A Novel Application to Optimize Utilization for Non-Urgent Air Transfers

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Author contribution

RDM and MA conceived the study. RDM, MA, and LW designed the study and were responsible for data collection. RDM, MA, and LW performed the data analysis. All authors interpreted the results. RDM wrote the initial manuscript draft. All authors revised subsequent manuscripts and approved the final draft. RDM takes responsibility for the manuscript as a whole.

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Abstract

Introduction

Air ambulances provide patients with timely access to referral centers. Non-emergent transfers are planned for efficient aircraft use. This study compares a novel flight planning optimization application to traditional planning methods.

Methods

This prospective study compared real-world use of the application to traditional methods in a large air medical system. Each day was randomized to application use or manual methods. Descriptive statistics compared the resulting schedules through ratios of distance flown and cost to minimum distance required.

Results

Manual methods were used on 33 days to plan 479 requests, yielding 181 flights, 856 flying hours and 289,627 kilometers (km) flown. Ratios of distance flown and cost were 1.47 km flown and $4.98 per km required. The application was used on 25 days to plan 360 requests, yielding 146 flights, 639 flying hours and 216,944 km flown. The corresponding ratios were 1.4 km flown and $4.65 per km required. Average distance flown per distance required decreased by 5% ($p=0.07$), and average cost per average required distance decreased by 7% ($p=0.03$) when using the application.

Conclusions

Prospective, real-world use of the application results in efficiencies when planning non-urgent patient transfers. Additional savings may be possible through further application refinements.

Introduction and Background

Aircraft dedicated for air ambulance use carry out interfacility patient transfers and provide timely access to referral centers for those requiring this type of specialist care. While some of these transfers are emergent and time-dependent, others are non-emergent and can be scheduled and routed to ensure efficient use of aircraft.

The commercial airline industry has comprehensive programs and infrastructure to ensure flight schedules and aircraft utilization are optimized to ensure maximum passenger traffic and revenue. Air ambulance services operate on a much smaller scale, do not operate on a fixed schedule, and cannot predict demand or utilization due to the nature of their service. However, air ambulance services have the same need to optimize utilization to minimize cost while meeting the demands of the health care system. Efficient deployment of air medical resources can enhance access to these services while potentially decreasing cost due to optimized resource utilization.

This study examines the implementation of a novel optimization application derived from historical call, aviation, and financial data for scheduled patient transfers in a provincial air ambulance system. The application was developed in partnership between an air medical and critical care land transport agency and internationally-recognized leader in developing systems to optimize resource allocation and scheduling in emergency services and the airline industry.

Objectives

The goal of this study was to assess the impact of an optimization application ('application') on aircraft utilization in a provincial air ambulance system. The study hypothesis is that an optimization application will result in decreased aircraft utilization, with resultant decreases in cost, while meeting all scheduled patient transfer requirements.

Methods

Study design

This study was carried out in two phases. The first phase was a retrospective, offline comparison of scheduled patient transfers with traditional manual planning methods performed by experienced flight planners as part of their regular duties. The second phase was the prospective, real-time assessment of the application's impact on utilization after live deployment in the dispatch centre. The study was approved by the Research Ethics Board at Sunnybrook Health Sciences Centre.

Study setting and population

Ontario is a large Canadian province (approximately 1.1 million km^2 or 424,600 $miles^2$) with a mix of urban, suburban, rural, and remote areas. The health care system is publicly funded and serves a population of approximately 13.5 million. Ornge Transport Medicine is the publicly funded air medical transport system providing all air medical patient transfers in Ontario. Ornge is Canada's largest air medical and land critical care transport provider, carrying out approximately 19,000 patient transports annually. Ornge uses a fleet of 26 aircraft and 4 land vehicles to carry out these transfers. The fleet remained the same during this study. Approximately half the transfers are for patients with non-emergent conditions that are scheduled.

The Ornge Communications Centre (OCC) is the provincial air ambulance dispatch centre, and processes and dispatches all air ambulance and land critical care transfer requests in Ontario. It also coordinates all scheduled, non-emergent patient transfers that require use of an air ambulance or land critical care transfer vehicle. Dispatch staff use a dedicated dispatch software system to process and document all requests for transfer by air ambulance. The dispatch database contains all relevant flight and schedule information for this study.

