IMPACT OF AIRPORT NOISE REGULATIONS ON NETWORK TOPOLOGY AND DIRECT OPERATING COSTS OF AIRLINES

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Abstract

Due to growing demand for air transportation, airport noise can be reasonably expected to increase. This, coupled with an increasing awareness of airport noise issues, suggests that the number and restrictiveness of noise regulations will increase. Noise regulations affect airlines, and compel them to alter their operations to minimize the impact of the regulations on their operating cost. The main operational changes for airlines are the network of airports they service (network topology), and the fleet utilization to service this network.

This paper presents a framework to study the impacts of noise regulations on the network topology and direct operating costs for airlines. The study uses this framework to examine four types of noise regulations, and compares the effectiveness, advantages, and disadvantages of these regulations on airlines from 2008 to 2015.

1 Introduction

"There is sufficient scientific evidence that noise exposure can induce hearing impairment, hypertension, ischemic heart disease, annoyance, sleep disturbance, and decreased school performance [1]." The growing awareness of the detrimental aspects of aviation noise has led to the formation of active noise control groups that include community, airline, and airport representatives. These groups have imposed airport noise regulations to minimize the adverse impact of noise exposure. Operational restrictions, operational procedures, noise taxes, and noise exposure limits are some common examples of noise regulations.

Because the noise regulations force airlines to adapt their network and fleet utilization, the airlines deviate from their optimal minimum direct operating cost (DOC). The DOC for an airline includes costs that are directly attributable to the airline's operations such as fuel costs, maintenance costs, crew costs, etc. Considering the same revenue, a lower DOC implies a higher profit.

Rather than studying the impact of noise regulations only at the regulated airport, this paper explores the effect of noise regulations at the national airspace level. Thus, this study attempts to understand the operational changes due to noise regulations, and the costs of these changes to airlines.

2 Methodology

This study aims to combine the regulatory and operational aspects of aviation to illustrate the impact of noise regulations on airline operations. The study uses a calibrated network forecasting algorithm, a resource allocation problem, and an airport noise model to investigate the impact of noise regulations. Fig. 1 illustrates the concept of the simulation model.

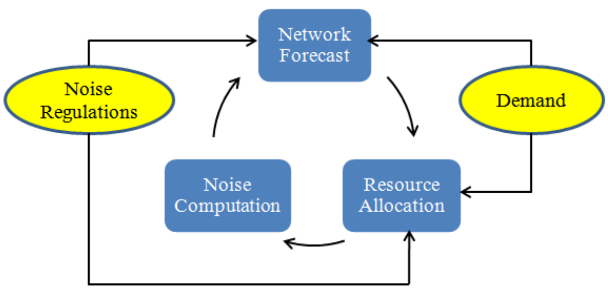

Fig. 1: Simulation concept overview

The simulation begins by forecasting the next year's network structure by using the existing network structure and the projected demand. This is followed by optimally allocating the fleet to meet the demand over the network, while satisfying the specified noise constraints. The noise at each airport is computed using the results of the resource allocation. The cycle starts over when the new network is determined using the existing network, projected demand, and current noise levels.

Section 3 presents the network forecasting algorithm, while Sections 4 and 5 detail the resource allocation process and the noise model, respectively.

3 Network Forecasting Algorithm

A network forecasting algorithm predicts the addition and removal of links in the network. To study the operational changes due to noise regulations on an airline's network, it is critical to be able to predict the change in an airline's network. Integrating this capability into the simulation helps understand the nature and extent of an airline's response to a regulation.

To limit the scale of the problem this study uses the FAA's OEP-35 airports to represent the air transportation network. The OEP airports are commercial airports that serve major metropolitan areas and serve as hubs for major carriers. More than 70 percent of passengers move through these airports.* These airports are chosen, because they cover a wide geographic area, they support a significant percentage of the passenger demand, but a small enough subset to be computationally inexpensive.

