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Application of Operations Research in the Airline Industry

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Abstract:

Airlines handle sizeable volumes of passengers and freight, thereby requiring robust strategies that are formulated with the help of Operations Research techniques. Reeling under the cloud of COVID-19, several airlines have been forced to revisit their plans while striving for profitability. Literature and previous accounts have delineated the prominence of scheduling and forecasting for airlines to be able to service profitably. Therefore, there is an apparent necessity for models based on mathematical and statistical principles to forecast tentative circumstances in this sector and derive the most fruitful alternatives. The paper examines three relevant critical aspects – Route planning, Fleet management and Pricing. The paper addresses these factors by way of a Transportation Problem, Monte Carlo Simulation and a Game Theory Matrix respectively. The approaches adopted are demonstrated on Microsoft Excel. The findings of the analyses carried out indicate a trend of airlines switching to modern fuel-efficient widebodies and reduction of ultra-long-haul routes. This study considers a multitude of factors paving way for further research to consider solutions for problems of greater complexity.

Keywords **—Route Planning, Fleet Management, Competitive Pricing, Operations Research, Transportation Problem, Monte Carlo Simulation, Game Theory**

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I. INTRODUCTION

Aviation is one of the most "global" industries, bridging continents to link people, cultures, and enterprises. The air transportation industry has grown into a key segment of the world economy in the one hundred years since Orville and Wilbur Wright's first flight.

Over the years, the industry has continued to expand. It has weathered crises and proven long-term resiliency, establishing itself as a necessary mode of transportation. Air transport has historically increased in size every 15 years, outpacing most other businesses. In 2016, aeroplanes carried around 3.8 billion people around the world, totalling 7.1 trillion revenue passenger kilometres (RPKs). Air freight carried 53 million tonnes of cargo, totalling 205 billion freight tonne kilometres (FTKs). Every day, about 10 million passengers and USD18 billion worth of cargo are transported by around 100,000 planes (Aviation Benefits: Contributing to Global Economic Prosperity, 2018).

Operations Research uses mathematical and statistical methods to answer optimization and simulation questions that refine decision-making(Korstanje, 2020). Upon translation of a business question into an optimization question, it is inherent that a clear objective of a cost to minimize or a benefit to maximize is known.

The airline industry is an operations-intensive business. OR has been very important in assisting the airline industry and its infrastructure in maintaining strong growth rates and transitioning from a novelty that served an elite clientele to a mass-market service business.

The field of operations research has tremendously impacted the management of airlines. The exclusive air transport market is very competitive and to gain an advantage in this industry the airlines turned to various techniques of operations research. Moreover, the competition is posed not only by fellow air carriers but also ground transportation modes.

COVID-19 was proclaimed a pandemic by the World Health Organization (WHO) in March, 2020. Daily life has changed all around the world from that day onwards. Since the start of the crisis, air travel has been one of the worst-affected global industries. A full-fledged global transportation crisis has resulted from the ongoing COVID-19 pandemic. It became clear quickly that it would develop into a crisis unlike any other, forcing the industry into survival mode, with traffic and revenue losses. In 2020, industry revenues stood at $328 billion, which is around 40 percent of the previous year's. That's also the same revenue as in 2000. The sector isn't expected to grow a lot for many more years. It is projected that traffic won't return to 2019 levels before 2024 (Bouwer et al., 2021).

The goal for the airline industry, and for any other businesses for that matter, is profit maximization. To achieve this, strategic decisions have to be made to minimize operating costs and maximize revenue.

II. LITERATURE REVIEW

Given the importance attached to efficiency in a dynamic and competitive industry, airlines must utilize their limited resources in the best manner to maximize profits. To achieve this, an analysis of the airline's most profitable routes considering its fleet and crew strength as constraints must be conducted with the help of Operations Research (OR) techniques.

In terms of technology, it's safe to claim that aviation is one of the most sophisticated industries. A major factor that separates the bigger airlines from the crowd is their ability to manage a plethora of information and decision-making strategies, which makes it imperative to incorporate the use of OR in their actions. These actions vary from initial planning to resolving issues that may arise in the due course (Clarke & Smith, 2004).

