Concurrent Aircraft Design and Airline Network Design
Incorporating Passenger Demand Models

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Conceptual aircraft design and the network routes that they travel on are inextricably linked to passenger driven demand. Decisions made in the acquisition and subsequent allocation of aircraft assets to serve chosen links translate to latent passenger observations of ticket pricing and routes served between origin-destination (OD) pairs. It is proposed that such latency gives rise to a reflexive behavior in demand as subsequent operational decisions give rise to reflexive passenger demand conditions. In this paper, a unifying conceptual framework that builds upon previous works is proposed to concurrently design aircraft and the operational network by incorporating established passenger demand models. A conceptual scenario formulated and solved to exhibit the methodology employed and reflexivity of demand.

Nomenclature

\[ \begin{align*}
W/S & = \text{wing loading (lb/ft}^2) \\
T/W & = \text{thrust to weight ratio} \\
AR & = \text{aspect ratio} \\
C_{A,B,C}^{ij} & = \text{fixed cost of aircraft type ‘A,B, or C’ (respectively) flying route (i-j) ($/trip)} \\
x_{ij}^{p} & = \text{number of passengers with OD ticket ‘q’ traveling from origin (i) to destination (j)} \\
x_{A,B,C}^{ij} & = \text{number of aircraft type ‘A,B,or C’ (respectively) allocated to route (i-j)} \\
r & = \text{range (nmi)} \\
y_A & = \text{passenger capacity of aircraft type ‘A’} \\
t_{ij} & = \text{ticket price for travel from origin (i) to destination (j)} \\
q & = \text{passenger ticket itinerary (commodity)} \\
M & = \text{set of total passenger ticket itineraries} \\
N & = \text{set of city nodes} \\
outflow_{ij} & = \text{set of passengers departing from city node (j) on itinerary (q)} \\
inflow_{ij} & = \text{set of passengers departing from city node (j) on itinerary (q)} \\
netflow_{ij} & = \text{the net flow of passengers travelling on itinerary (q) at city node (j)} \\
S_{ij} & = \text{number of stops between city (i) and city (j)}
\end{align*} \]

I. Introduction

With ever increasing air traffic demand and the inherent need to capture an optimal market share, both aircraft manufacturers and operators alike are continually challenged to competitively provide better services, especially in the face of economic fluctuations. Such conditions demand integrated solutions that require the concurrent incorporation of design methodologies, allocation strategies and analysis of demand trends to accomplish better services at lower costs. The impetus in establishing such a paradigm is to further reduce the inherent “handoff” between aircraft design and allocation. Currently, aircraft design is independently done relative to a fleet’s allocation for a given aircraft. The operation of an airline and its services rendered is naturally subject to the scrutiny of passengers who dictate demand through observation of the resulting key metrics that include cost (tickets prices)
and routes offered by competing airlines. Naturally, other important factors such as passenger demographics and geographical considerations are also an integral part of the demand as well.

The notion of recursive demand feedback has long existed in sociological, economic and finance circles within the context of *reflexivity*\(^1\). The salient point of its economic implications is that supply and demand are inextricably linked entities as opposed to the traditional view that considers them independent factors that achieve some constant equilibrium state. Various econometric models\(^2\) have been used by airlines and the federal aviation administration (FAA) as a means of quantitatively categorizing and analyzing key factors that contribute to airline passenger demand. These factors are often times expressed in terms of airline operations, local geography and passenger demographic metrics to predict demand trends for city pairs given past information on key factors. These predictions have been used to examine causalities of interactions at various levels of the airline transportation system that range from passenger choices to terminal specific and even system wide levels of interactions. The current research work amalgamates aircraft systems design research previously by Mane, Crossley, Nusawadharna\(^3\), de Weck & Taylor\(^4\) with the use of econometric models reflected in works by Bhadra\(^5\), Hansen\(^6\) to achieve such demand feedback deterministically. This serves as a framework to incorporate potential reflexive demand influences in the design of the aircraft and the routes that the fleet will operate on.

