

From The Transportation Table to Column Generation: A Review Of 50 Operations Research Studies in Airline Planning with Two Replications

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Abstract—Most of the optimisation models that airlines use every day grow out of the transportation and assignment problems taught in a first course in Operations Research (OR), yet recent published applications of these classroom methods to aviation are small and seldom checked. This paper reviews 50 peer-reviewed studies, published between 1982 and 2023, that apply OR to nine airline planning stages, from network design to disruption recovery. Every reference was matched against the Crossref registry, and each study was classified by problem, model, objective, constraints, solution method, data, validation and region. The review finds three things. Methods moved from exact integer programming before 2000 to decomposition and integrated planning in the 2000s, and then to stochastic, multi-objective and machine-learning approaches after 2010. Nine studies report systems in daily use, with gains as large as US\$1.4 billion over three years. Twenty-eight of the 50 studies come from North America and only one from India. We also re-solve the two recent classroom-method studies in the sample: a transportation model for route selection is confirmed apart from a US\$492 rounding gap, while a crew-pairing assignment model is shown to rest on a cost matrix with 19 wrong cells, so that its true minimum layover is 52 hours rather than the 65.5 hours reported. The paper closes with a research agenda for carefully checked applications of classroom OR to Indian aviation.

Index Terms—Airline planning, assignment problem, crew scheduling, fleet assignment, literature review, operations research, replication, transportation problem

I. INTRODUCTION

Airlines were among the first businesses to adopt Operations Research. Aircraft, seats and crew time are costly and cannot be stored, so even small improvements in how they are allocated are worth a

great deal. American Airlines put the value of its seat-inventory models at about US\$1.4 billion over three years [1], and Delta expected around US\$300 million over three years from its fleet model [2].

Planning normally proceeds in stages: network and route design, schedule design, fleet assignment, aircraft maintenance routing and crew scheduling, followed by operational tasks such as revenue management, gate assignment and recovery from disruptions [3], [4]. Each stage has its own body of models, and several surveys cover single stages in depth [5]–[12].

There is, however, a gap between this literature and the way OR is first taught. An introductory course covers linear programming (LP), the transportation problem, solved with Vogel's Approximation Method (VAM) and the Modified Distribution (MODI) method, and the assignment problem, solved with the Hungarian method. Industrial airline models look far more complicated: multi-commodity network flows, set partitioning, column generation and Bender's decomposition. Recent studies that apply the classroom methods directly to airline problems are few, small and rarely verified.

This paper makes three contributions. First, it reviews 50 verified studies across nine planning stages with one common coding scheme, showing how methods, data and settings changed over four decades. Second, it shows that every major airline model is an extension of a transportation, assignment or LP model from the introductory course. Third, it re-solves two recent classroom-method studies, confirming one and correcting the other, and uses the result to set out a research agenda.

II. REVIEW METHOD

A. Selection of Studies

The review is structured and purposive: 50 studies were chosen so that every planning stage and every decade from the 1980s onward is covered. A study qualified if it was a peer-reviewed journal article, applied an OR model to an airline or airport planning or operations problem, and stated both a model and a solution method. Within each stage we took the most influential studies together with recent work from 2015 to 2023. Ten surveys [3]– [12] were read as background and are not counted among the 50.

B. Verification

Candidates came from the surveys and from Crossref bibliographic searches by stage and technique. On 9 October 2026 every included DOI was resolved in the Crossref registry, with title, authors, year and journal checked; 48 of the 50 studies matched. The remaining two have no registered DOI and were checked against their published PDFs. Citation counts were taken from OpenAlex on the same date, and abstracts from OpenAlex and Semantic Scholar.

C. Coding Scheme

Each study was coded on the fields in Table I, which follow the usual steps for analysing an OR application. For 15 studies the publisher does not release the abstract to open indexes; these were coded from a short-indexed summary, and their details are flagged for checking against the full text.