Contributions of Operations Research are in several areas like leg-based and network-based seat inventory management, air traffic control, etc. Its main areas of focus are fleet assignment and maintenance routing. The size and complexity of the airline seat inventory control challenge prompted the creation of a solution, that being computerized Revenue Management (RM) systems that assess the level of demand at timely intervals while the flight is open for reservations. Nested booking limits and class protection levels were expressed using pictorial and graphical diagrams (Barnhart et al., 2003).

The focal point of the applications of Operation Research (OR) in Airlines (Etschmaier& Rothstein, 1974)was the development of a functional framework, and each component corresponded to the four main applications of OR, those being the development of schedules, controlling of overbooking, management of engines and scheduling of crew. Flight schedule refers to the timetable adopted by an airline between destinations with aircraft, crew, and maintenance staff assigned. (Kogutek Jamie, n.d.) Optimizing the problem of flight schedules is done by considering social, economic, and political factors. The problem is divided into phases of development where customer demand, revenues, and the number of aircrafts available with capacity per aircraft is inputted to give optimal air travel routes for flights. A linear programming model to schedule flights, aiming for maximizing the difference between cost and revenue has been presented, to which constraints can be added to schedule flights as per the need of the user. The authors nonetheless assume the demand to be constant irrespective of the time period and have overlooked the effect of competing airlines which would not be the case, in reality, thereby having some degree of impact on decisions. It was also suggested that the effective crew scheduling was not practical only by solving as Assignment Problem (Hungarian Assignment Method) as it failed to incorporate any complex limitation that practically exists and suggested that solving by heuristic search method was much more reliable. For engine cycle management, many different methods were developed by investigators, of which, simulation method, albeit with variations, was commonly proposed.

Scheduling a route must have certain objectives as per Camilleri, (2018). An effective route or schedule must be one where passengers are satisfied along with maximum feasible aircraft utilization and productivity of crew. An aircraft on ground does not generate any revenue, hence planners strive to make aircraft fly round the clock, minimizing turnaround time. Complications begin when planners are faced with the task of balancing and thereby achieving high load factor as well as a high frequency of flights as misjudging either could cost the airline dearly. Airlines will also attempt to widen their connection network from key airports as it would then augur well to serve direct as well as stopover routes. The price of landing slots restricts financially, meanwhile, many European airports also impose night curfews on air traffic and these factors must be taken into account.

Consequently, the stages of flight scheduling and fleet assignment are critical in the airline planning process (Birolini et al., 2021). Given the reciprocal relationship between air transportation supply and demand, one of the most important aspects of these models is to create effective methods for both, incorporating estimation of overall market demand and allocating passengers among available itineraries in a single market. This paper introduces a novel mixed-integer nonlinear flight scheduling and fleet assignment optimization model in which air travel demand generation and allocation are both endogenized at the same time. The model can optimize mid-size hub-and-spoke networks in an acceptable amount of time, according to computational testing based on realistic problem examples.

The route scheduling for either passenger or cargo flights is described to be an 'NP-Hard' problem, such that it is a non-linear mixed-integer program with solutions that are not easy to obtain. Since the aircraft fleet is often heterogeneous, different factors and restrictions come into play, more so for cargo flights that have fluctuating demand (KARAOGLAN et al., 2011).

Passenger demand forecasting is critical to identifying the key routes an airline would want to fly to. A study incorporated the system dynamics model to assess the qualitative and quantitative factors and their relative impact on the overall demand with estimated upper/lower bounds based on scenarios (Suryani et al., 2010). Consumer feedback on certain qualitative factors noticeably affects the outcomes, highlighting the importance of facilities offered on-board. Passenger Load Factor is a measure of an airline's revenue-generating ability as compared to its rivals and this was estimated with the assistance of Decision Trees (Laik et al., 2014).