The optimization application was developed as a partnership between Ornge and The Cornell College of Engineering's School of Operations Research and Information Engineering (ORIE). The application is a complex computer modeling application with optimization algorithms designed to provide solutions that meet all patient transfer demands while optimizing flight time and cost (1). The model was built using Ornge's dispatch, aviation, and finance data, and the optimization application resulting from the model has been tested operationally (1,2). The application provides valid flight scheduling and planning solutions, but its actual impact on aircraft utilization has not been formally assessed.

Study protocol

Phase 1

The first phase of this study retrospectively examines all flight schedules and routes planned by the OCC for non-urgent fixed wing transfers from fifty (50) randomly sampled dates between July 1, 2010 and February 28, 2011. Schedule and route planning information was retrieved from the dispatch database for each randomly selected day.

The investigators calculated the total flying time and distance flown for all schedules and routes each day based on actual reported flight times captured in the dispatch database, as reported by the aircraft pilot-in-command. The investigators determined the flights where a patient was on board, and where there was no patient on board, based on dispatch information. The daily cost was determined using data from actual invoicing records and financial data for each flight.

The investigators also examined each route flown to determine differences in distance flown and flight time for each actual flight reported by the pilot compared to each optimized flight derived from aggregate historical and operational data.

The investigators then used the application to derive optimized flight schedules and routes for each of the fifty randomly selected dates. The data required by the application include patient origin, destination, required pickup time (if any), required drop-off time (if any), level of care, patient escort (if any), and whether the patient has any infectious disease precautions.

The total flying time and distance flown for each proposed schedule and route were calculated by the application, based on aggregate historical flight and operational data. The flights where a patient was on board the aircraft were also determined. Cost for each flight was calculated based on data from financial records.

The investigators used expert opinion from a senior, experienced flight planner to determine the validity of each flight schedule and route plan proposed by the application.

Phase 2

The second phase of this study was the prospective evaluation of the application in real-time use after the application was integrated into routine dispatch operations in the OCC.

Flight planners involved in planning of non-emergent patient transfers were first trained in application use prior to the study period. Training was delivered by education personnel and one investigator (MA) based on a training package developed by the education personnel in cooperation with the investigators. The training package included a self-directed reading component done on the flight planner's own time, followed by a 2 to 3 hour didactic training and a 3 to 4 hour hands-on training session with the application itself. The application was installed at the non-emergent flight planner's work station on completion of the training period.

The investigators collected and examined all flight schedules and routes planned by the OCC for non-urgent fixed wing transfers between June 8 and August 17, 2011. Flight planning was

randomized to either optimization application use or manual methods, based on predetermined randomization maintained by one investigator (LW). Schedule and route planning information proposed by the application was stored in the OCC dispatch system, and retrieved at the beginning of each day shift. A single flight planner planned each day.

The total flying time and distance flown for each proposed schedule and route were calculated by the application based on aggregate historical flight and operational data. The flights where a patient was on board the aircraft were also determined. Cost for each flight was calculated from financial records.

The investigators also retrieved data from the previous day's schedule and routes to determine actual flying time and distance flown for each route, and any differences in distance flown and flight time for each actual flight reported by the pilot compared to that derived from aggregate historical and operational data.

The investigators used expert opinion from a senior, experienced flight planner to determine the validity of each flight schedule and route plan proposed by the application, and determine reasons for any deviations in planned versus actual schedules and routes.

Patient transfers were excluded in phase 1 or phase 2 if they are categorized as emergent or urgent, not scheduled for the next day, or not carried out by an air ambulance.

Outcome measures

The primary outcomes were the differences in cost of each flight schedule each day, comparing manually derived flight schedules and those derived by the application. An additional phase 2 primary outcome is the comparison of difference in distance flown for each flight between the

actual route flown and the optimized route, as a ratio (referred to as distance flown per required distance), to compare the relative efficiencies of the application and traditional manual methods.

Secondary outcomes included differences in time and distance flown each day, differences in proportion of empty legs flown, the proportion of valid plans proposed by the application, and comparison of difference in distance and time flown for each flight from each flown route and the optimized route. An additional phase 1 secondary outcome is the proportion of valid plans proposed by the application.

Sample size justification

The selection of 50 random dates in phase 1 represents a sample of approximately 20 percent of eligible dates and flights. Historical data indicates the demand for scheduled patient transfers does not fluctuate by week or month, and the sample represents a balance between available data and number of flights required to generate a sufficient sample.

We intended to capture all scheduled patient transfers during Phase 2. However, the timeframe we selected would allow for a loss of up to 20% of eligible study days without major differences between the phase 1 and 2 sample sizes.

