Optimization Models in Aircraft Assignment and Airline Disruption Management – A Systematic Review of Literature

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Abstract

In an airline, fleet-related assignment decisions are crucial to the overall airline profitability and these are being subjected to increasing complexities with time. Aircraft assignments are concerned with the allocation of a profitable aircraft to flights, given the constraints of airline fleet and flights the airline operates; the objective is to maximize airline profitability. A large range of constraints related to operations, passengers, airports etc. are to be satisfied in such an allocation. Initial fleeting decisions so made are often unable to complete as planned owing to the highly unpredictable, interdependent and regulated environment airlines operate in. Airlines almost never experience a day without disruptions, as observed in the research conducted. Fleet re-assignment aims at minimizing the cost of the disruption while ensuring operational continuity by using remaining resources and satisfying the additional constraints thus created. This study presents optimization models related to fleet assignment and re-assignment, adapted from Operations Research literature with their applicability analyzed, constraints considered and performance evaluated. The review brings up the need to address specific operational constraints of airlines; especially those of medium scale, taking aircraft seating configurations and specifics into consideration in the models to enhance practicality, in addition to accommodating real needs of airlines such as handling parallel disruptions.

Keywords
Fleet Assignment Models, Fleet Reassignment, Operations Optimization in Airlines, Operations Research

1. Introduction

The operations of an airline have high fixed costs while the industry reflects many externalities and dependencies (such as oil prices and security concerns). The demand is not very volatile and the supply is constrained in many airlines. The industry operates by selling flights using aircraft that are leased in the long term, the utilization of which may not be optimal due to the many externalities involved. Planning and operational processes of such an industry entail many constraints and uncertainties. Concepts related to operations research and optimization are therefore, of interest to the industry. One of the most important resources an airline handles is identified to be its fleet, good management of which decides the profitability of the airline to a great extent.

Initial fleet assignment decisions concern the generation of a set of routes the airline chooses to operate and deciding on the frequency of operation so as to maximize profit, based on factors like traffic estimates, revenue as origin-destination pairs subject to aircraft characteristics, operations costs and some operating restrictions. This decision is followed by the assignment of departure times and a profitable aircraft type to each flight, given the set of aircraft and operational routes of the airline. This deals with the aircraft types, each having different capacities, equipment

capabilities and availabilities, fuel requirements, maintenance operations, airport gating, operational costs (fuel consumption, crew wages, landing fees, ATC charges etc.) and potential revenues and assigns them to the pre-determined flights. The objective of this process is providing the optimum number of seats to the passengers at the optimum price.
As seats are an airlines product, offering a large number of seats, on one hand, implies greater sales and on the other hand, implies higher operational costs. The objective, therefore is, maximizing the offered capacity and minimizing operational costs.

According to Sherali et al. (2005), the assignment of an aircraft with a lesser capacity would generate lost customers ("spilled customers") while the assignment of one with a greater capacity would generate unsold ("spoiled") seats. Aircraft seats are also identified to be "perishable", unsold seats at flight departure do not yield revenue. Hence, fleet-related decisions have a high level of impact on revenues, which is highly susceptible to deviations from the original schedule. When an aircraft initially assigned to a flight fails to carry out its operations (possibly due to technical problems, crew logistics, operational issues etc.) a recovery plan has to be set up, to continue operations with the remaining resources. Therefore, fleet re-assignment focuses on generating a recovery schedule for the airline, which minimizes the impact caused by the disruption and the resulting financial loss, promotes resource utilization to maximize operational continuity by reducing its deviation from the original schedule. Disruptions affect the airline industry in two perspectives; impact on air carriers and impact on customers. In terms of the impact on customers, increased travel time, accommodation and food costs, missed connections and switching to alternative transportation modes or not travelling at all (opting video conferencing etc.) are identified. These effects ultimately affect the brand image and profitability of the air carrier and cause losses in terms of customer satisfaction and loyalty. In terms of the impact on air carriers, as crew and fleet are operated on scheduled times, disruptions cause extra crew costs, costs concerning disrupted passenger re-accommodation, aircraft re-positioning, rescheduling flights and re-booking passengers on alternative flights. A single disruption could set in motion a chain of subsequent disruptions, the cost of disruptions so caused is estimated to be about 8% of airline revenue ($60 billion worldwide) [Amadeus white paper, 2016] and could be broken down to the following areas:

- Cost to Passengers- time lost due to flight delays, cancellations, missed connections,
- Cost of lost demand due to alternative options,
- Cost of compensating disrupted passengers,
- Cost of rescheduling- runway capacity limitations etc.
- Crew and aircraft repositioning costs.

