, which can measure the level of supply and demand; it shows the balanced form of the structure that can be analyzed and measured from both the ways & due to that it will have surety of its success.

It's very delight to know that not only the private sectors but also the government bodies need some accurate forecasts about tourism infrastructure such as accommodation site, planning and transportation development.

This model of neural networking will become the one which can cover the all kind of spaces that has been untouched yet.

Here it's very important to know that how the old model and the new one get differ from each other so that we come to realize that the applications we are going to use is having its own importance.

The traditional model, which is "AHP MODEL" that has been used at earlier stages of the industry, was not using the regression structure within its format while the new model, which is using the auto regressions structure within its structure.

Each structure that has been applied till today has its own advantages and disadvantages closely related to particular applications.

For e.g. recurrent neural network are primarily designed to time series prediction, because they are able to store information about time but on the contrary side its parameters settings and learning algorithms are much more complicated and the calculation time is too long.

Hence we required the in its advanced form of technology.

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APPENDIX

Appendix 1

Revenue Management in Airline Ticketing

Questionnaire

Background Information

This questionnaire is designed to get important information from air travellers who frequently travel between New York [JFK] and Dubai. Information includes traveller preferences in terms of preferred airlines, preferred time [in a year] of travel, frequency of travel, preferred class of travel and preferred services by the air lines during the travel

The furnished information will be primarily used to determine the passenger preferences and ultimately recommend the airlines for further improvements / changes.

This questionnaire is divided into two major parts

1. Traveler's demographic information
2. Traveler's preference information

Demographic information:

1. Which Town / City you live in?

City__________________________ Country ____________________________

2. What is our occupation? [Please tick √ one]

a) Student b) Professional

c) Business Owner d) Worker

3. What is your age? ______________________________

4. What is you Gender?

a) Male b) Female

5. *Do you have any Physical Disability?*

a) Yes b) No

6. *Your Highest Education Level?*

a) High School b) Associate Degree

c) Under Graduate d) Graduate [Masters]

e) Graduate [Ph.D.] f) Other Profession Degree [Doctor, Lawyer]

7. *What is your preferred airline for travel?* ________________________

Preference information

This section will ask you to provide your preference information regarding different evaluation criteria. Please try to fill this section as accurately as you can. Your co-operation will be very useful in improving the services / facilities by the airlines.

Evaluation Criterion

- ✓ Travel time
- ✓ Ticket cost
- ✓ Airline past history [in terms of safety and accidents]
- ✓ Airline reliability
- ✓ Services [Provided by airlines, including food, no. of free check-in baggage's]

Scale:

Please use the following scale in filling in formation in the tables below

1 5

[Not important] [Most important]

1	**Not important**
2	**Somewhat important**
3	**Important**
4	**More important**
5	**Most important**

In the following table we are trying to determine which of the above said evaluation criterion is important to you compared to other criterion

[redacted]					
[redacted]	1	2	3	2	4
		1	4	5	3
			1	3	4
				1	2
					1

Travel time is preferred over ticket cost 2 times, over airline past history 3 times, over airline reliability 2 times and over services provided by 4 times.

Ticket cost is preferred over airline past history by 4 times, over airline reliability 5 times and over services by 3 times.

Use the above scale and method to fill the following table.

[redacted]					