It is estimated the samples in phase 1 and 2, as outlined above, would each result in approximately 800 patient transfers, 300 flights, 1500 flying hours, 500,000 kilometers flown, and aviation expenditures of $1.75 million. This will provide sufficient size to perform meaningful comparisons, identify small differences (if present), and provide an assessment of optimization in each phase of the study.

Data analysis

Time, distance, and cost were analyzed and reported as continuous variables using descriptive statistics. Differences in daily time, distance, proportion of empty legs, and cost between the actual and optimized schedules and flight plans were reported as a mean $\pm$ standard deviation, and compared using the t test (paired – phase 1; unpaired – phase 2), with $p<0.05$ considered significant.

Difference in distance and time flown for each flight from each flown route and the optimized route were reported as a mean $\pm$ standard deviation, and compared using the t test (paired – phase 1; unpaired – phase 2), with $p<0.05$ considered significant.

Flight schedules were categorized as valid or non-valid based on expert review. We report the proportion of valid schedules as a proportion of total possible schedules. Reasons for deviation from planned schedules were reported using descriptive methods.

The comparison of difference in distance flown for each flight between the actual route flown and the optimized route is expressed as a ratio, comparing the relative efficiencies of the application and traditional manual methods. A ratio of 1 represents the optimal, straight-line distance between two points, with ratios approaching 1 representing increasingly efficient flight planning, with minimal empty legs and distance flown along non-direct routes.

Results

Phase 1

There were 838 requests for non-urgent transfers (daily mean 16.8 $\pm$ 5.4) during this study period. All requests were met by schedules and plans proposed both by dispatch staff and the optimization application. The application demonstrated statistically significant improvements in all outcome measures in this phase. Table 1 summarizes the results for Phase 1. All schedules and plans proposed by the application were deemed valid on expert review.

Phase 2

There were 839 requests for non-urgent transfers during this study period. To meet all requests, dispatch staff planned 327 flights, resulting in 1495 flying hours, 506,571 kilometers flown, and a total cost of $1,706,412.

The flight planner assigned to long-term planning had been trained in application use on 58 of the 71 days (81.7%) during the study period. Therefore, randomization of flight planning, to either "manual" or "study" methods, was only possible on 58 eligible days. Randomization resulted in a comparison of days where the average daily requests, distance, and hours flown did not differ significantly between the two methods (Table 2). The average daily cost savings was $912 (3%; p=0.39).

The average daily required distance (the sum of distances between origin and destination for each request on a given day) on manually planned days was 5982 kilometers, while on days when the application was used it was 6215 kilometers (Table 2). This discrepancy in required distance arises due to sampling variability, and disguises the true impact of the application.

The measure of distance flown per distance required is a measure of efficiency, with the latter being the minimum distance required to complete a given request. Values for this ratio approaching 1 indicate improved efficiency and less empty leg flying. When this is used to examine efficiencies in flight planning and aircraft allocation, differences emerge between the manual and study methods.

The average distance flown per distance required decreased by 5% (p=0.07) when comparing manual and study methods. The amount of empty leg flying also decreased by 10% (p=0.047), and the average cost per average required distance decreased by 7% (p=0.03). While this does

not approach the theoretic maximum savings of 12% with an optimal flight schedule without any changes taking place during the day, it does show improvements over manual methods.

Table 2 summarizes the results and efficiency calculations for Phase 2. Table 3 summarizes the comparison between manual, real-world application use, and theoretical maximum optimization.

Discussion

Airlines attempt to reduce cost through better use of resources and improved schedules to remain competitive (3,4). However, matching flight schedules to customer demands is a complex, difficult task. Airlines use operations research methods to generate flight, crew, and maintenance schedules based on determining the route to be served, namely origin and destination; and schedule, namely frequency and timetable, to which the particular route is to be served. Large commercial airlines are willing to invest in optimization methods because of their significant savings (5,6).

Air ambulance operators may have some predictable origin-destination pairings due to locations of specialty centers, patterns of referral, or other system or economic factors, but they do not typically have two days with identical requests for service. In general, scheduling air ambulance flights is potentially more difficult because illness is an unscheduled event, but not all illnesses require emergent, time-sensitive transport. These requests for transport can be scheduled on a non-emergent basis.

Therefore, a new "schedule" for service is necessary each and every day to ensure consistent, optimal resource use that minimizes cost while ensuring that all requests for patient transfer are serviced. This concept of "on-demand air ambulance transportation" requires the operator to meet all demand for timely service yet manage a diverse and finite set of expensive, highly constrained resources to meet this demand.