3.1 Existing Model

DeLaurentis, et al. [2] presented and compared several network forecasting models. Amongst the models presented, the fitness-function forecasting algorithm was selected for this study because the model is node-based, which is appropriate for airport-related studies, and externalities (e.g. airport noise) can be easily incorporated into the model. In this model, the existence of a link in the next iteration depends on the fitness value of the link.

This network forecasting algorithm computes a fitness value for each node (i) in the network based on node degree (k), eigenvector centrality (x), clustering coefficient (CC), population (p), and nodal weight (w). Eq. (1) presents the fitness function formulation presented by DeLaurentis, et al. [2]. The fitness value of each link in the system is a product of the fitness values of the nodes, which define the link. This approach follows the fundamentals of a scale-free network, [3] because nodes with higher fitness values have a higher probability of constructing a new link.

$$\eta_i = \frac{CC_i}{\sum CC_{NAS}} + \frac{k_i}{\sum k_{NAS}} + \frac{w_i}{\sum w_{NAS}} + \frac{x_i}{\sum x_{NAS}} + \frac{p_i}{\sum p_{NAS}} + externalities \tag{1}$$

Another advantage of this algorithm is that it only uses the previous year's network to predict the subsequent year's network topology. Thus, less data is required to initiate the model.

DeLaurentis, et al. [2] used this algorithm to predict the addition of new links in the network with an average accuracy of 16.64% for the years 1990 to 2005. Here, accuracy was defined as the ratio of the number of correctly predicted routes to the number of actual new routes.

3.2 Modified Network Forecast Model

Although airlines both add and remove links every year, DeLaurentis, et al. [2] did not predict the removal of links from the network. Moreover, the parameters used in the fitness function were equally weighted. There is a possibility that a weighted fitness function might provide better results. This paper explores these two possible improvements.

The original model used a probability threshold to determine if a particular route will be added to the network. This study specified the number of links to be added (deleted), and

* http://www.faa.gov/about/office_org/headquarters_offices/ato/publications/oep/faq/Airports/index.cfm

selected the links with the highest (lowest) fitness values for addition (deletion).

To reinforce the scale-free network structure, airport demand growth was incorporated as a parameter into the nodal fitness function. Moreover, in addition to the fitness function of the two nodes, the strength of an existing link (i.e. demand between the two nodes) was used to evaluate node-pairs for addition and deletion of new links.

To summarize, the improvements to the model were using a weighted fitness function, including airport demand growth in the fitness function, and using the strength of a link to determine the link's fitness. This study tested these improvements using historical data from 1990 to 2007.

3.2.1 Historical Data

To compute the parameters in the fitness function, the model required network information, and data on demand and population from 1990 to 2007. The Bureau of Transportation Statistics (BTS) maintains a comprehensive database of airline-reported domestic passenger demand information beginning from 1990[†]. This database was used to obtain network and passenger demand information.

For each OEP-35 airport, the county-level decennial census reports were used to compute the population for the corresponding metropolitan areas in 1990 and 2000[‡]. The Census Bureau also provides yearly population estimates based on the decennial United States census, which was used to compute the metropolitan population in 2007. The populations in the intervening years were interpolated based on the populations in 1990, 2000, and 2007. Care was taken to use the same area for population estimates despite changes in the reporting format and classification of areas.

3.2.2 Demand distribution

An important aspect of a network forecasting model is to distribute the demand on a network structure. While the FRATAR algorithm is the most widely used method of generating trip distributions [4], this algorithm has significant limitations which make it unusable in our analysis. Our study explores new network structures, and the FRATAR algorithm does not have a basis to determine the demand on new routes because it determines the optimal forecast trip distribution based on the current trip distribution.

Fig. 2 presents a flow chart of a new algorithm developed to allocate demand over an evolving network.