Moore et al., (2021)talks about increased capacity of transit vehicles like airplanes, school buses and trains without increasing the risk of COVID-19. This is done by household grouping heuristic. Ideal social distancing considering some passengers are from the same household is done through two types of models. Based on the capacity and configuration of the vehicle, a mixed-integer programming model is utilized the allocate seats to passengers while following norms of required physical distancing. The second model explores the opportunity of grouping households. Lack of airport capacity is a hindrance in the growth potential of global air travel. A novel modelling and solution framework is suggested which enables the dynamic allocation of the airport's resources. The proposed framework, TFI "Timing Flexibility Indicator"(Katsigiannis&Zografos, 2021), along with endogenous and dynamic capacity constraints, improves airport capacity utilization, thus leading to improved airport slot schedules with reduced displacement and improvements in terms of displaced slot requests and passengers.

Delays and cancellations are inevitable which makes it crucial to be backed up by a recovery process strategy in times of contingency so that it can be initiated without any time delay to limit losses to the extent possible (Petersen et al., 2012).

With the recent COVID-19 outbreak, the airline industry faced a major setback. Umpteen flights all over the world were cancelled in order to prevent the spread of the virus. The global harm is already abundantly clear, and some airlines have declared bankruptcy, with forecasts that the number of insolvent airlines will considerably increase in the coming months. Given that aviation has such a large impact on economies and society, the primary goal of this article was to address, emphasize, and connect the key repercussions of COVID-19 on aviation mobility, as well as to examine its future implications. Based on data from relevant sources related to the airline sector, air transport mobility in Europe (EU) was investigated. The findings revealed that COVID-19 had a steady impact on air transport mobility in the EU (Nižetić, 2020), with a peak in April when the number of flights in the region dropped by more than 89 %. The pandemic had little effect on cargo traffic, and in certain cases, it even rose due to the need for medical supplies in the fight against the disease.

Pricing is a highly sensitive variable to ponder over for decision-makers. Given the usually high price sensitivity to demand as well as cross-sensitivity, pricing must be considered after understanding consumer preferences and competitors' strategies. This situation is explained as a non-cooperative Nash game (Sadigh et al., 2016). The objective is to then determine a strategy both rival firms would be sticking to. Nash equilibrium can also include the phenomena of recapturing passengers who have moved to the competitors (Garg & Venkataraman, 2020). It develops an algorithm to determine the pay-offs in the formulation of the underlying strategic form game between the competing airlines. The NE of this game is analyzed. By this, the problem of optimal seat allocation and pricing in a duopoly is addressed.

Each pricing strategy has its own set of drawbacks. The analysis of Airline Pricing Strategies (Lohmeier& Hess, 2008) gives an idea about setting the right fares. Further, this paper includes the importance of the airline industry and its influence on the economy and different pricing patterns and strategies of the international airlines and to what extent do they segment their markets by picking up two European airlines for demonstration – the German airline Lufthansa and the Swedish Scandinavian Airline System (SAS).

The use of the "multi-armed bandit" approach for airlines to seek higher revenues with dynamic pricing strategies dominating the pricing policies; the proposed method uses the consumers' willingness to purchase an ancillary service to identify meta-parameters that would adapt prices (Shukla et al., 2019). Results revealed a 43% increase in revenue per offer however this remains to be tested in an online setting.

De Boer (2003) investigated the dynamic inventory control drawback for one flight under imperfect market segmentation when clients book the cheapest available class that meets their requirements and is within their budget. Dynamic capacity management on airline seat inventory control has an impact on airline revenue management. The airline can carry more people by better matching demand and supply for seats, and the revenue management policy should be altered correspondingly. In airline revenue management, the most important question is how many seats to provide in each pricing class. This element of revenue management is known as the discount allocation problem. Airlines began offering connecting service through a centrally situated airport, allowing them to connect more city pairs with the same number of flights and so serve more people, increasing the difficulty of seat allocation. This was the part of revenue management that dealt with traffic. Another such problem is overbooking. By regulating the availability of each fare product for a particular fare structure, an airline can maximize revenue through overbooking and seat inventory control.

