A Network Flow-Based Approach for Post-Merger Airline Hub Consolidation

ABSTRACT

In the past decade, several airline mergers have taken place, driven by a motive to increase operational efficiency. The first problem the new airline must solve is to consolidate its post-merger network. Traditionally, airlines have used statistical techniques such as logistic regression to predict the capacities of routes in the post-merger network. We propose a new decision support tool, based on the transportation network model, to predict the future capacity of routes and provide recommendations on how to improve the efficiency of the post-merger network. The focus of this methodology is to minimize the cost for the airline considering the route network structures. This is achieved by using a network flow approach, which is solved using linear programming techniques. This approach has been validated using the Delta/Northwest merger of 2007-2008. Our results, using this approach, indicate that the total cost of the consolidated network as compared to Delta's actual 2013 post-merger network can be improved by 10 to 20 percent, which can be significant in dollar terms. Our approach was also able to predict the changes in the hub status among the major focus cities in the Delta network. These results demonstrate the potential of a network flow based model for improving post-merger network efficiency in the airline industry.

Keywords: network flow, transportation networks, linear programming, airline-hub consolidation, logistic regression, capacity reductions, optimization, and operations research.

Introduction

In the past decade, several mergers have taken place in the U.S. airline market. Most are driven by a motive to increase business efficiency [7]. After several of these mergers occurred, the airlines reorganized flight frequencies in their joint hub-and-spoke networks to improve capacity utilization. This was often achieved by focusing on consolidating the passenger flow through hubs where there was underutilized capacity. A merger is beneficial for an airline because it allows the consolidation of two networks for efficiency and can lead to an increase in profitability.

While a merger can be advantageous for an airline, it is a cause of concern for consumers because of the potential for an increase in airfares as competition decreases. In August 2013, this prompted the Department of Justice (DOJ) to postpone approval of the US Airways and American Airlines merger proposal. According to the DOJ, even a small increase in the price of airline tickets, checked bags or flight fees would cost consumers hundreds of millions of dollars [15]. As a result, some of the changes proposed involving route monopolies were negotiated through compromise. As shown, regulation would not allow airline companies to significantly increase prices and route demand. Airlines are beginning to develop new methods for consolidating their post-merger networks.

Traditionally, airlines have evaluated the merging of hub-and-spoke networks through statistical techniques. Techniques such as logistic regression are used to predict the capacities of certain routes within a network [6]. Last year, we conducted preliminary research regarding the pre- and post-2008 merger networks of Delta and Northwest Airlines. We developed statistical predictive models to help airlines decide which routes to cut and which ones to keep. However, this year we looked at a new decision support tool that can not only predict the future capacity of routes but can also improve the efficiency of the post-merger network.

The new decision support tool, based on a network flow approach, is solved using linear programming. The focus of this methodology is to minimize the cost for the airline considering the route network structures. Our decision support tool allows us to differentiate between flights through hubs and spokes to see which routes are heavily predicated on transiting a hub city. Based on the data from the Delta-Northwest merger in the second quarter of 2007, our model creates a network with a significantly lower cost compared to both the logistic regression model and the actual post-merger network implemented by Delta. This approach can also predict the cities in the post-merger network that would be upgraded into hubs and those that would be downgraded from being a hub. The results from this approach compare favorably when compared to traditional methods.

Methods and Models for Airline Network Consolidation

This research proposes a new decision support tool to create a cost effective post-merger network. In this paper, we used data from the Delta-Northwest merger in 2007 to implement a network flow based algorithm to model the capacity reduction decisions for post mergers. The primary goal of our research was to create a network that would be able to save costs for the airline while keeping prices the same for consumers. Our research identifies which hubs were being underutilized, allowing us to de-hub certain airports and reduce capacity on certain routes. Similarly, it identifies cities where the volume in passenger flow would suggest an upgrade to hub status. The methodology can be broken down into two sections: a Network Flow model for mergers, and a linear programming solver. The methods proposed in this paper were coded using the *NetworkX* package in *python* and the *linprog* package in *Matlab* [13,14].