The high frequency of occurrence and cost associated with disruptions affect airline profitability to a great extent, particularly as airlines operate under extremely uncertain and cost-intensive environments. Operations deviations from the schedule have a great ability to propagate in such a way that these ultimately impact the whole business process of the airline as brought out in the Amadeus white paper (2016), depicted below in Figure 1. In addition, it also elaborates the downstream impact of a few disruptions where it sets a chain of subsequent disruptions in motion, highlighting the importance of a holistic approach to efficient operations management in the industry. The fact that the problem grows exponentially after a few subsequent disruptions as a result of low solution bandwidth is also shown.

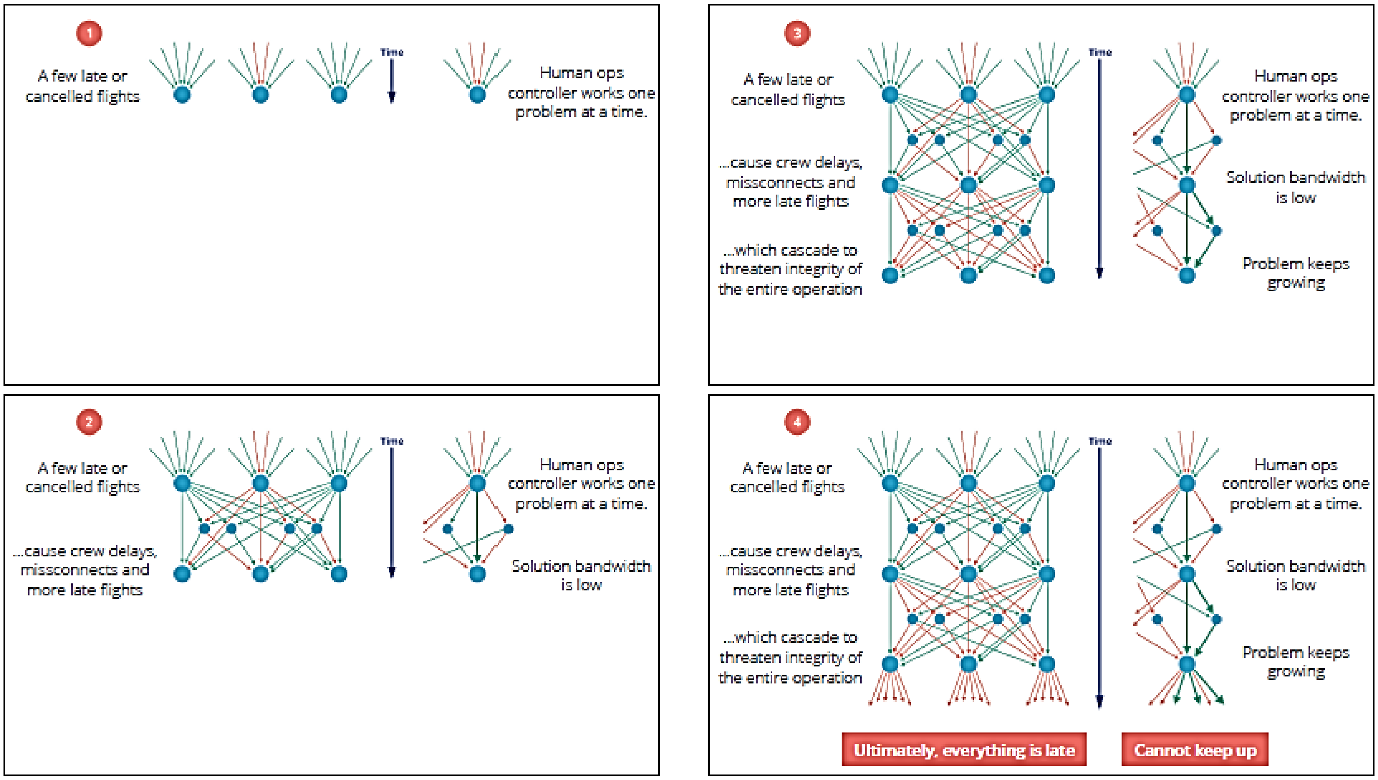

Figure 1. Reasons for airline operations control problems to expand virally (Amadeus White Paper, 2016)

2. Overview of Optimization Models

2.1 Basic Models in Fleet Assignment

Optimization models in airline fleet assignment are found to be divided into several areas on the basis of resource specificities and time horizon. The planning process could be presented in different frameworks that relate to six different optimization problems, according to Mancel and Mora-Camino (2006).