This problem is no different from scheduling private jet services on a few hours or days notice based on individual demand (7) to organizing daily flight schedules for guests vacationing at remote safari lodges (8).

Human variability in planning this type of "on-demand air transportation" scheduling can result in cost variations. The flight planner needs to identify the aircraft, crew, select a set of patients to be serviced from the list of requests for transfer, and determine the suitable routing and schedule for that aircraft. The possible permutations and combinations are numerous, and grow exponentially as the list of requests grows. A preliminary investigation into inter-planner variability in this setting revealed nearly 20% difference in cost between three flight planners given the same set of requests (RD MacDonald, unpublished data).

The first phase of this study revealed potentially promising results. Retrospective analysis showed a potential savings between 12 and 16%, depending on the assessed outcome. These figures were considered optimistic because theoretical savings were not likely to be realized in a dynamic, real-time setting, but they were comparable with 10% savings realized in a comparable on-demand service where schedules differed each day (8). Use of the application also decreased time to generate schedules from several hours to less than an hour (RD MacDonald, unpublished data), resulting in increased human resource availability for call-taking and flight planning for emergent, time-sensitive transport requests.

The second phase examined results of randomized application implementation in real-time. Flight planners accepted the application and were able to use it with little difficulty after a single introductory training session. The results of phase 2, based on real-world implementation, differed from phase 1. While savings were noted in each outcome, the difference in daily cost between manual and application-derived schedules was not as significant. Nevertheless,

measures in route planning and aircraft allocation did demonstrate significant efficiencies that translate to cost savings.

A post-hoc analysis of outcomes identified a number of factors that accounted for the differences between potential and actual savings. Schedule interruption and subsequent recovery was the dominant factor accounting for the differences noted. The interruptions were typically due to emergency transfer requests, weather conditions, delays in ground ambulance responses, and last-minute cancellations. The most common interruptions were last-minute aircraft requests to transfer patients with emergent, time-sensitive conditions. These unanticipated events required flight planners to interrupt patient transfers that were already planned and in progress, manage the time-sensitive request, and carry out a schedule repair afterwards. The potential for non-optimized and costly decisions increases as flight planners experience time pressure to make decisions and potentially re-allocate aircraft for unexpected emergency requests. Despite these factors leading to suboptimal performance, we did find a savings in the cost per kilometer flown of approximately 7%. This represents more efficient resource utilization that translates into a true savings.

Rapidly changing weather conditions were also commonly encountered, requiring aircraft to be rerouted or diverted to alternate locations. Our study did not prospectively collect data on weather-related interruptions, so the impact of this factor is not precisely known. There is no literature in the air medical transport setting to describe the frequency of such unscheduled events, but delays may occur in up to 10% of commercial flights (9).

The result of unscheduled events in this study required the flight planner to manually re-plan part or all the schedules for one or more aircraft, or put in service additional aircraft to cover the gap created by emergent requests or inclement weather. In this study the resulting changes were planned without the benefit of the application's full optimization potential. These factors likely

account for the differences in outcomes noted between phase 1 and phase 2. The next version of the optimization application will incorporate a schedule repair option, enabling flight planners to manage schedule disruptions in real-time.

Limitations

This study has several limitations. There may be differences in actual versus optimized flight times and distances. These differences may exist due to pilot need to deviate on a particular flight, such as diverting from the intended flight path due to weather or air traffic, whereas optimized times and distances are based on aggregate historical data that reflect mean times and distances. The protocol is designed to identify and report any possible outlying flights, and use expert opinion to provide insight into such differences.

Times and distances will also vary depending on direction of flight (such as east-west versus west-east) and wind patterns on the date and time of flight. However, the optimization algorithms and financial calculations take into account actual data from specific origin-destination pairings that are origin- and destination-specific, thus eliminating this potential limitation.

The price of jet fuel has a major impact on cost. The market price fluctuated considerably during this study. However, jet fuel prices for Ornge aircraft are fixed due to long-term contracts with fuel providers, and remained constant during both phases of this study. Therefore, jet fuel price fluctuations do not influence the cost analysis of this study.