THANK YOU

Appendix 2

MATLAB Code for Neural Network Optimization in Airline Ticketing

```
% MATLAB Program for Back Propagation neural net for
airline ticketing

clc
clear all
alpha=0.5;
x1=unifrnd(-0.5,0.5,1,100)

for i=1:1:100
    x2(i)=(-1)^i*sqrt(.25 - x1(i)*x1(i));
end
for i=1:1:100
    r(i)=x1(i)^2+x2(i)^2;
end
X=[x1;x2];
w=unifrnd(-1,1,2,50);
for k=1:1:2
    for l=1:1:50
        W(k,l)=w(k,l);
    end
end
for k=1:1:2
    for l=1:1:50
Wold(k,l)=W(k,l);
end
end
for t=1:1:100
for j=1:1:100
for l=1:1:50
    D(l)=((X(1,j)-Wold(1,l))^2)+((X(2,j)-Wold(2,l))^2);
end
for l=1:1:50
    if D(l)==min(D)
        L=l;
        L
    end
end
for l=1:1:50
    if l==L-1 && L-1>=0
        for k=1:1:2
```

```
            Wnew(k,l)=Wold(k,l)+alpha*(X(k,j)-Wold(k,l));
        end
    else if l==L
            for k=1:1:2
                Wnew(k,l)=Wold(k,l)+alpha*(X(k,j)-
Wold(k,l));
            end
        else if l==L+1 && L+1<=50
                for k=1:1:2
                    Wnew(k,l)=Wold(k,l)+alpha*(X(k,j)-
Wold(k,l));
                end
            else
                for k=1:1:2
                    Wnew(k,l)=Wold(k,l);
                end
            end
        end
    end
end
for k=1:1:2
    for l=1:1:50
        Wold(k,l)=Wnew(k,l);
    end
end
end
t=t+1;
if t==10
    xlswrite('CLUS',D','Output','A5');
    for k=1:1:2
        for l=1:1:50
            W10(k,l)=Wnew(k,l);
        end
    end
else if t==20
        xlswrite('CLUS',D','Output','B5');
        for k=1:1:2
            for l=1:1:50
                W20(k,l)=Wnew(k,l);
            end
        end
    else if t==30
            xlswrite('CLUS',D','Output','C5');
            for k=1:1:2
                for l=1:1:50
                    W30(k,l)=Wnew(k,l);
                end
            end
        else if t==40
                xlswrite('CLUS',D','Output','D5');
```

```
                for k=1:1:2
                    for l=1:1:50
                        W40(k,l)=Wnew(k,l);
                    end
                end
            else if t==50
                    xlswrite('CLUS',D','Output','E5');
                    for k=1:1:2
                        for l=1:1:50
                            W50(k,l)=Wnew(k,l);
                        end
                    end
                else if t==60
                        xlswrite('CLUS',D','Output','F5');
                        for k=1:1:2
                            for l=1:1:50
                                W60(k,l)=Wnew(k,l);
                            end
                        end
                    else if t==70

xlswrite('CLUS',D','Output','G5');
                            for k=1:1:2
                                for l=1:1:50
                                    W70(k,l)=Wnew(k,l);
                                end
                            end
                        else if t==80

xlswrite('CLUS',D','Output','H5');
                                for k=1:1:2
                                    for l=1:1:50
                                        W80(k,l)=Wnew(k,l);
                                    end
                                end
                            else if t==90

xlswrite('CLUS',D','Output','I5');
                                    for k=1:1:2
                                        for l=1:1:50

W90(k,l)=Wnew(k,l);
                                        end
                                    end
                                else if t==100

xlswrite('CLUS',D','Output','J5');
                                        for k=1:1:2
                                            for l=1:1:50
```

```
W100(k,l)=Wnew(k,l);
                                                  end
                                              end
                                          end
                                      end
                                  end
                              end
                          end
                      end
                  end
              end
          end
      end
alpha=alpha*0.9616;
end

xlswrite('CLUS',X','Input','A5');
xlswrite('CLUS',W','Weight','A5');
%xlswrite('CLUS',Wnew','Weight','E5');

for l=1:1:50
    hold on
    grid off
    plot(W(1,l),W(2,l),'b*')
    plot(W10(1,l),W(2,l),'gh')
    plot(Wnew(1,l),Wnew(2,l),'r+')
end
xlabel('W1')
ylabel('W2')
title('Plot of cluster units')
legend('Initial cluster units','cluster units after 10
epochs','cluster units after 100 epochs')
```