- Network design problem – for the long term, airports to be served etc.,
- Fleet design problem- for the long term, size and composition of the fleet of the airline,
- Fleet scheduling problem- frequency and timing of each leg of the flight (arrival and departure times) in a planning period,
- Fleet assignment problem- assignment of a suitable aircraft type to each flight leg,
- Aircraft routing problem- for the short term, a sequence of flight legs to be operated for each aircraft,
- Crew management problem- designing a work schedule for each crew member for flight legs.

Though these problems pertain to different frameworks, they are directly or indirectly linked to each other, the outputs of one problem is therefore fed into the other in a sequential manner to prevent sub-optimal final outputs. Fleet Assignment Problem is found to be challenging, both industrially and academically. The first model for this problem has been proposed by Ferguson and Dantzig in 1955, the objective is the maximization of profit for a given flight schedule. This model relates to the areas of fleet assignment and aircraft routing. The model has been revised in 1956 by the same authors, by introducing stochastic levels of demand. A model to assign aircraft to flights has been developed by Simpson (1978) with the objective of satisfying demand and minimizing operational costs.

Abara (1989) has introduced a basic framework for the fleet assignment problem; a linear program that could either maximize profits or minimize operational costs. Here, the availability of the fleet at each airport in the course of time is represented using a time-space network. This model, however, has computational limitations and has not been adopted by airlines due to efficiency constraints.

Götz et al. (1999) have approached the problem using simulated annealing based on a local neighbourhood search, to reduce computation time up to 75%. From more recent researches in this area, Ozdemir et al. (2011) propose a fleet assignment model using the data from Turkish Airlines. The objective of the model is minimizing the cost and determining the optimal number of aircraft grounded overnight at each airport by assigning the most appropriate fleet type to flights. The model is solved using integer linear programming. In Li and Tan (2013) an optimization model of the Fleet Assignment Problem is proposed. The objective function of this model is revenue maximization, and it considers the difference in scheduled flights and aircraft models in flight areas and mean passenger flows. The model is solved using a self-adapting genetic algorithm.

2.2 Integrated Models

The basic models have been extended to accommodate and integrate with problems related to the rest of the airline planning process. In Clarke et al. (1996) a model that extends the standard fleet assignment model to integrate crew and maintenance considerations is proposed. The network size and complexity are identified to increase radically with each additional adaptation. Barnhart et al. (1998) have proposed an integrated model which incorporates both fleet assignment and aircraft routing while Desaulnier et al (1997) has proposed a similar approach. The model proposed by Rushmeier and Kontogiorgis (1997) presents an event-activity network in which the sequence of activities that can be operated by a particular aircraft are represented, thereby integrating aircraft routing problem with the fleet assignment. This algorithm has been used by USAir's Schedule Development Environment with a reported benefit of $15 million per year [Mancel and Mora-Camino, 2014]. Yan and Tseng (2002) integrate scheduling and fleeting by incorporating passenger demands in the proposed model. They have adopted the origins and destinations (O–D pairs) method to define passenger paths and omitting legs, thereby allowing the model to select the legs for composing passenger routes. Aircraft routing and crew scheduling are integrated into Ahuja et al. (2004) and a multi-criteria optimization model is proposed using a large-scale neighbourhood search to allow the solution of large-scale problems. A fleet assignment model with time windows has been proposed by Rexing et al. (2000) with the objective of minimizing the number of aircraft and the cost of operation given the flight schedule. This uses a heuristic algorithm and time windows where the arrival and departure time is based on a preferred time in a certain interval. Fleet assignment and fleet maintenance are modelled in El moudani and Mora-Camino (2000). A dynamic approach which mixes a dynamic programming algorithm to assign the fleet and a heuristic technique to solve the embedded maintenance scheduling problem is proposed for a medium charter airline. On the data provided them, this approach has appeared to significantly reduce the operations costs of the airline [Mancel and Mora-Camino, 2014]. In Sherali et al (2005) traditional fleeting models are revised by including additional constraints, such as considering itinerary based demand forecasts and the recapture effect, as well as investigating the effectiveness of alternative approaches such as randomized search procedures.