**II. Problem Statement and Methods Used**

The fundamental scope of this research is to simultaneously determine the best design of a new aircraft coming into commercial passenger service, the optimal network route structure that minimizes the cost of transporting passengers to their destinations (or maximize profits) and the resulting aircraft allocation subject to reflexive demand trends. The approach uses a subspace decomposition method as previously established\(^3\). It has been extensively shown that such a decomposition method not only addresses the issue of tractability in such concurrent forms of engineering but also exhibits the potential cost savings and conceptual design improvements that can be reaped from it\(^3\). This can be in the form of a more fuel efficient aircraft or even a less polluting one, depending on the metric to be minimized.

The monolithic form of the problem is essentially separated into a series of smaller optimization sequences that are then solved separately and sequentially over an iterative loop. Figure 1 exhibits the overall architecture of the decomposed problem. The monolithic optimization problem is broken into smaller sequences that begins with a systems level optimization problem, proceeds to an aircraft design level optimization problem and then on to the multi-commodity network flow problem. Here, the econometric demand feedback works in conjunction with the minimum cost multi-commodity solution by providing estimated demand for a chosen network route configuration.

![Figure 1: Architecture of overall concurrent design scheme](image)

The top (systems) level optimization is to minimize the fleet direct operating cost (Fleet DOC) subject to attributes (variables) of the newly designed aircraft; that being range and passenger capacity. These are subject to

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the constraints of what typical interval values of aircraft range and passenger capacity. This is a mixed integer problem (MIP) with the range as a continuous variable and passenger capacity as integer, and can be solved either through enumeration or a branch and bound algorithm. Solutions at this level represent the optimal solution for the aircraft to be designed in terms of passenger range and capacity.

The resulting values of range and passenger capacity are passed on to the aircraft optimization section of the decomposition. Here, the NASA developed Flight Optimization System (FLOPS ver. 6.1) code is used to size the aircraft and estimate its takeoff gross weight (TOGW) and operating costs for a given passenger capacity, design range, and cruise velocity. In this case, the cost per trip is generated for each aircraft given all the possible ranges it could serve on the network. Trip lengths that are beyond the range of the aircraft are assigned a very high cost per trip coefficient value that serves as a penalty for the proceeding network optimization. The aircraft design variables are aspect ratio (AR), thrust to weight ratio (T/W), and wing loading (W/S). The resulting nonlinear programming problem (NLP) is solved within the FLOPS software package using an array of nonlinear optimization algorithms. An alternative measure that can be used in order to reduce computational burden of the cyclic optimizations is through the use of response surfaces that can also be generated through the FLOPS software package.

The resulting cost coefficients for each route encompassing both the existing (C_{ij}^{0}) and to be designed aircraft (C_{ij}^{A}) are then passed to the network design problem where a multi-commodity flow problem is solved using the well known GAMS software package that utilizes the renowned CPLEX solver to solve the resulting integer programming (IP) problem. The resulting network allocations are then use to calculate average ticket costs for ticket itineraries (origin-destination pair) and number of stops which are passed on to the econometric demand model as inputs. The econometric model in turn is a regression based representation of the demand for the routes specified. The regression model can be thought of as a response surface that gives passenger demand, given a route structure (links) and ticket price. Projected demand from the econometric model is then fed back recursively over finite horizon of time to estimate demand trends and resulting costs associated with it.

A. Concurrent Aircraft Design and Network Design

The network is modeled as the well known multi-commodity flow problem. In this case, the ‘commodities’ are the origin-destination (OD) pair tickets demanded by passengers. In order to get to a destination, the ticket holder needs to travel on a particular itinerary to arrive at the chosen destination. This can simply be thought of as the tickets (commodities) traveling on the routes of the airline network. Modeling of the network design portion as a multi-commodity problem expounds upon assumptions and modeling of network flows in preceding literature. This formulation enables the tracking and minimization of overall cost subject to requirements of each individual ticket itinerary as opposed to the ‘general flow’ of passengers as a whole on the network as otherwise previously done.