A Network Flow Model for Airline Mergers:

The formulation of this network is based on the transportation problem in linear programming [2]. This is a classically used model in operations research for optimizing transportation networks [3]. Networks are typically modeled as graphs, $G(V,E)$ where V are the nodes and E are the edges between nodes. For our problem, we constructed a network consisting of origin, destination and hub cities as the nodes of the graph. Passenger travel between nodes is later modeled as flow through the edges of the graph. This setup allows us to model the airline network as a tripartite graph with origin cities as the left layer, the hub cities as the center layer, and the destination cities as the right layer. All the cities were mapped as origin nodes and destination nodes, and the six hub cities were mapped as hub nodes in the middle. The network from each airline was merged into a common larger candidate network (details are explained in the data section). An example of a tripartite graph is shown in Figure 1.1.

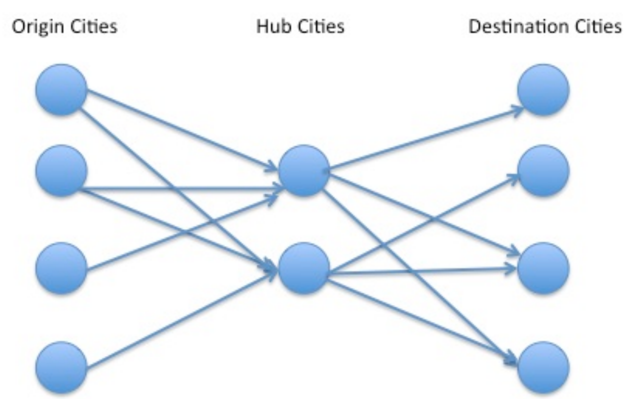

Figure 1.1 – Tripartite Graph

For modeling mergers, we consider the network for Airline 1 as $G_1(V_1, E_1)$ and for Airline 2 $G_2(V_2, E_2)$. The candidate post-merger network is generated as a union of these two graphs, $G(V,E)$ where $V = V_1 \cup V_2$, and $E = E_1 \cup E_2$. In addition to the tripartite graph, a source and sink node were added to the network. The source node sends out all units of flow to the origin cities and the sink node receives all the units of flow from the destination cities. The three major attributes we considered while designing the network were capacity, demand and cost.

Capacity

For the transportation problem, the flow on a given edge *e* is denoted as *f(e)*. For our problem, the capacity of any edge is the amount of available seats on any given route and is denoted by *c(e)*. We created the capacities for our network in a unique way. Because our network is a tripartite graph, any route that flies through a hub is shown as two different edges: one going from the origin to the hub and one going from the hub to the destination. For example, a route that is LAX-ATL-JFK would be broken up as LAXO-ATLH flight followed by ATLH-JFKD flight. In order to differentiate between origin, hub and destination cities, key letters O, H, and D, respectively, are added to the end of each airport code. The determination of capacities for all the routes in the tripartite graph is based on a specific procedure. The demand on a given edge is calculated by adding the passenger flow over all O-D pairs that use that edge. The edge capacity is then calculated by dividing total edge demand by the Load Factor. In the airline industry, Load Factor is defined as used seats divided by total available seats. This procedure is enumerated below.

- For all the routes that were strictly from Origin to Destination with no hub connection point, the number of passengers was added as a demand attribute to that given edge.
- If there is a route that is Origin – Hub – Destination, the number of passengers flying that route is added to the edge Origin-Hub and Hub–Destination. For example, if LAX-ATL-JFK had 100 passengers, the 100 passengers would be added to the LAXO-ATLH route and then 100 passengers would be added to the ATLH-JFKD route.
- For edges from the source node to all the origin nodes, the upper bound capacity is equal to the total number of passengers leaving that airport every day. This ensures that the passenger flow from each city (pre-merger) is preserved. Alternately we can model this

by imposing lower bound constraints on each of these edges to ensure that the flow is satisfied.

- From the destination nodes to the sink node, the capacity is equal to the total number of passengers coming into that airport every day. (As before, these can also be modeled with lower bounds).
- Finally, we take the Load Factors for every given route and then calculate the capacities for each edge in the network. For example, say the LF is .85 for route LAX-ATL and .90 for the route ATL-JFK. The tool will search the network for any edges that contain these two cities, and then calculate the capacity by dividing the number of passengers by the LF.