2.3 Preventive Approaches

Achieving a perfect system in airline operations planning, execution and taking a preventive approach is a challenging task, given the high levels of uncertainty and dependability of operations on many uncontrollable factors as shown by industry dynamics. However, preventive approaches have been incorporated into models related to initial fleet assignment, to minimize the occurrence of disruptions to some extent. Based on the model proposed by Hane et. al (1995), Belannher et al (2003) have proposed a model using a branch and price algorithm considering time windows and the fact that revenue of a flight depends on its schedule.
To facilitate the swap option for fights in case of a disruption, Ageeva (2000) has proposed an aircraft routing model that permit overlapping routes in the solution.

Rosenberger (2002) presents a stochastic model of airline operations and states that major domestic airlines almost never experience a day without disruptions and that the frequency of disruptions is however, ignored by airline planning models. The paper states that the quality of the plan is evaluated under the assumption of ideal/optimistic operating conditions i.e. all the flights take off and land as scheduled, which is rarely the reality.
It is shown that the performance of the plan in operations (when executed) is a better measure of its quality. The difficulty in determining the performance of a plan when operated, a priori due to unforeseen future disruptions is also brought out. Flight schedules are normally made several months ahead of departure but Winterer (2004) proposes a model where swapping and retiming fights close to the day of departure are enabled. The algorithm has used data from European Airlines and proves to be efficient.

Rosenberger et al (2004) have proposed a model that increases operational robustness by "reducing hub connectivity" using short sequences of flights starting at a hub. This demonstrates that under certain conditions, it is possible to cancel entire sequences with only a few changes on other flights to keep an efficient schedule. Kang (2003) has described a method to decompose the flight schedule into independent sets (called "layer") of flights so that a disruption in one set does not affect flights of other sets. Smith (2004) has proposed a model to accommodate for disruption inconveniences by limiting the number of fleet types allowed to serve each airport.
The additional constraints limit aircraft dispersion in the network thereby making solutions more robust in terms of crew planning, maintenance planning and operations. He has further integrated revenue management in the model to make the solution responsive to demand.

2.4 Optimization Models in Fleet Re-Assignment

Aircraft assignments often deviate from the original schedule due to technical failures, operational requirements and other unforeseen circumstances which can be termed as disruptions. They could be caused by one or more factors.
Duck et al. (2012) states that there are two kinds of delays namely, primary delays and reactionary delays. Primary delays are out of the regulation of airline operations control such as delays due to air traffic control instructions. Reactionary delays occur due to activities of airline operations control such as receiving instructions to wait for a late aircraft. Both these kinds cause disruptions, and re-scheduling has to be done in order to recover airline operations. The process of re-scheduling, termed disruption management, obviously yields higher costs than the original schedule. The task of the controllers, therefore, is to find the minimal cost option for aircraft, crew rescheduling while satisfying operational constraints. The remaining resource constraints and the shortest time to get the operations back on track are also to be considered and the solution has to be generated real-time.

As shown in Mariani (2015) and Clausen (2007), the most common recovery options available for an airline are,

- Cancelling
- Delaying/ Re-timing
- Diverting or ferrying aircrafts
- Swapping aircraft between scheduled flights; a chain of swaps may be necessary to recover.
- Rerouting flight crew or calling reserve flight attendants (stand-by resources) as needed by the aircraft and/or flight change.
- Reschedule or compensate for passengers according to the nature of the change.

Many other components like cargo, catering etc. add to the cost function of the operation.

The background study was done on a medium scale international airline for this research indicated that disruption recovery decisions, have aircraft availability as the major constraint. Other resources such as crew are relatively easily available on standby whereas the options are limited when it comes to aircraft. Configurations and specifications have caused many aircraft of the same fleet type to be unavailable at a given time. For instance, the availability of one type of narrow-body aircraft is less, as the fleet has different seating configurations. Therefore it is identified that aircraft are the scarce and the most costly, hence critical resource to recover in the event of a disruption. The models reviewed in this paper give a greater weight to aircraft re-assignments than to other problems in the sequence. According to the paper by Zeybekcan and Ozkarahan, airline re-planning process is completed sequentially due to its complexity and resource intensiveness i.e. aircraft re-assignments are made first, the results of that determine the crew scheduling which is solved after. The paper states that it is more applicable to consider each problem separately since the integrated problem makes the solution more difficult and complex due to a large number of variables to be considered and increased number of constraints to be satisfied.