TABLE I CODING SCHEME APPLIED TO EVERY STUDY

Field	Categories or content
Planning stage	Network and route design; schedule design; fleet assignment; maintenance routing; crew scheduling; integrated planning; disruption and recovery; revenue and seat allocation; gate assignment
Main technique	Classical LP, transportation or assignment; network or graph algorithm; exact integer programming; decomposition; heuristic or metaheuristic; stochastic; multi-objective; analytical or game-theoretic; machine-learning hybrid
Data	Real airline or airport data; real market data; hypothetical; none; not confirmed

Field	Categories or content
Validation	Used in practice; tested on real data; test instances; simulation; worked example; analytical
Region	North America; Europe; Asia; India; not specified
Also recorded	Problem, objective, constraints, method, software, key result, strength, limitation, link to classroom methods

III. THE CLASSROOM ROOTS OF AIRLINE PLANNING MODELS

Each of the nine stages extends one of three models from the introductory course, as Fig. 1 shows. Network, schedule and fleet decisions move capacity through a network over time, so they extend the transportation problem. Crew, maintenance, gate and recovery problems match resources to tasks, so they extend the assignment problem. Seat allocation divides fixed capacity among competing demands, which is the core of linear programming.



Fig. 1. Airline planning stages, the number of reviewed studies in each, and the classroom model that each stage extends.

Two formulations make the link concrete. In the classroom assignment problem, x_{ij} equals 1 when resource i is given task j , and the total cost is minimised with every resource and every task used exactly once:

$$\begin{aligned} \text{Min } Z &= \sum_i \sum_j c_{ij} x_{ij} \quad (1) \\ \sum_j x_{ij} &= 1 \text{ for each } i \end{aligned}$$

$$\sum_i x_{ij} = 1 \text{ for each } j$$

$$x_{ij} \in \{0, 1\}$$

Crew pairing keeps the same structure but let's one column, a crew trip p of cost c_p , cover several flights; a_{fp} equals 1 when trip p includes flight f :

$$\text{Min } Z = \sum_p c_p x_p \quad (2)$$

$$\sum_p a_{fp} x_p = 1 \text{ for each flight } f$$

$$x_p \in \{0, 1\}$$

Fleet assignment, in turn, is a transportation problem repeated over a grid of airports and times, with a separate flow for each aircraft type [13].

IV. DESCRIPTIVE RESULTS

Solution methods changed in three clear phases (Table II). Before 2000, exact integer programming was the most common approach, used in 7 of 21 studies. In the 2000s, decomposition methods led with 7 of 15 studies, chiefly column generation and Bender's decomposition for larger and joint models. After 2010 no single method dominates: metaheuristics, multi-objective and stochastic models and a machine-learning hybrid all appear. Classical transportation and assignment methods appear in only four studies, and after 2010 only in the two classroom-level studies.

TABLE II STUDIES BY MAIN TECHNIQUE AND PERIOD

Main technique	1982–1999	2000–2009	2010–2023
Classical LP / transportation assignment	2	0	2
Network or graph algorithm	1	0	0
Exact integer programming	7	6	2
Decomposition	4	7	2
Heuristic or metaheuristic	4	0	4
Stochastic or probabilistic	2	1	1
Multi-objective	0	0	2
Analytical or game-theoretic	1	1	0
Machine-learning hybrid	0	0	1
Total	21	15	14

The settings are concentrated geographically (Table III). Twenty-eight studies are set in North America; only one, on the Bhubaneswar–Kolkata route, uses Indian data. At least 33 studies use real airline, airport or market data, and nine describe systems that airlines actually used (Table IV): at American Airlines for fleet assignment, crew pairing and seat inventory, at Delta for fleet assignment, at Frontier for passenger mix, at Western for booking limits and at American Eagle for re-fleeting.