An illustrative example is performed to establish the concurrent aircraft and network design using the multi-commodity formulation. A hypothetical case of demand between four cities with the corresponding demand itineraries realizations is shown in Figure 3. This model extends the original Bazaraa and Jarvis problem used in prior literature to include hypothetical itinerary information in the passengers travel. Demand is assumed to be symmetric in this case with passengers traveling on return trip itineraries. Two types of preexisting aircraft with passenger capacities of 140 and 150 respectively serve the three routes, with a third aircraft type being the newly designed aircraft. The objective is to minimize the direct operating cost of transporting passengers to their intended destinations through the introduction of a new ‘yet to be designed aircraft’ and concurrent optimization of the route structure.
The method of solution follows the previously established structure of decomposition with the network optimization being part of the decomposed subspaces. Equations (1-7) represent the integer programming (IP) multi-commodity problem statement for the network portion of the design. The objective function as shown in equation (1) represents the total cost of flights served by each aircraft type due to their corresponding allocations on the routes served. Equations (2) and (3) enforce the condition that the total passenger capacity due to allocation of aircraft on routes sufficiently services the passengers entering and leaving any node point (or city). Hence, nodes with passengers departing for a chosen destination would result in a negative number per ticket itinerary at each node. Equation (4) explicitly deals with flow balance of passengers within the network and ensures that it is equal to the net passenger flow at each node. This assumes a perfect balance of passengers within the system, making it a conservative network flow. Nodes with passengers departing on a particular itinerary will result in a positive flow at the departure node and a negative flow number at the destination. A simple example is that if a passenger is traveling on a ticket (commodity, \( q \)) from DEN to SEA, then the net flow of that commodity ‘\( q \)’ of ‘DENSEA’ will be (+50) at origin Denver and (-50) at destination Seattle. Equations (5-7) deal with trip limits of each aircraft type for the fleet within the course of a quarter.

\[
\begin{align*}
\text{min} & \quad \sum_{q} \sum_{i} \sum_{j} C_{ij}^A X_{ij}^A + C_{ij}^B X_{ij}^B + C_{ij}^C X_{ij}^C \\
\text{subject to:} & \\
\sum_{i} X_{A}(i,j) \text{CAP}_A + X_{B}(i,j) \text{CAP}_B + X_{C}(i,j) \text{CAP}_C & \geq - \sum_{q} \text{outflow}(q,j) \\
\sum_{i} X_{A}(i,j) \text{CAP}_A + X_{B}(i,j) \text{CAP}_B + X_{C}(i,j) \text{CAP}_C & \geq \sum_{q} \text{inflow}(q,j) \\
\sum_{i} X_{p}(q,i,j) - \sum_{j} X_{p}(q,i,j) + X_{C}(i,j) & = \text{netflow}(q,j) \\
\sum_{i,j} X_{A}(q,i,j) & \leq \text{triplimit}_A \\
\sum_{i,j} X_{B}(i,j) & \leq \text{triplimit}_B \\
\sum_{i,j} X_{C}(i,j) & \leq \text{triplimit}_C \\
X_{P}, X_{A}, X_{B}, X_{C} & \in \text{integer}
\end{align*}
\]