Clausen (2007) shows that controllers deciding on the recovery strategy have limited IT-based decision making support, and are content with a single course of action, which may not be optimal, owing to the complexity of and time consumption by recovery action planning. It is therefore clear that recovery actions are not compared or assessed and a formal optimality is not reached. The paper states that the controllers have no way of assessing the quality of the decision they are about to execute. The downstream effects on subsequent flights due to disruption propagation are also dealt with, the same way. This causes a major profit downturn for the airline. Theodorovic and Guberinic (1984) have proposed a network where nodes represent flights on a given airline network, and arcs are the total time losses on individual flights with the aim (objective) of minimizing the total passenger delay on the airline network. The problem is solved by branch-and-bound methods.

Teodorović and Stojkovic (1989) in the paper "Model for Operational Daily Airline Scheduling" have presented a model with the objective of minimizing the total number of cancelled flights. It also takes the minimization of total passenger delay into account, in case the previously mentioned model returns schedules with equal numbers of cancellations. The model allows cancellations, re-timings and swaps. It is formulated as a lexicographic optimization problem and a heuristic algorithm is used to solve it.

Argüello et al. (1997 and 1998) have presented an approximation scheme and a greedy randomized adaptive search procedure (GRASP) for the problem, with the objective of minimizing the costs of re-assignment. Here, cancellations, delays and aircraft substitutions are accommodated. Two models are presented; the resource assignment model and the multi-commodity flow model. A third model, the time band approximation model, is founded on a time-based network representation. A case study on a Taiwan air carrier is presented in Yan and Yang (1996) where a decision support framework is proposed. It is based on a basic schedule perturbation model constructed as a dynamic network from which several perturbed network models are developed for re-scheduling after disruptive situations. These network models are formulated as pure network flow problems or network flow problems with side constraints. The objective in all models is to minimize the cost of schedule repair, which includes passenger revenue. The former is solved using the network simplex method while the latter is solved using Lagrangian relaxation with subgradient methods. Thengvall et al. (1997) present three multi-commodity network-type models. The first is a pure network with side constraints, the second is a generalized network, and the third is a pure network with side constraints in which the time horizon is discretized. Each model allows for cancellations, delays, ferry flights, and substitution between fleets and sub fleets. In the first two cases, the objective is to maximize a "profit" function. In the third case, the objective is to minimize the sum of cancellation and delay costs. The first model of the lot has been found to be the most efficient. All the above models have each been tested using data from different airlines with different fleet sizes and aircraft types. Filar et al. (2001) present a review of literature on how disturbances at a given airport could be handled and suggestions are made on how singular perturbation theory could be used to analyze disruptions.
Mariani (2015) provides an analysis of available models for disruption management in the airline industry. In addition, the paper also presents some approaches to model the cost of delays with an analysis.

With increased competition in the industry parallel to the demand for air travel and variations in airport and aircraft limitations, the problems of flights scheduling, fleet assignment and re-assignment have become all the more critical. At the same time, improvements and diversification in Operations Research methods (particularly in terms of heuristics and metaheuristics), as well as increased computer hardware specifications with increased software performance and efficiency have enabled the development of multiple approaches in solving the Fleet Assignment problem efficiently and in ways that take the real and dynamic needs of airlines into account.

The following reviews of literature present more recent and diversified approaches to the problem, with highly complex and computationally advanced solutions and models.

Abdelghany et al. (2008) illustrate a decision support tool for airlines with a case application for a US air carrier. This tool integrates a schedule simulation model and a resource assignment optimization model in a rolling horizon modelling framework with the aim of minimizing flight delays and cancellations. The schedule simulation model component of the tool projects the list of disrupted flights in the system, as a function of the severity of anticipated disruptions. The resource assignment optimization model component examines resource swapping and flight re-quoting possibilities to generate a schedule recovery plan. A modified travelling salesman model is proposed in Wu et al. (2017) using a distributed computation approach to integer programming. The distributed computation proposed is based on Dang and Ye's iterative method for integer programming. The paper proposes an approach to split the problem into two subproblems; one- to generate sets of the feasible flight routes for each aircraft fleet type simultaneously, using a distributed implementation of the iterative method for integer programming. Two, the feasible flight routes are reassigned to the available aircraft in each fleet to form a recovery plan. Lee et al. (2017) present a model for disruption recovery where a stochastic model of congestion is integrated across a network of airports, the formulation is done as a stochastic mixed-integer program. The results suggest that the integration of airport congestion scenarios can reduce expected recovery costs by 1% to 4%. Integer programming and polynomial-time algorithms based on primal-dual schema are illustrated in Manyem (2017) where combinatorial algorithms are used to solve the two problems of, single airport ground-holding with cancellations and that without cancellations. The paper reviews the NRJ model (Navazio and Romanin-Jacur; one of the earliest ground holding optimization models) and introduces a different set of variables to accommodate cancellations.