TABLE III STUDIES BY REGION

Region	Studies
North America	28
Not specified	11
Europe	5
Asia (excluding India)	5
India	1

TABLE IV STUDIES BY TYPE OF VALIDATION

Validation	Studies
Tested on real airline data	23
Tested on test instances	11
Used in practice	9
Analytical	3
Simulation	2
Hand-worked example	2

V. SYNTHESIS BY PLANNING STAGE

A. Network and Route Design (8 studies)

Hub-location modelling began with a quadratic integer program tested on flows between US cities [14]; linear integer versions of the main hub problems followed [15]. Later work added link capacities and routing rules [16], showed analytically when direct service is better than hub-and-spoke [17], and brought competing airlines in through a two-stage game [18]. More recent studies let demand respond to the network itself, using an econometric demand function inside a mixed-integer model for a large European airline [19], or rank candidate long-haul routes against two objectives [20]. At the classroom end, seats from three hubs are allocated to five cities as a transportation problem [21].

B. Schedule Design (6 studies)

Schedule and fleet decisions are now usually made together. Time-space network models support joint fleet routing and timetabling [22], [23]; integrated flight-selection and fleet models were tested on data from a large US airline [24]; the timetable can be re-optimised while bookings arrive [25]; and passenger-choice models now sit inside the optimisation [26], [27].

C. Fleet Assignment (8 studies)

Fleet assignment is the clearest success. An integer linear programme was built for American Airlines [28]; Delta's model chose aircraft types for about 2,500 daily flights across ten fleets [2]; and exact solution at full scale became practical, with an optimality gap of at most 0.02% [13]. Later work added flexible departure times [29], the value of whole passenger journeys [30] and origin-destination revenue [31], emissions as a second goal [32] and uncertain demand through two-stage stochastic programming [33].

D. Aircraft Maintenance Routing (4 studies)

Every aircraft must reach a maintenance base within a set interval. Rotations have been built with Lagrangian relaxation [34] and with fast graph algorithms [35]; day-to-day versions add limited maintenance capacity through branch-and-price [36] or combine an exact model with a quick heuristic [37].

E. Crew Scheduling (9 studies)

Crew pairing is a set-partitioning problem, equation (2). It produced early recorded savings at American Airlines of US\$18 million a year [38] and over US\$20 million a year [39]. Exact methods followed: branch-and-cut [40], a tighter duty-period formulation [41] and column generation for monthly Air France rosters [42]. Flexible departure times with aircraft-count checks lowered crew costs further [43]. Recent studies use memetic search [44] and a neural network inside column generation [45]. A six-flight Indian case is solved with the Hungarian method in [46].

F. Integrated Planning (4 studies)

Planning stages one after another can give poor or even unworkable plans. Bender's decomposition has been used to join aircraft routes with crew trips [47], fleet with crew pairing [48], and all three stages in one model [49]; another study moves key maintenance

choices into crew planning [50]. Each reports gains over sequential planning.

G. Disruption and Recovery (5 studies)

Recovery models re-plan within hours. The earliest study re-dispatches aircraft after a shortage to limit passenger delay [51]; later one's repair crew plans in near real time [52], reroute aircraft and test the result by simulation [53], build robustness into the original plan [54], and recover aircraft and passengers together with a GRASP metaheuristic [55].

H. Revenue and Seat Allocation (3 studies)

A network LP set the best passenger mix by fare class at Frontier Airlines [56]; the expected marginal seat revenue rule set booking limits at Western Airlines [57]; and American Airlines' seat-inventory system produced the largest benefit recorded in this review [1].

I. Gate Assignment (3 studies)

At Toronto airport, the gate plan in use made passengers walk 32% more than the LP minimum, while a simple heuristic came within 3.9% of it [58]. Time-indexed integer models with connecting passengers [59] and exact and beam-search algorithms [60] followed.

VI. REPLICATION OF TWO CLASSROOM-METHOD STUDIES

We re-solved both recent classroom-method studies by hand and checked the results by computer.