Hence, combining the issues of both routes and pricing lends the idea of sharing the burden by making an agreement with another airline. Codeshare agreements are a customary industry practice where airlines of regions geographically apart agree to serve each other's passengers by using their primary hubs as a convenient and seamless one-stop journey. The airlines then do not try to undercut each other, as they are now accessing a greater customer base thanks to the agreement. The given situation modelled using a sequential game (for instance chess), reported that it resulted in better schedule optimization and reduced overall costs (Bilotkach, 2006).

Earning profits concurrently with a horde of constraints such as those enlisted above is challenging. Using the Bayesian conditional probability theorem (Androshchuk& Rooney, 2019), an airline's profits can be evaluated by being mindful of the effect on profit due to changes in individual variables. These were indicated to be customer service, costs, and tied-up capital as per the research.

Therefore, the objective of writing this research paper is to use Operations Research (OR) techniques to formulate and solve problems pertaining to fleet, route management along with pricing decisions for the same. It is also intended to critically analyze and evaluate the benefits and limitations of using such a technique in differing circumstances.

III. ANALYSIS & FINDINGS

This research paper employs various statistical and operations research models in an attempt to simulate real-world scenarios. Data is collected from secondary sources, or generated randomly, due to the absence of adequately reliable information, using Microsoft Excel with bounds that mimic practical life. Further in this section, three critical aspects of airline management are analyzed with operations research techniques.

A. Route Selection

Airlines have to undertake significant market research and demand study to assess if there is an opportunity for them to service the route and earn profits along with understanding operational constraints (Kasturi et al., 2016).

To enhance the process of deciding on which destination to add, this paper attempts to provide a solution with a Transportation Problem (TP) Model, which is a special type of Linear Programming Problem (LPP). The TP Model seeks to optimize available routes from a particular origin to destination to achieve minimum cost.

To demonstrate this, the paper takes a hypothetical scenario of an airline based in the United States of America (USA) which is looking to add new routes. Many carriers in the USA operate international routes using a hub and spoke approach, providing connections to smaller cities via focus cities. Therefore, Table 1 demonstrates data on profit generated per seat sold on a particular sector along with demand for destination across the country, while considering capacity restrictions at already overworked hubs.

To formulate the above-given information as a TP problem, a dummy row is added, to balance the supply with demand, to be able to proceed with solving the solution. Additionally, profits values are converted to 'Opportunity Loss' values which are defined as the amount foregone when compared to choosing the most profitable route which in this case is ATL-AMS with $116/seat. The following matrix is then established as a result.

The Vogel's Approximation Method (VAM) is an iterative procedure for computing the initial basic feasible solution (IBFS) of a transportation problem using penalties. For further improvements from the IBFS, the MODI method (Modified Distribution) is put to use. The problem was solved using the Solver add-in for MS Excel. Table 3 shows the distribution of seats on various routes. Any allocation in the dummy row indicates forfeiture of allocation of seats for the particular destination, in this case fully for SFO and partly for DEL.

To summarise, Table4 maps the solution provided in Table 3 in a simpler, tabular format.

Transportation Problem Formulation - Profit in dollars per seat sold for each route

	Amsterdam (AMS)	San Francisco (SFO)	London (LHR)	New Delhi (DEL)	Tokyo (NRT)	Supply from Hub Cities
Atlanta (ATL)	116	31	71	19	49	1200
New York (JFK)	35	12	108	70	49	900
Los Angeles (LAX)	54	14	65	19	105	900
Demand for Destinations	550	930	1250	620	900	3000 ≠ 4250

Table1: Transportation Problem Formulation

Opportunity Loss Matrix with the addition of a Dummy Row to balance the problem

	Amsterdam (AMS)	San Francisco (SFO)	London (LHR)	New Delhi (DEL)	Tokyo (NRT)	Supply from Hub Cities
Atlanta (ATL)	0	85	45	97	67	1200
New York (JFK)	81	104	9	46	68	900
Los Angeles (LAX)	63	102	51	97	12	900
Dummy Row	116	116	116	116	116	1250
Demand for Destinations	550	930	1250	620	900	4250