Demand

For any given network, each node has an attribute called demand, which indicates how much flow a node wants to send or receive [1]. Demand can simply be expressed as (flow into a node) – (flow out of a node). For this problem, the demand would be the number of passengers into a city minus the amount of passengers leaving that city. Since the network is set up as a tripartite graph with source and sink nodes, the demands of all the cities (origin, hub and destination) would be 0 because the flow into the node must always be equal to the flow out. The source and sink nodes, however, have different demands because they either send out all units of flow or receive all units of flow. The source node capacity would be the sum of all out edges and the sink node capacity would be the sum of all in edges.

Cost

In this paper, we examine cost as a determinant in creating an optimal network across two carriers after a merger. In order to model this in our network, the cost would be assigned to each route that corresponds to one or more edges in our network. The cost per seat is the cost incurred by sending one unit of flow on that edge. This section provides a description of how these costs were estimated based on data made available from the Delta-Northwest route network preceding the merger in 2007.

In order to determine the cost per seat for each of the 523 non-directional origin and destination pairs (NDOD) in the Delta/Northwest route network in 2007, the following approach was taken:

- For Delta/Northwest in Q2 2007, we pulled all the available seat miles (ASMs) from the schedule tool and the total aircraft operating cost from the Form 41 data in Diio Mi.
- The ASMs and aircraft operating costs were assigned to each of the aircrafts operating in the network. The aircrafts include the 757, CRJ, MD88, 757-200, A320, 737-800, 767-300, A319, 757-300, 767-400, DC9, CRJ-700, DC9-50, MD90, ERJ-140, ERJ-170, ERJ, A330-300, Saab 340, MD80, CRJ-200, 777, ERJ-300, AT72, EM2, De Havilland 8, 767 and the Beechcraft 1900.
- In order to facilitate the process, the ASM percentage by aircraft was calculated and each aircraft was classified as regional, mainline, or wide body. All aircraft CRJ-900 and above (at least 0.95% by ASM) had exact cost per available seat mile (CASM) values tabulated. For the rest of the aircrafts under 0.95% by ASM, average values by classification (regional, etc) were calculated.
- In a separate sheet, a 524 by 29 cell table was created to determine the final, most accurate CASM and then convert it into cost per seat. For each of the 523 NDOD pairs, a weighted CASM was determined based on each aircraft's CASM and ASM contribution in that route. For example, in the LGAMDW route, the E170 had a CASM of $0.073 and held 0.99 market share, therefore the E170 CASM contribution would be $0.072.

- Once the weighted CASM was determined, it was adjusted by length of haul to create a more accurate CASM. With short regional routes, it would theoretically be a very low cost to operate, but the landing and takeoff costs highly skew that result. Adjusting by length of haul allows the cost metric to become more accurate. The formula used was $Weighted\ CASM/(\sqrt{\left(\frac{Individual\ LOH}{Average\ Network\ LOH}\right)}$. The weighted CASM is taken and divided by the quotient of the route-specific length of haul and the network's average length of haul (764.1006 miles).
- Finally, to determine the length of haul adjusted cost per seat, the LOH adjusted CASM was multiplied by each route-specific LOH. Again, in the example of LGA-MDW, the LOH adjusted CASM was $0.075, and the cost per seat was $54.57 ($0.075 * 725).
- Each of the cost per seat metrics was used in running the model.