A. Route Selection as a Transportation Problem [21]

The study allocates 3,000 seats from three US hubs (Atlanta, New York JFK and Los Angeles) to five destinations with 4,250 seats of demand, maximising profit. We balanced the table with a dummy row of 1,250 seats, converted profit to opportunity loss, found a first solution with VAM, handled degeneracy with a very small quantity ϵ , and reached the optimum after two MODI iterations (Table V).

Our allocation is identical to the papers, but the paper reports US\$289,758 instead of US\$290,250. Four cells of its opportunity-loss table differ by 1 from the stated profits, which points to rounding; the optimal allocation is unaffected.

TABLE V OPTIMAL SEAT ALLOCATION IN [21], RE-SOLVED

Route	Seats	Profit/seat (US\$)	Profit (US\$)
Atlanta–Amsterdam	550	116	63,800
Atlanta–London	650	71	46,150
New York–London	600	108	64,800
New York–New Delhi	300	70	21,000
Los Angeles–Tokyo	900	105	94,500
Total	3,000		290,250

San Francisco is dropped entirely and 320 seats of New Delhi demand are left unserved. The case uses hypothetical data, partly generated in a spreadsheet.

B. Crew Pairing as an Assignment Problem [46]

The study pairs six outbound and six return flights between Bhubaneswar and Kolkata so that total crew layover is smallest, with a minimum rest of 5 hours. A crew may be based at either city, and the shorter of the two possible layovers is used. When we rebuilt every cost cell from the published timetable, 19 of the 36 values in the paper's matrix were wrong. Seventeen errors come from afternoon and evening times written in 12-hour form being read as morning times, for example a 15:00 departure used as 03:00; two come from one row of the matrix being copied from another. The Hungarian iterations in the paper are arithmetically sound, and 65.5 hours is indeed optimal for the matrix the authors used. With the corrected matrix the method needs three rounds of new zeros, and the result was confirmed by an exact solver and by checking all 720 possible pairings (Table VI).

TABLE VI REPORTED AND CORRECTED RESULTS FOR THE CREW-PAIRING STUDY [46]

Measure	Reported in [46]	After correction
Optimal pairing	O1–R6, O2–R3, O3–R4, O4–R2, O5–R1, O6–R5	O1–R6, O2–R4, O3–R5, O4–R1, O5–R3, O6–R2
Total layover	65.5 h	52 h
Wrong cells in cost matrix	–	19 of 36
Reported pairing at the true times	Not reported	89.5 h
Number of optimal pairings	One reported	Two (O4–R2 with O6–R1 is also optimal)

At the true times the pairing recommended in the original paper costs 89.5 hours, 72% above the real optimum. Adopting the corrected plan would save 37.5 crew-hours a day on this one route, about 13,700 hours a year.

C. What the Replications Show

In both studies the textbook algorithm was applied correctly; the weak point was the data. One study rest on generated data, the other on a cost matrix whose errors appear as soon as each cell is recomputed from the timetable. By contrast, the industrial studies in this review test their models on real data or check a heuristic against an exact benchmark [58].

VII. DISCUSSION AND RESEARCH AGENDA

A. Classroom Models as Building Blocks

The review traces a direct line from introductory OR to industrial practice. Fleet assignment is a transportation problem extended over time and aircraft types; crew pairing and rostering widen the assignment problem from one-to-one matching to covering each flight with one trip; gate assignment is an assignment problem with time conflicts; and the passenger-mix problem is a transportation-type LP in which connecting passengers draw on two flights. Teaching these links shows students why VAM, MODI and the Hungarian method matter beyond the textbook.

B. Integration and Uncertainty

Every joint model in the sample reports or argues for gains over sequential planning. Since 2010, studies have added uncertain demand [33], passenger choice [26], [27], environmental goals [32] and machine learning [45]. Classroom-level studies have not followed: both recent ones treat a single stage with fixed data.