An approach based on ant colony optimization is proposed in Sousa et al. (2015) where they have automated the problem solving of aircraft assignment problem and the re-assignment problem. Dynamic scheduling and re-scheduling of flights is done using a sliding window. The aim is to minimize the cost to the airline resulting from disruptive situations. Samà et al. (2012) discuss the management of take-off and landing operations in the presence of traffic disturbances in a terminal control area. The decision support system is based on a rolling horizon framework. The problem is modelled via an alternative graph formulation, i.e. a detailed model of air traffic flows in the Traffic control area. Aircraft rescheduling and rerouting algorithms are used to solve it. A truncated branch and bound algorithm for aircraft rescheduling with fixed routes, a tabu search scheme for combined aircraft rescheduling and rerouting, and the first in first out (FIFO) rule that is used as a surrogate for the dispatchers behaviour are compared. Through the research, they have found that the solutions produced by the optimization algorithms are of better quality compared to FIFO, in terms of delay and travel time minimization. However, the optimization approaches are found to require frequent re-timing and re-routing in consecutive time horizons.

The following table (Table 1) based on Mariani (2015), provides a summary of the models mentioned and other models available.

Table 1. Summary of models

Authors	Year	Approach	Options			Recovery			Objective function	Solution approaches
			Cancel	*Delay*	*Swap*	*Crew*	*Multi-fleet*	*Passenger*		
Theodorovic and Guberinic	1984	Connection Network		✓	✓				Min: Total passenger delays	Branch and bound
Theodorovic and Stojkovic	1990	Connection Network	✓	✓					Min: Number of cancellations and delay minutes	Lexicographic Dynamic Programming, Goal Programming, Greedy Heuristics
Theodorovic and Stojkovic	1995	Connection Network	✓	✓	✓	✓			Min: Total number of canceled flights, total passenger delays	Lexicographic Dynamic Programming, Goal Programming, Greedy Heuristics
Talluri	1996	Connection Network			✓		✓		Min: Swapping costs	Heuristic algorithm for swapping
Yan and Tu	1996	Time Line Network	✓	✓	✓		✓		Max: Total system profit	Lagrangian relaxation with subgradient methods
Yan and Yang	1996	Time Line Network	✓	✓					Max: (Revenue - Costs)	Lagrangian relaxation with subgradient methods
Arguello et al.	1997	Time Band Network	✓	✓	✓		✓		Min: Rerouting and cancellation costs	GRASP (Greedy Randomized Adaptive Search Procedure)
Lou and Yu	1997	Integer programming		✓					Min: Percentage of flights delayed more than 15 mins	LP relaxation
Thengvall et al.	2000	Time Line Network	✓	✓	✓				Max: (Revenue - Costs)	LP relaxation, Rounding Heuristic
Bard et al.	2000	Time Band Network	✓	✓					Min: Delay and cancellation costs	LP relaxation, Branch and Bound
Rosenberger et al.	2003	Connection Network	✓	✓	✓	✓			Min: Rerouting delay and cancellation costs	Aircraft Selection Heuristic
Andersson and Varbrand	2004	Connection Network	✓	✓	✓		✓		Max: (Revenue - Costs)	Column Generation
Abdelghany et al.	2008	Mixed Integer Programming	✓	✓	✓	✓			Min: Resources assignment cost, total delay cost and cancellation cost	Rolling horizon
Eggenberg et al.	2009	Constraint Specific Network	✓	✓	✓		✓	✓	Min: Operating, cancellation delay costs, Passenger inconvenience costs	Column Generation, Dynamic Programming
Sousa et al.	2015	Meta heuristic	✓	✓	✓				Min: Operational cost	Ant colony optimization
Wu et al.	2017	Integer programming		✓	✓		✓		Min: Revenue loss	Distributed computation
Lee et al.	2017	Mixed Integer Programming	✓	✓	✓		✓		Min: Cost of recovery	Dynamic stochastic optimization, Stochastic queuing
Manyem	2017	Integer programming	✓	✓					Min: Cost of delay	Primal- Dual schema

3. Discussion

The models presented in this review relate to airline operations optimization. Preventive approaches have been taken to minimize the occurrence of disruptions, in fleet assignment models. It is identified that initial aircraft assignments are carried out with minimum slack allocation so as to maximize resource utilization since the industry is cost-intensive. Therefore, it is noted that most preventive models are constrained and requires other procedures to be carried out in the case of a disruption. It is also identified that achieving a highly preventive system is challenging due to the practicalities of the industry, given its many dependencies and uncertainties. Models concerned with disruption management, therefore, hold a significant point of impact on overall airline performance. Most of the models available consider the problem of re-assignment sequentially through the planning process. It is noted that controllers have minimum support in evaluating the effect of the proposed plan on overall flight plans, once executed. In addition, it is also learnt that inherent airline requirements, company specifications, fleet configurations and unique operations and features of an airline hinder the practical implementation of most of the models.