Table 2: Conversion of values to solve Transportation Problem

Transportation Problem - Allocations of Passenger Seats when solved by Vogel Approximation Method (VAM)

	Amsterdam (AMS)	San Francisco (SFO)	London (LHR)	New Delhi (DEL)	Tokyo (NRT)	Supply from Hub Cities
Atlanta (ATL)	550	0	650	0	0	1200
New York (JFK)	0	0	600	300	0	900
Los Angeles (LAX)	0	0	0	0	900	900
Dummy Row	0	930	0	320	0	1250
Demand for Destinations	550	930	1250	620	900	4250

Resultant Profit (Max)	**$2,89,758**

Table 3: Solution of Transportation Problem

Flight Schedule	**Route**	**Seats**
Atlanta to Amsterdam	ATL-AMS	550
Atlanta to London	ATL-LHR	650
New York to London	JFK-LHR	600
New York to New Delhi	JFK-DEL	300
Los Angeles to Tokyo	LAX-NRT	900

Table 4: Tabular Representation of Data

B. Fleet Assignment

Airlines have historically operated at wafer-thin operating margins therefore it is of utmost importance for airlines to minimize available seats flying empty. The costs and revenues are highly sensitive and dependent upon available seat kilometres/miles(ASK/ASM)(Feriyanto et al., 2016).

Once a flight sector is decided, the right aircraft must be deployed that caters best to the demand. Disruptions like the COVID-19 pandemic, liquidation of a major airline such as Jet Airways in India in 2019, and closures or suspension of air traffic over airspaces of certain countries under conflict post challenges and require airlines to revisit the assignments of aircraft on certain routes (Li & Tan, 2013).

The lockdowns and quarantine measures imposed due to the pandemic has been a bane for airlines due to the sheer unpredictability and stringency of these measures. This research paper aims to forecast passenger demand using a Monte Carlo Simulation Model (Okafor et al., 2019) that takes into account the effect of the active coronavirus case prevalence in either the origin or destination of a route. Countries or cities with higher caseloads are likely to be either enforcing longer quarantine measures or other countries might have debarred citizens from such countries to prevent a rise in infections (Garrow&Lurkin, 2021). Therefore, a higher caseload would cause demand to significantly fall making it unviable to operate large wide-body aircraft on certain routes.

Table 5 presents a fleet with various aircraft types of a hypothetical airline with data for each aircraft considered to be an average estimate mirroring a realistic scenario. Larger aircraft generate a higher profit margin as they are equipped with much more modern equipment and have premium seat facilities and are usually operated on long-haul journeys.

Apart from the cost economics, the demand for a particular route must be estimated accurately. In the model presented in this research paper, an average of one thousand simulated values is used to predict the expected (adjusted) demand denoted by D_{adj} for a particular route. The Monte Carlo Simulation provides a reasonably good estimate and a large number of simulations allow for major variations in the final value to be eliminated.

$$D_{adj} = \frac{1}{1000}\sum_{i=1}^{1000}\left(\mathcal{D}_i^{(1-2\psi)}\right)$$

Where $\mathcal{D} \sim N(\mu, \sigma^2)$ indicating demand for a ticket on a particular route under normal circumstances and ψ is a statistical value randomly generated (using Excel RAND function) to model the growth rate of coronavirus cases in a country, following Chi-square distribution (χ^2).

Once the expected demand is finalized, the profit expected from operating each route with a different aircraft type is calculated and noted in Table 6. The cells that are 'N/A' indicate the route is not serviceable by the particular aircraft as it doesn't have adequate range, keeping cover for contingencies.