The method of solution follows the previously established structure of decomposition with the network optimization being part of the decomposed subspaces. Equations (1-7) represent the integer programming (IP) multi-commodity problem statement for the network portion of the design. The objective function as shown in equation (1) represents the total cost of flights served by each aircraft type due to their corresponding allocations on the routes served. Equations (2) and (3) enforce the condition that the total passenger capacity due to allocation of aircraft on routes sufficiently services the passengers entering and leaving any node point (or city). Hence, nodes with passengers departing for a chosen destination would result in a negative number per ticket itinerary at each node. Equation (4) explicitly deals with flow balance of passengers within the network and ensures that it is equal to the net passenger flow at each node. This assumes a perfect balance of passengers within the system, making it a conservative network flow. Nodes with passengers departing on a particular itinerary will result in a positive flow at the departure node and a negative flow number at the destination. A simple example is that if a passenger is traveling on a ticket (commodity, \( q \)) from DEN to SEA, then the net flow of that commodity ‘\( q \)’ of ‘DENSEA’ will be (+50) at origin Denver and (-50) at destination Seattle. Equations (5-7) deal with trip limits of each aircraft type for the fleet within the course of a quarter.

![Figure 4](image-url)
A comparative study was performed to contrast potential savings that the concurrent optimization of both a yet to be designed aircraft and its network would have over purely optimizing the network itself without the introduction of a new aircraft. Figure 4 exhibits the two resulting route configurations as a result of the optimizations that were carried out. As can be seen, the Network only optimization yielded trips solutions that resulted in a directly connected network where as the introduction of a newly designed aircraft facilitated a more serially connected configuration. This is of course a simplified situation where there are no further restrictions on the network configuration beyond the issues of aircraft range and net demand. The cost savings however were still notably significant with the concurrent design paradigm as the simultaneous optimization of the new aircraft and chosen routes yielded a Fleet DOC of $63834 compared to the network only optimization that yielded a Fleet DOC of $83997.

The top level optimization of the overall fleet direct operating costs can be performed as an unconstrained minimization problem. However, the example problem size is small enough to enable the use of simple enumeration. The solution space is mapped out and lowest cost is then selected as the optimum design point with the corresponding passenger capacity and range. Figure (1) shows the solution space from the enumeration performed for the concurrent aircraft and network optimization problem. The resulting optimum aircraft design for the modified Bazaraa and Jarvis problem corresponds with an aircraft with passenger capacity of 280 passengers and a range of 1200 miles. A comparison of the main aircraft characteristics are exhibited in Table 1 with Aircraft A being the optimal design to be introduced. A worthy note on the observed solution space is that it is clearly multimodal with multiple minima existing throughout it. For a larger class of problem size, the use of a branch and bound or simulated annealing will be more useful in finding the optimal solutions due to the large computational expense.

![Figure 5: Solution space for concurrent aircraft and network optimization](image)

<table>
<thead>
<tr>
<th>New Aircraft (A)</th>
<th>Aircraft B</th>
<th>Aircraft C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity (pax)</td>
<td>280</td>
<td>140</td>
</tr>
<tr>
<td>Range (nmi)</td>
<td>1200</td>
<td>1000</td>
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<td>Takeoff Distance (fixed) (ft)</td>
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</tr>
<tr>
<td>Aspect Ratio (AR)</td>
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</tr>
<tr>
<td>Thrust to Weight (T/W)</td>
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<td>0.283</td>
</tr>
<tr>
<td>Wing Loading (lb/sqft)</td>
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<td>125</td>
</tr>
<tr>
<td>Fuel Weight (lbs)</td>
<td>34969</td>
<td>16561</td>
</tr>
</tbody>
</table>

Table 1: Comparison of aircraft designs

B. Passenger Econometric Demand Modeling

Various methods have been previously used in order to estimate passenger travel between origin-destination pairs. The techniques employed range both in geographical scope and temporal considerations (daily, quarterly, yearly estimations). The FAA utilizes a network flow based Fratar-TAF implementation in order to estimate such traffic flows on a daily basis. Recent research has increased the fidelity of such methods and incorporated more sophisticated methods such as neural networks in order to improve the estimation at the terminal level. Other methods include a more econometric approach that employs regressions in order to statistically determine correlations and causality between passenger travel preferences, demographics and airline operations.
Previous literature has shown success in the use of log-linear demand models\(^5\) to reflect passenger demand preferences for travel in the continental United States given factors such as ticket price, gross domestic product, private income, presence of low cost carriers and aircraft size among examined factors. The literatures cited have shown promising results in modeling demand at both the macro-scale (passenger demand for contiguous regions) and studies even at the airport hub/terminal scale\(^6\). An added benefit in log-linear models is also the intuitive interpretation of the coefficients that reflect the elasticity/sensitivity of the variable of interest to the regressors. For simplicity and as an illustrative example, a log-linear demand model with two factors of interest was used to serve as an econometric model for the four cities of choice. Demand for the six bidirectional routes served between the four chosen cities was modeled as a series of equations.