As many airlines have fleet configurations and different compositions of the fleet, solutions that consider the fleet structure of an airline could be developed, for empirical significance. The review identified the need to address specific operational constraints of airlines; especially those of medium scale, take aircraft seating configurations and specifics into consideration in the models to enhance practicality, in addition to accommodating real needs of airlines such as handling parallel disruptions. Two or more disruptions occurring parallelly would require a recovery plan generation where the overall optimal solution considers resource allocation to both situations inclusive, instead of treating them as two separate or independent disruptions; without optimizing the two disruptions independent of each other.

Though there are many models proposed for fleet assignment and re-assignment, the underlying approach is more or less similar in most cases. Fleet assignment problem has algorithms that have been tested to be optimal. Models consider each problem in the airline planning process; (networking, fleeting, routing, crew allocations) in sequence. If two of the problems are considered together, it is considered as an integrated model. From the perspective of the overall solution to the flight assignment problem, the solutions given by less integrated approaches could be sub-optimal. In which case, the process has to be iterated with different values given to decision variables. This could interfere with the time available for decision making. Model optimization in terms of computational efficiency is therefore important and evaluation is difficult for each of the models. Even though integrating all the options for a recovery plan (cancel, delay, swap) in the solution to recover most of the process (passengers, crew, aircraft, ground operations) by considering costs related to all the affected components (aircraft, crew, passengers, ground operations) could be the optimal solution, it could be infeasible if computation time exceeds decision-making time; especially as disruption recovery plans have to be made in a matter of minutes in real-time. It is also noted that modelling the whole process radically increases problem complexity – number of variables and constraints and is therefore approached in a sequential pattern. Computation time seems to increase drastically with the increasing complexity of the solution. The weighting of costs in the objective functions models the situation better as suggested in the models reviewed. The downstream impact of a recovery action could also be simulated as it is identified that decision-makers have minimum practical and software-based support.

It was identified that in most models, the multi-fleet situation is minimally modelled but is the real scenario in airlines. In the practical scenario, recovery action calls for professional experience. In that case, mathematical modelling could be a decision-support system unless it models the rationale/logic behind expert behaviour when performing recovery procedures. However, an explicit mathematical model could serve as valuable support for decision making.

Heuristic and Meta-Heuristic models seem to have promising applications in this problem. Recent research has utilized related concepts to solve this problem. The overall overview of the study could be presented as below (figure 2); operations research concepts have theoretical and empirical significance in the areas of fleet assignment and routing, integrating fight assignment with the rest of the planning framework, preventive approaches and disruption management. Aircraft assignment is approached with minimum or no slack allocation as variations of the basic fleet assignment problem. It has also been largely integrated with the rest of the functions of the airline planning process, such as crew assignment. Aircraft assignment has a basic underlying model addressed as the Fleet Assignment Problem (FAP) where the objective is to assign aircraft to each of the scheduled flights constrained by the demand by passengers, operating cost, and targeted revenue of each fleet type.

It is identified that predictive analytics and similar approaches linked to artificial intelligence are being employed in the solution of the fleet assignment problem. Disruption management has been particularly addressed in the industry, hence in the framework shown in figure 2, where the cost variables are identified to be aircraft, crew, ground operations and passengers; in a disruptive situation, each of those elements has to be recovered at a minimum cost.

The study indicated that one or more of these variables have been addressed in varying levels in the models available. Options available to overcome an operational disruption are identified to be cancelling, swapping and delaying; the models have addressed one or more of them in the reviewed literature. Crew recovery is minimally addressed similar to passenger recovery: Neither is the cost of disruption from the point of view of passengers captured enough, if at all. As airlines offer a highly competitive product, the cost of losing a passenger could have an infinite impact on the overall cost.