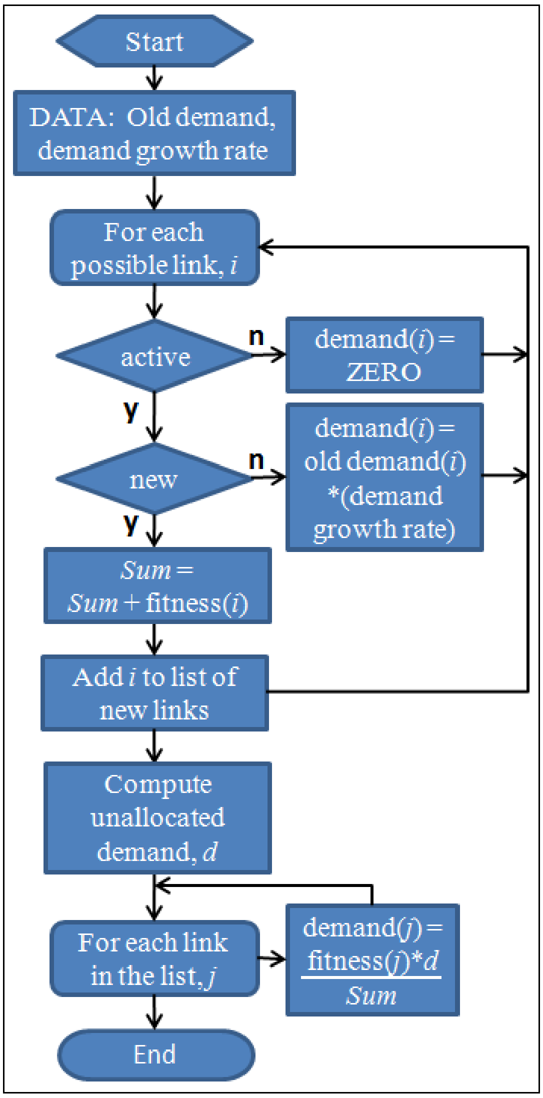

Fig. 2: New demand distribution algorithm

In this algorithm, the new demand for existing links is equal to the product of the old demand values and the demand growth rate. The unallocated demand is defined as the difference

† http://www.transtats.bts.gov/Fields.asp?Table_ID=311
‡ http://www.census.gov/

between the total new demand and the new demand allocated to the existing links. This unallocated demand is distributed amongst the new links in proportion to their fitness values. This algorithm works with both increasing and decreasing demand scenarios.

3.3 Calibration

The network forecasting algorithm is calibrated by determining the weighting of the fitness function that produces the maximum prediction accuracy of the algorithm as defined in Section 3.1. This paper uses an optimization approach to identify the optimal weighting for the parameters in the fitness function. Fig. 3 presents the decomposition scheme for the optimization problem.

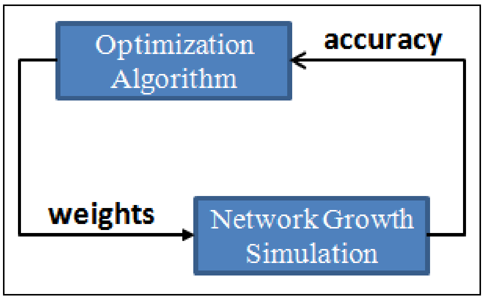

Fig. 3: Decomposition scheme for optimization

Because an unconstrained nonlinear optimization technique (simplex search method) was unable to handle the numerous local minima present in the solution space, this study used the genetic algorithm presented by Crossley, et al. [5] to find the optimal weighting. Initial experiments showed that route addition and route deletion emphasized different components of the fitness function. Therefore, developing separate weighting functions achieved the best prediction accuracy.

Table 1 presents the optimal weighting for the route addition and deletion processes. These values show that the clustering coefficient, eigenvector centrality, and demand growth were more important to predict the routes that should be added, while node weight, population, and link weight were more important for forecasting route deletion.