A Linear Programming Model

As previously stated, the methods used in this paper are based on the transportation network model in linear programming. In this section, we look at the application of the maximum flow/minimum cost algorithm solved through linear programming using the simplex algorithm. We compare the results derived by the model to the logistic regression model as well as the true observed outcome in the 2013 network. This section will be broken down into three subsections: equality constraints, inequality constraints and solving the transportation problem. The linear programming formulation for the transportation network, with *V* nodes, *E* edges, is given below.

$$Min \sum_{i=1}^{|V|} \sum_{j \in O(i)} c_{ij} \times x_{ij}$$

$$s.t.$$

$$\sum_{j \in I(i)} x_{ij} - \sum_{j \in O(i)} x_{ij} = 0; \qquad i \in |V|$$

$$l_{ij} \leq x_{ij} \leq u_{ij}; \qquad i, j \in |V|$$

The decision variables in this formulation are x_{ij}, which represents the flow on edge e_{ij} (from node i to node j), and c_{ij}, which is the unit cost to send one unit of flow along edge e_{ij}. We are seeking to minimize the objective Z, which is the total cost of flow. The equality constraint is the conservation of flow for each node (this adds as many equations as nodes in the network). $O(i)$ is the set of all nodes that are connected to i by outgoing edges and $I(i)$ is the set of all nodes that are connected to i via incoming edges. The inequality constraint provides lower (l_{ij}) and upper (u_{ij}) bounds on the capacity for each edge.

Solving the Transportation Problem

Complexity of our formulation

In linear programming, the constraints given in the formulation can be represented geometrically. A high dimensional polyhedron is created, where the number of faces are determined by the total number of equality and inequality constraints. The optimal solutions are the extremum points, which are the intersection points, the edges or the faces of the polyhedron [2]. The running time to solve a linear programming problem is polynomial. There are two common algorithms used to solve linear programs: the interior point algorithm and the simplex algorithm. The interior point method is a well-known linear programming algorithm that has a worst-case complexity of polynomial time [17]. The simplex algorithm has worst-case complexity of exponential time (as shown by the Klee Minty problem [3]); however, on average the algorithm runs quite fast and is competitive with the interior point method. The simplex method moves along the edges on the polyhedral, each time decreasing the value of the objective function, while the interior point algorithm starts from the interior of the polyhedral and after each iteration decreases the value of the objective function while moving toward the extremum points [17]. In several cases, including ours, the simplex algorithm runs faster than the interior point algorithm. Using the *linprog* package in Matlab, we examined both the interior point algorithm and the simplex algorithm to compare running times. Since the size of our network was small enough, both algorithms solved the problem quite quickly, but the simplex algorithm was slightly faster.

Simplex Algorithm Application

All methods proposed in this section were coded using the *linprog* package in Matlab. Our application of the simplex algorithm allows for a set of solutions, which identifies the optimal path of passenger flow through the network. The value of the decision variable x_{ij} contains a value for the number of passengers who should be sent through that edge. Based on the results, airline companies would be able to set a given load factor for all edges, and create new capacities that would greatly decrease costs. In addition to finding the optimal flow values for each edge, we added a slight modification to the algorithm to address each of the hubs in the network. If a route flies through a hub and the flow on that edge is less than 10% of the upper bound capacity, the model would make the upper bound of that particular edge 0, and then re-run the simplex algorithm to create a new optimal flow value.

Data

All the data was collected from the Diio Mi database, which consists of different airline industry performance metrics, published by the Department of Transportation. For this paper, the data was restricted to the top 158 domestic cities. The following data sets were used:

- First data set was a 5 x 3168 table that included origin, connection point, destination, passengers per day and revenue. The data was combined for both the Delta/Northwest networks for Quarter 2, 2007. For this paper, the connection points were limited to the hubs.
- Second data set was a 525 x 2 table that included route and load factor (total passengers / total capacity.)

Logistic Regression

As another basis for comparison, a logistic regression model was created in order to predict if each route in the Delta/Northwest network would reduce in capacity by 30%. The logistic regression function is shown below.

$$\beta(c,x) = c_0 + c_1 \times L_f + c_2 \times AF_m + c_3 \times \left(\frac{M_l}{L_f}\right)^2$$

$$h_\Theta(x) = \left(\frac{1}{1+e^{-\beta(c,x)}}\right)$$

The beta function, $\beta(c,x)$, is a special form based on an understanding of the domain knowledge of the airline industry. Regression coefficients c_0, c_1, c_2, c_3 are estimated to fit this function to the observed post-merger network. L_F is denoted for the variable load factor, AF_m is denoted for the variable average fare/mileage, and M_l denotes percentage mainline. Using a gradient algorithm in machine learning, each route is predicted to be a '1' or a '0', with '1' meaning that the route would decrease by at least 30% and '0" meaning that it would not.