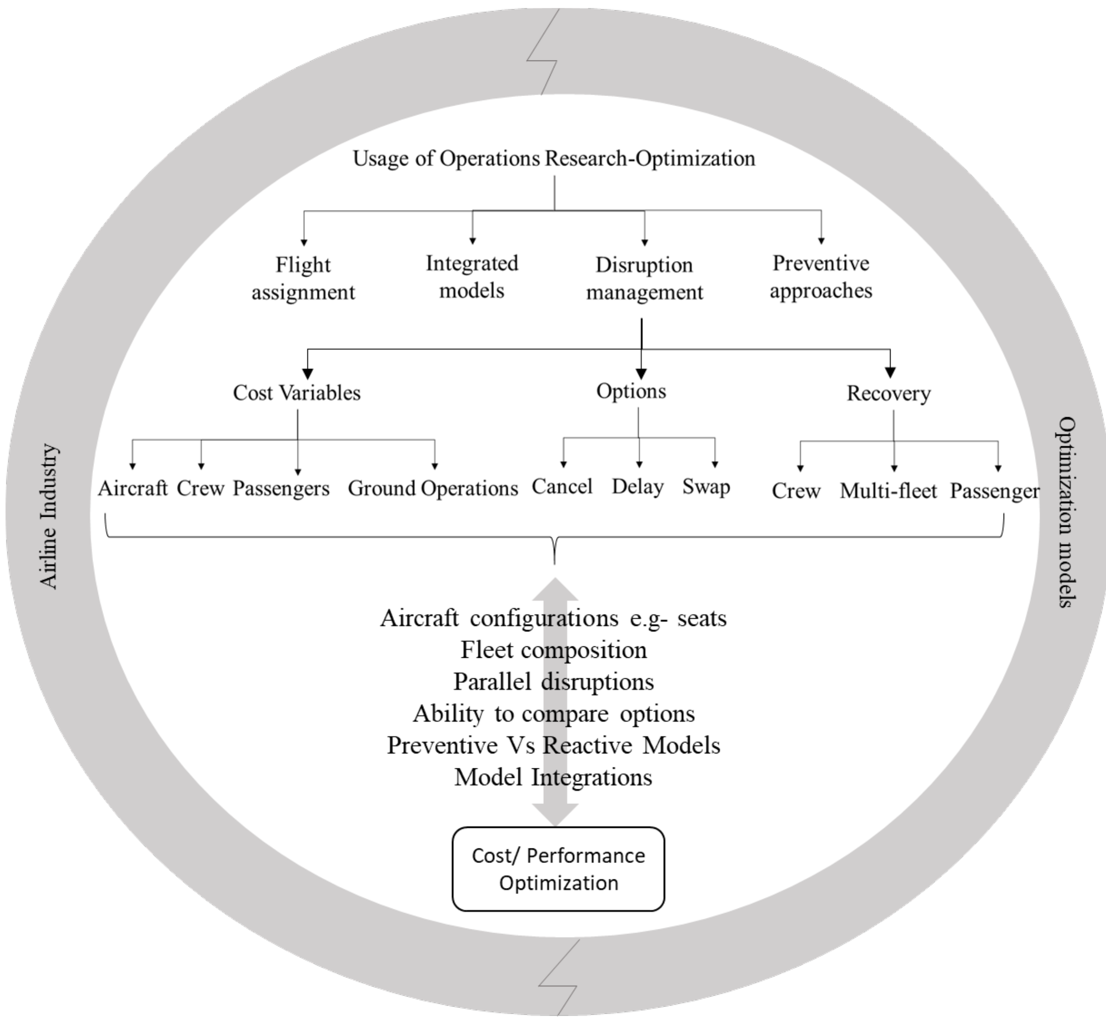

Figure 2. Optimization framework in the airline industry

4. Conclusion

This paper serves as a guide to identifying logical and defined models available in the areas of aircraft assignment and re-assignment, systematically. Aircraft assignments allocate profitable aircraft to flights, with the constraints of the airline fleet and flights that the airline operates and the objective of maximizing airline profitability. Additional constraints related to operations, passengers, airports etc. are to be satisfied. Initial aircraft assignments often get disrupted owing to the industrial environment of the airline business. Fleet re-assignment, therefore concerns minimizing the cost of the disruption while ensuring operational continuity using remaining resources and satisfying the additional constraints created. Many optimization models have been proposed in relation to fleet assignment and re-assignment, and are found to have a great level of applicability in the industrial context. The constraints considered by them and their performance are being challenged, given the computational abilities of software being developed. The study systematically reviews current literature and identifies the available models in terms of the constraints, functions and performance for airline disruption management and consequent aircraft reassignment problem.

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