Table 1: Parameter weights for fitness function

Parameter	Addition	Deletion
Node Degree	0.7937	0.9524
Node Weight	3.8095	4.9206
Clustering Coefficient	3.5714	1.3492
Eigenvector Centrality	3.0159	1.9048
Population	0.0794	0.3968
Demand Growth	1.2698	0.0794
Link Weight	2.5397	3.3333

Fig. 4 presents the yearly accuracy of the weighted and un-weighted fitness functions in forecasting changes in the network. Addition accuracy is defined as the percentage of actual additions predicted by the algorithm. Deletion accuracy is defined similarly. The plot shows that the fitness functions were better at forecasting addition of routes than deletion of routes. The average prediction accuracy improved from 62.93% to 80.10% for route addition, and from 23.8% to 55.69% for route deletion. This study used the weighted fitness function model obtained from the calibration process, because it forecasts the network changes better than the un-weighted function.

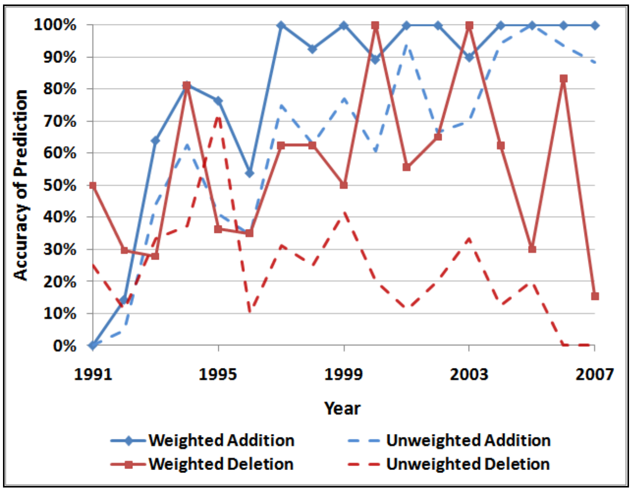

Fig. 4: Prediction accuracy

The considerable difference in prediction accuracy of the un-weighted model presented here compared to DeLaurentis' model [2] is attributed to the difference in the size of the network. The gains from weighting the parameters are significant, but cannot be directly compared to the values presented by DeLaurentis, et al. [2].

3.4 Noise externalities

DeLaurentis, et al. [2] briefly discussed the possibility of introducing externalities into the forecasting algorithm. In the simulation model, the effect of noise on the network structure was investigated by treating airport noise levels as externalities in the fleet forecasting algorithm.

In this study, the proportion of an airport's contribution to the network's noise area was subtracted from the airport's fitness value. The noise externality is un-weighted, which penalizes airports with higher noise levels. The noise model is described in Section 5.

4 Resource Allocation

As stated earlier, airlines will adapt to noise regulations by changing the way they utilize aircraft to satisfy demand and lower operating costs. A resource allocation model provides a way to determine the nature and extent of an airline's response to the noise regulations. Thus, resource allocation provides a way to approximate the behavior of airlines under these new constraints.

This paper used a scaled-down adaptation of the resource allocation approach presented by Zhao, et al. [6]. To simplify the resource allocation problem, this approach does not make distinctions for individual airlines, so it assumes that a benevolent monopolistic airline serves the network to satisfy all the passenger demand.

This study also used the fleet abstraction presented by Zhao, et al. [6], where the entire fleet is divided into six seat-based classes. A combination of the most flown aircraft in 2005 in each class (representative-in-class aircraft), and the aircraft with the newest Entry-in-Service (EIS) date as of 2005 (best-in-class aircraft) represent all aircraft operations in a particular class. The two categories provide a distinction between the standard and the latest technology in each class. Table 2 presents the class definitions and the selected aircraft types in each category.