\[
\begin{align*}
\ln(D_{\text{SEAP}}) &= [1 \ x_{\text{SEAP}} \ \ln(S_{\text{SEAP}})] \\
\ln(D_{\text{SEAC}}) &= [1 \ x_{\text{SEAC}} \ \ln(S_{\text{SEAC}})] \\
\ln(D_{\text{SEADEN}}) &= [1 \ x_{\text{SEADEN}} \ \ln(S_{\text{SEADEN}})] \\
\ln(D_{\text{SELDEN}}) &= [1 \ x_{\text{SELDEN}} \ \ln(S_{\text{SELDEN}})] \\
\ln(D_{\text{SEAPX}}) &= [1 \ x_{\text{SEAPX}} \ \ln(S_{\text{SEAPX}})] \\
\ln(D_{\text{SEPHX}}) &= [1 \ x_{\text{SEPHX}} \ \ln(S_{\text{SEPHX}})] \\
\end{align*}
\]

\(5\)

A separate log-linear equation is used for each route to mitigate some of the effects that heteroskedasticity may have on trying to perform the regression with a single equation to serve all routes – resulting in the above system of equations. The symmetric nature of demand reduces the 12 possible routes to a system of 6 equations as shown in Equation (5). A subscript such as ‘DENSEA’ denotes travel both ways between Denver and Seattle. Additionally, the generated coefficients can be directly interpreted as the route specific demand elasticity with respect to ticket price and number of links. Some key simplifications and assumptions are made for the demand model presented. First, is that only the two most perceived significant factors are chosen – average ticket prices and numbers of links between origin and destination. There are naturally other factors at play such as gross domestic product (GDP), private income (PI), population density and such. The greatly varying distances of travel and demographic variances for each city pair can also give rise to differing preferences towards ticket pricing, travel links and even the possibility of alternatives to air travel. Previous research has also indicated the impact that aircraft size has on both the operations and passenger preference for longer haul flights. Such complexities can be addressed with the use of more sophisticated models and a selection of factors that are apropos to the analysis. The inclusion of regression variables directly related to the attributes of the aircraft can also be used to influence the econometric feedback mechanism. However, for the purposes of simplicity, the above model is used within a limited frame of collected data to highlight the conceptual framework that is introduced.

Data from the Bureau of Transportation Statistics (BTS) DB1B and T100 Market schedules were compiled and used to generate a quarterly data set comprising of average ticket prices and number of links for the years 2002 and 2003. Total passenger travel for itineraries between the four chosen cities were taken from the T100 Market data that publishes such information among other metrics. The average ticket price was determined from the DB1B Market (10%) passenger sampling data that furnishes anonymous individual passenger costs (ticket paid price) on a monthly basis. This was then aggregated quarterly for all airlines serving origin-destination routes between the four cities resulting in 8 observations of data. Explicit information on the number of stops was not furnished. Therefore, the difference between passenger miles flown and actual miles travelled was used to infer the number of stops. It was assumed that there were two flight links/segments for itineraries that reported greater miles flown than actual travel miles. An ordinary least squares regression (OLS) is performed and the resulting statistical properties of the demand model are listed in Table 2. Issues of biasness, consistency and efficiency in the regression are not considered for the OLS regression performed here as only a small sample data set (8 observations) is used for conceptual purposes. Additionally, the OLS performed here can be thought of as an indirect lease squares (ILS) as the regression estimates the demand portion of a ‘supply-demand’ system of equations\(^8\).