The logistic regression allows us a way to take into consideration the several factors that Delta was working with during its merger which are captured through the form of the beta function, $\beta(c,x)$. These are all contributing variables in the beta function, $\beta(c,x)$. In the results section of this paper, we compare the results proposed by the linear programming solver to the results of the logistic regression.

Results and Discussion

In this section we look at the different approaches used to evaluate the efficacy of our decision support tool. We compare the cost of flow predicted by our tool to Delta's calculated results from 2013, five years after the merger. We compare the outcome of each route, in terms of capacity reduction, predicted from our model compared to the true results of each route that Delta published in 2013. Finally, we look at each city at a macro level to see how our model did in comparison to Delta regarding the hub-status of major cities in the network.

A Comparative Analysis

In order to compare the cost of flow (Z^*) predicted from our tool to the cost implied by Delta's actual post-merger network (Z^d) we used the following method. We estimate the cost of the Delta network using data from the Delta post-merger network in 2013. For routes where Delta had reduced the capacity by 30%, we reduced the upper bound capacity in our network by 30% and estimated the cost by adding the product of the cost and upper bound capacities for each edge in the network. Note: to keep the comparison analogous, we used the 2008 costs for the edges of the network, since Delta costs in 2013 reflected, in part, changes in the cost and price structure. The results for this prediction scenario are shown below, in Table 1.1. In addition, we also evaluate the results for additional scenarios where the load factors are at different levels i.e. 100%, 90% and 80% (remembering that load factor is the total seats occupied/ total available seats for any route). This is necessary, since airlines will rarely plan the route capacity to be at a 100% load factor since this risks unfilled demand due to variations in demand over the year. In our first comparison, we analyzed the cost savings compared to actual Delta results if the load factor for the passenger flow values predicted by our decision support tool were 100%, 90%, and 80%. Increasing the capacity of the edges in the network to correspond to 90% and 80% and then finding the optimal flow corresponding to each of these networks achieves this.

LF Scenarios	Lin Prog Cost	Delta's Cost	Difference (%)
100%	8.218	11.25	27%
90%	9.13	11.25	19%
80%	10.27	11.25	8.70%
(All cost values in millions of dollars)			

Table 1.1: Comparison between Delta's cost and our cost

The 100% load factor scenario is based on all seats being full and allows for a situation where the airline would make the most money. The 100% scenario computes a cost of flow of $8.218 million per day for our condensed network. This means that if all flights were full every day, the airline would be spending $8.218 million dollars to operate and run the network. Using the methods shown in the beginning of this section, the estimated cost of flow for Delta in 2013 would be $11.25 million per day. In this 100% load factor scenario, our tool proposes a network that is 27% cheaper than Delta's estimated cost. The 90% load factor scenario provides a more idealistic scenario for airlines, as for every 10 seats available, 9 would be filled. In this scenario, our tool has a cost of flow of $9.13 million, which is still nearly 19% less than Delta's estimated cost. Lastly, we look at the 80% load factor scenario. This is a conservative approach for airlines that may have more seats available. In this scenario, our tool has a cost of flow of $10.27 million, which is 8.7% cheaper than Delta's estimated cost. The costs are always compared to the observed post-merger Delta network.

Edges	Z^*	Z^d	Comparison
1	0	0	TRUE
2	1	1	TRUE
3	1	0	FALSE
4	0	1	FALSE
5	1	0	FALSE
6	1	1	TRUE
7	0	0	TRUE
8	0	1	FALSE

Figure 1.2: Table for first 8 routes

For further comparison, we looked at all 1,812 routes, and checked to see how well our predictions compared to what actually happened to Delta in 2013. For illustration purposes, a table for some routes is set up, as shown in Table 1.2. For each route we compare the actual outcome post-merger in 2013 (shown in column Z^d) against the predictions using the network flow model (Z^*). An outcome is 1, if the route capacity is reduced by 30% or more, and 0 otherwise. If the two outcomes match, the last column indicates a TRUE; if they do not match, it indicates FALSE.