C. Research Agenda

- 1) Indian aviation. Only one of the 50 studies uses an Indian route, although published timetables and fares make domestic case studies straightforward.
- 2) Whole-aircraft capacity. Route-selection transportation models treat seats as divisible; supply could instead be expressed in aircraft loads, with impossible routes given a prohibitive cost M .

- 3) Connecting passengers. Classroom models treat routes as independent; a two-leg network LP, as in [56], adds this with little extra effort.
- 4) Several goals. Emissions, crew fairness and passenger time can be added through goal programming or compromise programming [20], [32].
- 5) Reproducibility. Classroom-method studies should publish their data together with a spreadsheet-solver or code check of the hand working.

D. Limitations

The 50 studies were chosen for coverage and influence rather than through an exhaustive database search, so the counts describe this sample, not the whole field; a systematic extension would add documented Scopus or Web of Science searches and a PRISMA flow diagram. Fifteen studies were coded from short summaries. Only English-language journal articles were included, and each study was coded once by a single team.

VIII. CONCLUSION

Four decades of airline OR rest on the allocation ideas taught in an introductory course. Across 50 verified studies, the field moved from exact integer programming to decomposition and joint planning, and then to models with uncertainty, passenger choice, emissions and machine learning, and nine studies document real savings. The classroom end of the literature has not kept pace: of the two recent studies we re-solved, one relies on hypothetical data and the other reports a wrong optimum, 65.5 hours where the true minimum is 52. Real Indian routes, careful data checks and openly shared working would let transportation and assignment methods give results that both students and airlines can rely on.

APPENDIX

TABLE VII THE 50 REVIEWED STUDIES BY PLANNING STAGE

Planning stage	Studies	Reviewed studies
Network and Route Design	8	O'Kelly (1987) [14]; Campbell (1994) [15]; Jaillet et al. (1996) [16]; Lederer and Nambimadom (1998) [17]; Adler (2001) [18]; Chang et al. (2019) [20]; Birolini et al. (2021) [19]; Kasad et al. (2021) [21]
Schedule Design	6	Yan and Young (1996) [22]; Yan and Tseng (2002) [23]; Lohatepanont and Barnhart (2004) [24]; Jiang and Barnhart (2009) [25]; Wei et al. (2020) [26]; Yan et al. (2022) [27]
Fleet Assignment	8	Abara (1989) [28]; Subramanian et al. (1994) [2]; Hane et al. (1995) [13]; Rexing et al. (2000) [29]; Barnhart et al. (2002) [30]; Jacobs et al. (2008) [31]; Ma et al. (2018) [32]; Kenan et al. (2018) [33]
Aircraft Maintenance Routing	4	Clarke et al. (1997) [34]; Gopalan and Talluri (1998) [35]; Sarac et al. (2006) [36]; Al-Thani et al. (2016) [37]
Crew Scheduling	9	Gershkoff (1989) [38]; Anbil et al. (1991) [39]; Hoffman and Padberg (1993) [40]; Vance et al. (1997) [41]; Gamache et al. (1999) [42]; Klabjan et al. (2002) [43]; Deveci and Demirel (2018) [44]; Tahir et al. (2021) [45]; Mallick et al. (2023) [46]
Integrated Planning	4	Cordeau et al. (2001) [47]; Cohn and Barnhart (2003) [50]; Sandhu and Klabjan (2007) [48]; Shao et al. (2017) [49]
Disruption and Recovery	5	Teodorović and Guberinić (1984) [51]; Lettovský et al. (2000) [52]; Rosenberger et al. (2003) [53]; Lan et al. (2006) [54]; Hu et al. (2016) [55]
Revenue and Seat Allocation	3	Glover et al. (1982) [56]; Belobaba (1989) [57]; Smith et al. (1992) [1]
Gate Assignment	3	Mangoubi and Mathaisel (1985) [58]; Haghani and Chen (1998) [59]; Karsu et al. (2021) [60]
Total	50	

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