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The \( t \)-statistic values are used as justifications for inclusion of significant factors and appropriateness of the overall model to be employed. The presented regression results are encouraging in that most of the cities exhibit acceptable t-statistics that have an absolute value over 1 for the generated coefficients. This indicates that the factors are significant in the model. Additionally, the coefficients make intuitive sense in that passengers are generally averse to ticket price increases and number of links. It is also very worthy to note that there are still significant effects that have not been accounted for as the \( t \)-statistic of the intercept is greatly significant in most of the regressions. However, there are some noted poor regression coefficients that were generated, namely in the case of the SEA-PHX and DEN-PHX routes that suffer from bad \( t \)-statistics In the case of the DEN-PHX route, it is encouraging that there is an adversity to the price increase but somewhat of an indifference to the average number of links. The strong \( t \)-statistic for the error term (intercept) indicates a strong presence of other factors at work as well. In the case of the SEA-PHX regression, there overall model is also poor in that although there is an intuitive sense on the adversity to price increases; the strong positive correlation to the average number of links does not seem to bear any intuitive logic to it. For overall consistency of the model to be employed, coefficients of both routes are still incorporated into the econometric model. For actual situations, a better analysis of factors may need to be done to yield more intuitive correlations and causalties for the demand.

Generally, econometric approaches to model demand such as in this four city case within a supply-demand framework by means of estimating a single equation has been referred to as the “identification problem” where variables in demand also exist as endogenous variables in the supply side of the set of resulting simultaneous equations. Here, the objective is however to estimate a single equation on the demand side as given. Previous literatures have used more sophisticated modeling and regression approaches such as Limited Information Maximum Likelihood Estimation (LIML)\(^5\), 3 stage least square (3SLS) and multinomial logit models that deal with an array of possible issues such as heteroskedasticity, multi-collinearity, selectivity biases and choice modeling to name a few.

C. Concurrent Aircraft and Network Design Incorporating Econometric Feedback

The concurrent engineering of the aircraft assets and airline routes represent the ‘supply’ side of the economic model where airline decisions to optimize routes are modeled through the multi-commodity network flow problem. The regression model on the other hand is the ‘demand’ side where passenger decision and responses are aggregated over a statistical model - in this case a simple OLS. The feedback loop between the two as exhibited in Figure 6 is the mechanism behind the idea of reflexive demand feedback. Quarterly decisions on the allocation (#links for ticket itineraries and average ticket prices) are looped recursively to the econometric regression to generated new quarter demands.

The objective now is maximum profit given reflexive demand traits within the overall established concurrent engineering framework. The problem statement is incorporate a ‘yet to be designed’ aircraft within an

<table>
<thead>
<tr>
<th></th>
<th>DEN-SEA</th>
<th></th>
<th></th>
<th>DEN-SLC</th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>Coeffs.</td>
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<td>Coeffs.</td>
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<td>0.7796</td>
</tr>
</tbody>
</table>

Table 2: OLS regression coefficients

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existing fleet’s operations and to predict expected future profit using the econometric regression model. Again, to simplify the problem, it is assumed that a nominal profit of $100.00 per passenger is added on top of the per passenger cost that is calculated using cost coefficients from FLOPS. This is indeed a simplification as additional costs that are not associated with the direct operating costs are not included here. Initial demand for each city pair is set at demand levels (2002 first quarter) as determined from the BTS T100 database for the four cities established. The overall optimization routine was performed with recursive demand being projected over a period of 8 quarters (2 years). Typically, the demand projection should be more reflective of a period consistent with the expected operational life of the aircraft to be designed. However, for the purpose of this simplified example, the projection is truncated to 8 quarters to reduce computation time. From an econometric analysis, the demand elasticity for specified factors changes with time due to aforementioned factors. This would require more sophisticated time series regression techniques and econometric considerations.