Different aircraft have different cost structures. Ornge has a variety of aircraft in its fleet and uses a variety of aircraft for scheduled, non-emergent patient transfers. The portion of its aircraft fleet dedicated to scheduled, non-emergent patient transfers is stable, and did not change during this study. However, these aircraft are sometimes used for emergent patient transfer due to time and location considerations, operational needs, and opportunity. While

these occurrences are not common, they were identified as one of the leading causes for suboptimal performance of the application in the phase 2 post hoc analysis. The ability to segregate part of the aircraft fleet to serve only one type is not feasible, and it may not be possible to determine the true impact of this factor.

We noted a potential Hawthorne effect in phase 2 of the study. The cost per kilometer flown in the "manual" arm of phase 2 was substantially less than that in phase 1, and was comparable to the application-derived arm of phase 1. While the reasons for this finding were not formally explored as part of this study, subsequent discussions with flight planners who had experience with the application between phase 1 and phase 2 indicate that their decision-making may have been influenced by knowledge obtained during their use of the application. For example, flight planners improved planning for patients undergoing outbound and return ("treat-and-return") flights scheduled on the same day. It is not possible to quantify this impact, but this may be a confounder of phase 2 results.

Finally, both phases of this study were carried out using the same group of flight planners who are experienced, senior communication center staff. Their experience would have the effect of biasing toward a null result because of their flight planning experience. The fact the application identified real-world savings in phase 2, even though it was being compared to an experienced cohort of flight planners suggests there may incrementally larger efficiencies and optimization outcomes when the application is used by less experienced staff.

Conclusion

Prospective, real-world use of a novel optimization application results in efficiencies when planning non-urgent patient transfers. While real-world use of the application does not result in full optimization potential, a net overall savings is nevertheless observed. Reasons for gaps

between full and observed optimization potential can be addressed by further refinements to the application.

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Table 1. Phase 1 – Comparison of Manual and Application-Derived Flight Planning
Total requests: 838
Daily mean requests: 16.8 ± 5.4

	Manual methods	**Application-derived**	**Difference (%[1])**	**P-value**
Total hours flown	1417	1253	164 (-12%)	
Average daily hours flown	28.3 ± 9.2	25.1 ± 7.9	3.3 ± 3.7	<0.05
Total km flown	481,381	417,156	64,225 (-13%)	
Average daily km flown	9628 ± 3070	8343 ± 2629	1284 ± 1133	<0.05
Total km flown empty (%)	170,872 (35.5%)	136,699 (32.8%)	34,173 (-20%)	
Average daily km flown empty	3417 ± 1,430	2734 ± 1144	683 ± 1061	<0.05
Total cost	$1,724,629	$1,440,622	$284,007 (-16%)	
Average daily costs	$34,493± $11,422	$28,812 ± $9,870	$5,680 ± $4,146	<0.05

[1]negative value represents decrease when comparing application-derived to manual methods

Table 2. Phase 2 – Comparison of Manual and Application-Derived Flight Planning

	Overall	Manual methods	Application used	Difference[1] (%)	P-value
Total request	839	479	360		
Days used	58	33	25		
Average daily requests	14.5 ± 5.8	14.5 ± 6.9	14.4 ± 4.5		NS
Hours flown – total	327	181	146		
Hours flown – daily average		25.9 ± 12.8	25.6 ± 8.0	0.3 (-1%)	0.45
Total kilometers flown	506,571	289,627	216,944		
Average daily km flown		8776 ± 4239	8678 ± 2711	99 (-1%)	0.46
Average daily km flown empty		3570	3325	245 (-7%)	0.27
Total cost	$1,706,412	$983,862	$722,550		
Average daily costs		$29,814	$28,902	$912 (-3%)	0.39
Kilometers required	352,799	197,421	155,378		
Average daily km required	6082 ± 2497	5982 ± 2879	6215 ± 1930		NS
Average km flown / average required distance		1.47	1.40	0.07 (-5%)	0.07
Average km flown empty / average required distance		0.60	0.54	0.06 (-10%)	0.047
Average costs / average required distance		4.98	4.65	0.33 (-7%)	0.03

[1]negative value represents decrease in comparison to manual methods

Table 3. Phase 2 – Comparison of Manual, Application-Derived, and Optimal Results

	Manual methods	**Application used**	**Optimal**[2]
Cost / day (mean)	$29,814	$28,902	$27,270
Daily cost / required distance ($; mean)	4.98 $\pm$ 0.13	4.65 $\pm$ 0.12	4.39 $\pm$ 0.09
P-value		0.03	0.02
Difference[1]	(baseline)	-7%	-12%

[1]negative value represents decrease in comparison to manual methods
[2]represents theoretical maximum optimization, with no interruptions or deviations