Table 2: Representative and best in class aircraft

Class	Seats	Rep.-in-class	Best-in-class
1	20-50	CRJ 200	ERJ 145
2	51-99	CRJ 700	ERJ 170
3	100-149	B737-300	B737-700
4	150-199	B757-200	B737-800
5	200-299	B767-300	A330-200
6	300+	B777-200	B 777-200

Eq. (2) presents the formulation for the resource allocation problem.

$$
\begin{aligned}
&\textit{Objective: minimize } \sum_{a=1}^{12} (DOC)_a \\
&\textit{Constraints:} \\
&\sum_{a=1}^{12}\left[C^a \cdot X_{i,j}^a\right] \geq D_{i,j} \\
&i, j \in 1,\ldots,35\,;\, i \neq j \\
&(Range)_a \geq (distance)_{i,j} \\
&i, j \in 1,\ldots,35\,;\, i \neq j\,;\, a \in 1,\cdots,12 \\
&(Field\ Length)_a \geq (Max\ Runway)_i \\
&i \in 1,\ldots,35;\, a \in 1,\cdots,12 \\
&\sum_{i=1}^{35}\sum_{j=1,\neq i}^{35}\left[\left(BT_{i,j}^a\right)\cdot(1+MT)+TA\right] \leq 24 \cdot n^a \\
&a \in 1,\ldots,12; \\
&\textit{Noise constraint}
\end{aligned}
\qquad (2)
$$

where,
i, j = airport indices, a = aircraft type,
C = aircraft effective capacity, D = demand,
TA = turnaround-time, BT = block-time,
MT = maintenance-time,
X = number of round-trips,
n = number of available aircraft

While Zhao, et al. [6] used revenue maximization as their objective, this study minimized the DOC of the airline. The objective function of the resource allocation problem reflects the airline's priorities. Because a lower DOC will result in increasing profit for the same revenue, this objective was considered a reasonable surrogate for airline behavior.

Constraint 1 checks that the demand between city-pairs is satisfied. Constraints 2 and 3 ensure that an aircraft allocated to a particular route can service that route by tracking the range of the aircraft, and the runway length of the airports. Constraint 4 prevents the over-utilization of aircraft. Constraint 5 is the placeholder for any noise constraints.

5 Noise Model

The noise model is an integral part of the simulation process. The noise model uses the operational information to compute the noise at each airport in the network. The FAA's Integrated Noise Model (INM) is the standard airport noise model. INM is unsuitable for fleet-level studies because of its long setup and computation times [7].

This study uses the noise model developed by Dikshit and Crossley [7]. This noise model uses a weighted-linear equation that estimates the area within the 65 dB Day-Night Level (DNL) contour around an airport as a linear function of the number of aircraft operations at that airport. Eq. (3) presents this noise model.

$$Area_i = \frac{1}{10000} \cdot \sum_{a=1}^{12} \left\{ \left(P_a \cdot \delta_i^{TO} + Q_a \cdot \left(1 - \delta_i^{TO}\right)\right) \cdot \left(N_a^{TO} \cdot X_{a,i}^{TO}\right) + \left(P_a \cdot \delta_i^{Arr} + Q_a \cdot \left(1 - \delta_i^{Arr}\right)\right) \cdot \left(N_a^{Arr} \cdot X_{a,i}^{Arr}\right) \right\} \quad (3)$$

where,
X = number of operations, a = aircraft type,
i = airport index, δ = day ratio,
TO = takeoff, ARR = arrival,
$N^{TO} = 10^{(EPNL/10)-7}$, $N^{ARR} = 10^{((EPNL-10)/10)-7}$,
P = daytime aircraft coefficient,
Q = nighttime aircraft coefficient

The noise model, specifically developed for fleet-level studies, uses the noise energy equivalent of the FAA-published noise levels at the takeoff, sideline, and approach certification points. The noise model accounts for the difference between departure and arrival operations, the effect of takeoff gross weight (TOGW) on the takeoff noise, and correlates well (normalized RMSE = 4.79%) with the predictions of FAA's Integrated Noise Model (INM). The model's linearity with respect to the number of aircraft operations allows its use as an objective or constraint in a resource allocation problem.

6 Data

The simulation model requires information on future population changes and passenger demand as inputs to the network forecasting algorithm. The study needs examples of currently-implemented noise regulations to simulate such regulations in the model. The following paragraphs describe the source of this data.