![Graphs showing demand behavior](image)

**Figure 7: Reflexive demand behavior observed**

**Error! Reference source not found.** shows computational results of the proposed framework where decisions on airline operations for the fleet over the network results in changing demand due to the nature of this feedback mechanism. This is naturally a simplification as there are other factors that directly influence changes in demand, including, economic conditions, seasonality, market competition, jet fuel prices and even geographic considerations such as weather. It can be clearly seen that demand is always in a state of flux as passengers choices change in line with quarterly airline decisions on which routes to service with varying aircraft combinations. The sensitivities of demand for each origin destination pair is reflected with the changing average fares and number of links. Most notably are the “DENPHX” and “SEAPHX” routes where demand does not change very much due to the low coefficients/sensitivities to both ticket price and number of links. The “DENSEA” and “PHXSLC” routes however, experience more significant fluxes as expected. Due to the relative simplicity of the regression model and limited data used, it is not possible to provide an objective comparison to actual demand trends that exist.

A distinct advantage in the design of a new aircraft and associated routes of operation in this manner is that the modeling incorporates explicit sensitivities and passengers preferences to travel service provided. In this case, the
two most prominent factors of fare and number of links are examined and this can of course be expanded to include
demographic information as well. As external fluxes affect demand either directly (due to change in aircraft
allocation on routes served) or indirectly (economic factors etc), there needs to be such information to facilitate the
allocation of aircraft more efficiently.

![Figure 8: Solution space for profit maximization](image)

Figure 8 above is the result of the total profits earned by the airline with the introduction of a new aircraft design.
The solution space is a result of the top level enumeration as carried out previously using the subspace
decomposition. The maximum profit is calculated as the summation of all profits for the simulated 8 quarters of the
aircraft life with the econometric demand feedback. Since this is now a maximization problem, the peaks are thus
the potential optimal points of interest and evidently there are multiple peaks. The maximum profit corresponds to
total revenue of $304 million with the optimal aircraft having a range of approximately 900 nmi and passenger
capacity of 300 pax. Note that better (more accurate) solutions may be yielded with a finer enumeration mesh or
with the use of global optimization methods that can solve (MIP) problems.

### III. Conclusion & Future Work

The work presented in this paper exhibits a unifying framework that incorporates concurrent aircraft and network
design with the econometric demand feedback. The notion of reflexive behavior is also introduced as part of the
feedback mechanism to represent shifts in demand due to observed changes in airline operations by passengers. The
architecture encompasses the design of both the aircraft and its operations to meet the expectations of demand trends
for routes served. This can be thought of as incorporating the sensitivity (elasticity) of passenger demands to factors
such as ticket prices and changes in operations (among other possible factors), within the design space. The
inclusion of such information in effect enables newly designed aircraft and operations to be customized for the
targeted passenger market. All of this is done within the framework of previously established subspace
decomposition method.

The example model provided is very limited and makes several prominent simplifications. Among these is the
consideration of only two primary factors in a limited data set for a network of four selected cities. Simplifying
assumptions are made through use of an OLS regression for the econometric modeling. These considerations are to
facilitate the conceptual introduction of econometric modeling within a systems design context. The intended
contributions in this paper are more focused on the underlying architecture proposed, the implications of
customizing aircraft design to meet demand trends and the notion of reflexive demand feedback.

The potential advantages to such an approach are the added benefits of designing the aircraft and operations
tailored to either maximize profit or minimize cost. The reflexive nature of demand can potentially be extended to

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better examine passenger travel trends and for strategic planning of airline policy and asset allocation to meet such demand characteristics. This naturally makes it amenable to a dynamic programming class of problems for both strategic and tactical asset design and allocation.

References


2 Transportation Research Board,”*Aviation Demand Forecasting”,*Transportation Research E-Circular Number E-C040, August 2002


8 FLOPS, Flight Optimization System, Software Package, Release 6.11, NASA Langley Research Center, Hampton, VA.