This measure allows us to calculate how many of the route predictions match the ones used by Delta in handling the merger. Of the 1820 edges in the network, 1,010 were a match (i.e. TRUE in the last column in Figure 1.2 above), indicating a match accuracy of about 55% for capacity reductions on all edges in the network. The differences explain the cost reductions achieved by the network model and provide a recommendation of which edges (i.e. routes which are a 1 for the network model and 0 for Delta) might need further evaluation in making the capacity reduction decisions by Delta post-merger. However, it may have been that Delta had other constraints and considerations while consolidating its hub capacities. These constraints may not be reflected in our model and hence the capacity reduction results of our model. In order to evaluate this possibility, we provide another comparison below regarding decisions about hub status for cities. This comparison shows that at a macro level the prediction of the network model is qualitatively very similar to the final decisions made by Delta regarding choice of large hubs.

Predictions at a Macro Level

Even though our model is a decision support tool, we can with some modifications use it to predict the future of all cities with regard to hub status. In this section, we discuss the constraints that need to be added to the network formulation to create a tool that can help airlines choose which cities to hub post-merger and which hub cities to de-hub post-merger. Typical rules used to decide the upgrade or downgrade of hub status for a city (post-merger) is based on the following consideration:

- Consider "big cities" as having 40 or more flights coming in and out of the city.
- If *all* the routes coming in and out of a city experience an increase in total passenger flow, then the city is upgraded to be a hub.
- If 70% or more routes experience (or are expected to experience) a decrease in total passenger flow, then the city status is downgraded to non-hub status.

Cities Gaining Hub Status

In order to evaluate the decisions concerning hub status, we analyzed the following nine big airports in our network: LaGuardia (LGA), Seattle (SEA), Chicago (MCO), Tampa (TPA), Columbus (CMH), Boston (BOS), John F. Kennedy (JFK), Los Angeles (LAX), and Indianapolis (IND). For each city, we evaluated the passenger demand based on flow determined by the linear programming solver. If the demands on 100% of the routes coming into or out of that airport were increased, the airport could become a hub. We looked at the percentages of the number of routes that increased capacity in all nine cities in Table 1.3.

Major Cities	Lin Prog Solution	Logistic Reg Solution
LGA	100%	82%
SEA	100%	70%
MCO	78%	42%
TPA	60%	52%
CMH	75%	60%
BOS	100%	57%
JFK	78%	81%
LAX	93%	66%
IND	80%	45%

Figure 1.3: Percentage of routes that increased in passenger demand

As clearly shown in Figure 1.3, LaGuardia, Seattle and Boston were the only major cities that had 100% of their routes increase in passenger demand. Comparing this to the logistic model proposed in the methods section, our new network flow approach produces much better results, since the logistic regression model did not provide good predictors for hub upgrades. However, in reality, the only two airports that gained hub status were LaGuardia and Seattle.

New York's LaGuardia Airport (LGA) is one of the busiest domestic-business traveler focused transportation centers in the United States. There are several routes run by Delta, such as LGA-BOS, LGA-DCA, and LGA-ORD, which comprise the industry-unique "shuttle route": There are flights on the hour; it operates out of a separate terminal in LGA; and it is normally comprised of mostly business travelers [4]. Some routes that maxed capacity includes: LGA-CHS (Charleston), LGA-GSO (Greensboro), and LGA-IND (Indianapolis) [10]. These routes all involve smaller spoke airports, which a hub typically services, as its goal is to transport people from point A to point B in the most efficient way. Our tool predicted that LaGuardia should become a hub based on an increase in capacity. According to an official Delta Air Lines press release in December 2011, the airline added, "more than 100 new flights and 29 key destinations" to its "new domestic hub" at New York's LaGuardia Airport [10].