The results suggest unfavourable profitability under most circumstances for the largest aircraft, Airbus A380-800 despite the highest profit margins per passenger at full capacity. The most allocated aircraft are Airbus A350-900 and Boeing 787-800 which are widebodies with extremely good fuel efficiency contributing to their lowest operating costs while being long-ranged to operate inter-continental routes. Short-haul aircraft such as Airbus A320-200 in the following case always generated a favourable result, albeit having much lower margins. The given schedule is a fair indicator that most airlines have indefinitely stored their 4-engine widebody aircraft due to dried-up passenger demand and airlines prefer operating multiple flights on most popular domestic short-ranged routes in order to compete with rivals on a non-price plank. A more detailed flight scheduling model could even consider the impact of the flight timings that could impact demand.

Aircraft Type	Aircraft code	Max Passengers	Max Range	Cost (CASK)	Revenue (RASK)	Profit Margin
Airbus A320-200	A320	144	6200	0.0595	0.0636	6.54%
Airbus A330-300	A333	305	11750	0.0565	0.0632	10.71%
Airbus A350-900	A359	283	15000	0.0511	0.0582	12.28%
Airbus A380-800	A388	447	14800	0.0535	0.0647	17.36%
Boeing 777-300ER	B77W	358	13650	0.0529	0.0597	11.50%
Boeing 787-800	B788	254	13530	0.0517	0.0591	12.59%

CASK/RASK = Cost/Revenue per Available Seat Kilometer

Table 5: Aircraft Details by Type

Route Details				Profit estimated						Aircraft Assigned	
Origin - Destination	Route Code	Expected Demand	Distance (km)	A320	A333	A359	A388	B77W	B788	Type	Code
Mumbai - Delhi	BOM-DEL	410	1,135	680	2,345	2,296	**2,964**	2,792	2,144	Airbus A380-800	A388
Mumbai - Bengaluru	BOM-BLR	149	832	**499**	-6,465	-4,785	-11,839	-8,318	-3,569	Airbus A320-200	A320
Mumbai - Chennai	BOM-MAA	297	1,032	619	1,592	**2,088**	-4,853	-1,239	1,950	Airbus A350-900	A359
Mumbai - London-Heathrow	BOM-LHR	397	7,221	N/A	14,922	14,606	13,059	**17,763**	13,643	Boeing 777-300ER	B77W
Delhi - London-Heathrow	DEL-LHR	299	6,744	N/A	11,215	**13,642**	-30,885	-7,329	12,742	Airbus A350-900	A359
Delhi - Abu Dhabi	DEL-AUH	284	2,281	1,367	1,722	**4,614**	-12,565	-4,435	4,310	Airbus A350-900	A359
Chennai - Singapore	MAA-SIN	167	2,925	**1,753**	-19,422	-13,778	-38,238	-26,118	-9,457	Airbus A320-200	A320
Delhi - Hong Kong	DEL-HKG	264	3,752	2,249	-1,986	3,430	-25,597	-11,846	**7,089**	Boeing 787-800	B788
Mumbai - Dubai	BOM-DXB	364	1,928	1,156	3,984	3,900	-649	**4,743**	3,643	Boeing 777-300ER	B77W
Mumbai - Singapore	BOM-SIN	328	3,920	2,350	**8,100**	7,929	-10,597	2,532	7,406	Airbus A330-300	A333
Mumbai - Bangkok	BOM-BKK	274	3,034	1,819	378	4,599	-18,669	-7,706	**5,732**	Boeing 787-800	B788
Delhi - Frankfurt	DEL-FRA	283	6,134	N/A	4,144	**12,408**	-34,286	-12,386	11,589	Airbus A350-900	A359
Mumbai - Paris-Charles de Gaulle	BOM-CDG	239	7,001	N/A	-14,871	-3,877	-59,183	-32,651	**6,910**	Boeing 787-800	B788
Delhi - Newark	DEL-EWR	261	11,786	N/A	N/A	8,827	-82,569	-39,211	**22,268**	Boeing 787-800	B788
Delhi - Tokyo-Narita	DEL-NRT	283	5,921	N/A	3,930	**11,914**	-33,168	-12,023	11,187	Airbus A350-900	A359
Delhi - Sydney	DEL-SYD	449	10,422	N/A	21,536	21,081	**52,298**	25,637	19,691	Airbus A380-800	A388
Bengaluru - San Francisco	BLR-SFO	249	14,004	N/A	N/A	**308**	-1,09,421	N/A	N/A	Airbus A350-900	A359
Delhi - Bengaluru	DEL-BLR	218	1,703	**1,021**	-5,888	-3,033	-16,718	-10,087	-441	Airbus A320-200	A320
Mumbai - New York-John F. Kennedy	BOM-JFK	318	12,551	N/A	N/A	**25,388**	-41,756	880	23,713	Airbus A350-900	A359
Bengaluru - Dubai	BLR-DXB	370	2,695	1,615	5,569	5,451	95	**6,630**	5,092	Boeing 777-300ER	B77W
Bengaluru - Hong Kong	BLR-HKG	253	3,959	2,373	-4,934	1,006	-29,913	-15,181	**7,155**	Boeing 787-800	B788
Mumbai - Hong Kong	BOM-HKG	308	4,278	2,564	**8,840**	8,653	-17,013	-2,268	8,083	Airbus A330-300	A333
Mumbai - Istanbul	BOM-IST	157	4,838	**2,900**	-35,251	-25,666	-66,444	-46,152	-18,564	Airbus A320-200	A320
Delhi - Singapore	DEL-SIN	290	4,152	2,489	4,520	**8,399**	-21,454	-6,764	7,845	Airbus A350-900	A359

Table 6: Final Assignment of Aircraft based on Estimated Profit

C. *Fare Management in Duopoly*

Pricing decisions are critical in any competitive market, more so in a duopoly where two firms control a very large proportion of market sales. Often the goal of firms in such a scenario is to maximize revenue and be the leading firm in the industry.

Game Theory is an analytical model used to arrive at decisions when two or more competing parties attempt to assess their best decisions considering the decisions that would expectedly be made by the rival. Various structures of the game theory exist, depending on the payoffs and consequently, different strategies exist based on the objectives of a given player in the problem (Shubik, 2002).

Taking an example of the popular business route, Dubai (DXB) to Singapore (SIN) which is serviced by a direct flight only by two airlines, Emirates and Singapore Airlines, both of which are highly-ranked airlines with similar fleet and quality of service. The game theory model can thus be applied to assess the effect of price changes on revenues.

Considering empirically, long-haul flights on business routes are relatively price-inelastic (PED) due to the absence of alternate travelling options.

Cross-price elasticity (XED) is often high in the case of duopoly as firms look to outpace each other, andconsumers are not really loyal to an airline unless there is a stark difference in the quality of service offered by the airline.

Table 7 shows the payoff matrix for the 3x3 game theory when a firm decides to change the price by -5%, 0%, or +5%. The assumed values for PED and XED are -0.8 and 1.2, respectively, for purposes of determining the changes in revenue. The values hold affinity with the cases in actual markets.

In the situation delineated above, a single Nash equilibrium exists when both airlines cut their airfares. This is because the best strategy for each airline irrespective of what the other airline does is when the price is reduced. However, this is not the best payoff for both airlines, as both lose 2% of revenues.

Even though the best strategy for both airlines as a whole is to earn 2% higher revenues for each airline by raising fares by 5%. However, the issue here is that firms cannot collude as that is regarded as an unfair trade practice and are restricted to do so. Also, the firms do not and cannot trust each other to not act in a way that mutually benefits both firms, hence both firms try to play it safe and end up reducing prices.

For the route Dubai (DXB) - Singapore (SIN), change in Revenue (%) EK - Emirates, SQ - Singapore Airlines			
Strategies	SQ cuts fare	SQ keeps fare unchanged	SQ raises fare
EK cuts fare	EK -2 SQ -2	EK +4 SQ -6	EK +10 SQ -10
EK keeps fare unchanged	EK -6 SQ +4	EK 0 SQ 0	EK +6 SQ -4
EK raises fare	EK -10 SQ +10	EK -4 SQ +6	EK +2 SQ +2

Table 7: Strategies in Game Theory Matrix

Practically, a likely outcome is that both airlines would leave prices unchanged as both airlines are aware of the fact that if they were to reduce prices, the other airline would waste no time in cutting fares to the same level. Therefore, neither airline would want to take the first step and bite the bullet of cutting prices and instead, only act in case the other airline makes any variation to their airfares.