Seattle is a hub of technological growth and opportunity in the Pacific Northwest. Additionally, it is the city that has the fastest route to Asia from the West Coast. For quite some time, Alaska Airlines, the hometown airline, dominated the unsaturated domestic market. However, that has begun to change of late. Our model suggests that Seattle is likely to see change in the post-merger world. Many of these routes involve important cities in the domestic and global economy, including JFK, LAX, IND and many other Delta hub airports [9]. According to the model, it looks like Delta's post-merger presence is to expand service on a dramatic level in Seattle, and break into markets where Alaska Air tends to dominate [9]. In 2012, Delta began to expand its Seattle presence in many routes, including JFK-SEA, a premium transcontinental route, for which lie-flat seats were installed for business class. In summer 2014, Delta coined Seattle as its newest hub [9].

Boston is a large focus city in the Delta network; however, it is unlikely for Boston to ever become a hub. As previously stated, Boston has a lot of passenger demand because it is part of the unique shuttle service for business travelers. Our model believed that due to the high passenger demand, and cheap carrier costs, Boston should become a hub. However, Boston is a focus city for many other airlines, and it would be very unlikely for Delta to win over several different airlines based on recent expansion [7]. JetBlue has a significant presence in Boston, which would pose difficultly for Delta to hub Boston.

Cities That Lost Hub Status

In trying to decide which cities should have lost hub status, we took a closer look at the six pre-merger hubs in the Delta/Northwest network. They were: Memphis (MEM), Cincinnati (CVG), Minneapolis (MSP), Atlanta (ATL), Detroit (DTW), and Salt Lake City (SLC). In order for any hub to lose hub status, 70% of the routes would have to lose capacity. The routes that were analyzed regarding each hub were the flights that used the hub cities as connection points. Figure 1.4 shows the percentage of all routes that reduced capacity in each hub.

Hub Cities	Lin Prog Solution	Logistic Reg Solution
MEM	81%	43%
CVG	38%	56%
MSP	60%	6%
ATL	68%	45%
DTW	52%	34%
SLC	42%	6%

Figure 1.4: Percentage that decreased in passenger demand

As shown in Figure 1.4, our tool predicted Memphis as the only airport to lose hub status. Compared to the logistic model, our new network flow-based model is more accurate.

In the old Northwest network, Memphis played an important role as a southeast regional hub that competed with Delta's Atlanta [5]. Since Memphis was a hub, our method looked at all of the routes that came into and out of Memphis, to see how passengers transiting Memphis would be affected in the new network. Some routes that were eliminated, specifically regional carrier service, which Memphis specialized in for many years, included Memphis (MEM) to Indianapolis (IND), Columbus (CMH), Kansas City (MCI) and Milwaukee (MKE) [5]. These are examples of routes that could be structured to now connect through hubs such as Detroit, Minneapolis, Atlanta or Cincinnati with much greater network reach than Memphis. In June 2013, Delta revoked hub status from Memphis, confirming the accuracy of our predictive model.

Conclusion and Future Research

In the open literature, there are no published tools available to predict optimal networks for post-merger routes. Our model provides a new alternative based on publicly available data, for an in-depth analysis of the airline network consolidation conundrum. Such a tool could be useful for various end users, such as airlines, analysts and Department of Justice. The network flow-based model successfully predicted three major changes that resulted from both the immediate and long-term effects of the Delta/Northwest merger. Our model serves as a tool that not only allows networks to create an optimal flow for post-merger networks but also is able to analyze the data in such a way that allows the airlines to determine which hub cities should effectively be reduced and potentially de-hubbed as well expanded and promoted to hub status. The methods proposed in this paper can be applied to any merger between two carriers in the airline industry.

The scope of this paper, which focused on looking at the domestic network, we could expand the model to investigate international implications as well. Furthermore, we can also look at the passenger breakdown on any given route by class of service. Additional research would permit us to create a sturdier network that not only meets cost demands but features competitive schedules and a compelling on board product.

This model provides several directions for the application of graph theory and linear programming to evaluate proposed airline mergers, from an efficiency and cost perspective. We hope to also expand our formulation into other transportation modes such as the bus and railway systems. The early research in this paper demonstrates a successful application of network flow methods at improving transport network efficiency. Further research might also incorporate of the relationship between passenger demand and fare changes within the airline industry.

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