Realistically, airlines, especially full-service carriers, avoid competing on price, and instead they would work on providing complementary services that would enhance customer value and experience of flying in an attempt to build some brand loyalty.

IV. CONCLUSIONS

There are no two opinions on the fact that most airlines have been operating inefficiently for a long time. Even before the pandemic, they have been posting losses that have continued to mount, hence there is a necessity to recognize the need for superior planning.

Operations Research techniques attempt to resolve poor utilization of resources and assists in working towards optimal usage. This research paper illustrated the application of the Transportation Problem for the decision on routes. The method highlighted the required allocation of seats on given routes to maximize profits whilst fulfilling the set passenger restrictions. The Monte Carlo Simulation provided an estimate of passenger demand traffic while working with variables following various probabilistic distributions based on the characteristics of the variable. This aided in assigning the correct aircraft for a given route enabling the airline to maximize not just overall but also individual route profits. Lastly, the Game Theory lays an important framework of strategies to adopt with respect to the pricing of flight tickets. This ensures an airline is not caught on the wrong footing on the price front, bearing in mind the immense competitiveness of this industry.

These tools eventually form part of the very sophisticated and arduous planning process albeit these models only base decisions on estimates. The techniques discussed in this research paper adopt a quantitative approach to planning and heavily rely on the accuracy of raw input data fed in. Ultimately, greater caution when retrieving data to be used as input can yield the airline more accurate estimates, despite their discrepancies, which would bring about better decisions. “Well begun is half done”, and the process begins with planning.

V. LIMITATIONS & RECOMMENDATIONS

The following fallacies were observed in the analytical models that were demonstrated above. To overcome them, a few suggestions are also provided.

A. Lack of precision of data and numerousassumptions.

The data utilized in the analysis above is only partially borrowed from data published online by airlines, however, a lot of assumptions are made to ensure the data is relevant. Revenue and cost per unit are considered to be linear while in reality, it need not follow a pattern but is often cubic and quadratic, respectively. The game theory model assumes competition only on the basis of price and virtually assumes, no passenger demand switch to non-direct flights. The number of assumptions made also means that these models in isolation should ideally be not used as part of developing strategies or roadmaps as they may have ignored technicalities. Backing these up with qualitative research is crucial for them to meaningfully act as an optimization model. Future research could use more sophisticated platforms to allow for more of such constraints to be considered.

B. Costs and revenues for a route are subject to frequent and significant fluctuation.

Due to a competitive environment and a whole host of costs involved, airlines cannot predict costs to perfection. Even if an airline were to hedge itself against Aviation Turbine Fuel (ATF) price volatility, they are still subject to changes in slot fees, maintenance and repair charges. Due to economies of scale, costs per unit do not remain uniform. Operating a single aircraft type such as Southwest Airlines (B737 only), will lead to significantly lower costs for spare parts, maintenance and flight deck crew salaries due to the homogeneity of the fleet. The above-presented models might not be able to account for these considerations, as simply, as they significantly raise the complexity of the problem.

C. The analytical models have not looked at the possibility of premium seat classes and cargo demand.

The methods featured in this research paper, or for that matter even in the extensive literature in this field of research, do not take into account different classes of seats in an aircraft and their impact on pricing strategies. Due to the minuscule proportion of premium seats on aircraft compared to economy class, these are ignored for simplicity however due to completely different cost economics, it might be worthwhile to base future studies that take into account this factor. Singapore Airlines had recently launched a long-haul route, on its brand-new Airbus A350-900ULR consisting of only premium economy class, operating from Singapore to New York (Pallini, 2021). This is a 19-hour flight, and a major reason for operating is cargo demand as opposed to passenger demand. Cargo is another important aspect that could be considered when scheduling flights, and future studies could reflect this factor.

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