6.1 Future Population Estimates

The U.S. Census Bureau projected state-level population estimates from 2004 to 2030[§]. The population growth around each airport was approximated to be the same as the population growth in the state(s) that contained the metropolitan areas corresponding to each airport. This computation used the percentage change values for the period 2000-2010 to estimate the populations from 2008-2010, and the change values from 2010-2020 to estimate the populations from 2011-2015.

6.*2* Future Passenger Demand

The 2007 and 2008 passenger demand was extracted from the BTS data mentioned in section 3.2.1. The Terminal Area Forecast (TAF) is the official forecast of aviation activity used to meet the budget and planning needs of

[§] http://www.census.gov/population/www/projections/projectionsagesex.html the FAA[**]. The 2009 TAF data was used to obtain the passenger demand at the OEP-35 airports for the years 2009 to 2015.

7 Noise Regulations

Noise regulations are mandated by the airport authority to reduce the negative impacts of airport noise on the surrounding community. Over the years, several different forms of noise regulations have been implemented. The Boeing Corporation maintains an up-to-date list of airport noise regulations[††]. This study explored the impact of implementing noise regulations at three airports – ATL, JFK, and PHL. These airports were selected because they were well connected to the other OEP-35 airports, and any operational changes at these airports would likely cascade throughout the network. Another reason was that between these three airports, they spanned a wide range of passenger demand levels.

This study considered four types of noise regulations – 1) airport noise restrictions, 2) noise taxes, 3) aircraft operations quotas, and 4) aircraft noise restrictions. For each type of regulation, six levels of severity were simulated. The following paragraphs discuss each of these regulations, and their implementation in the simulation.

7. 1 Airport Noise Restrictions

Airport noise restrictions specify the maximum noise levels at airports. This noise level may be specified using any metric (e.g. area exposed to noise, number of night-time awakenings, etc.). This study used the 'Area within the 65 dB DNL contour' as its metric, because the noise model measures airport noise using this metric.

Because the base year of this forecast model was 2007, the airport noise regulation was tied to the 2007 noise levels at the selected airports (i.e. the airport noise for any year could not be more than a specified percentage of the 2007 airport noise level). The six levels of severity tested for airport noise restrictions were 95%, 100%, 105%, 110%, 115%, and 120% of the 2007 noise levels.

7. 2 Noise Taxes

Noise taxes are a relatively new form of noise regulation. Noise taxes levy a fee (fixed or variable) based on the noise exposure of individual aircraft. The airport determines a threshold value, and all aircraft that are above the threshold have to pay the noise tax. Changing either the fee or the threshold value can vary the tax.

This study used an adaptation of the noise tax levied by the Adelaide Airport[‡‡]. The threshold value at Adelaide, which is computed as the sum of the departure, sideline, and arrival certification noise, is equal to 265 dB. Eq. (4) presents the formula to compute the noise tax levied on aircraft exceeding this threshold. The severity of the regulation was varied using the *rate* parameter. The six levels of noise taxes tested in order of decreasing severity were $1200, $1000, $800, $600, $400, and $200.

$$tax = rate \cdot 2^{(noise\_level - 265)/15} \tag{4}$$

7. 3 Aircraft Operations Quotas

Aircraft operations quotas limit the daily number of operations at any airport. This type of regulation may either have different quotas for different aircraft, or may only be applicable to certain types of aircraft.

This regulation was implemented similarly to the maximum airport noise regulation. The aircraft operations quotas limited the total operations at the selected airports to a specified percentage of the 2007 value. The six levels of severity tested for operational quotas in order of decreasing severity were 75%, 80%, 85%, 90%, 95%, and 100% of 2007 operations.

7.4 Aircraft Noise Restriction

Aircraft noise restrictions prohibit the use of certain aircraft at the selected airports based

** http://aspm.faa.gov/main/taf.asp

†† http://www.boeing.com/commercial/noise/list.html

‡‡ http://www.boeing.com/commercial/noise/adelaide.html

on their noise exposure. This regulation may be considered a special case of aircraft operations quotas.

This paper restricted aircraft types on the basis of either their arrival or departure certification noise levels. Because the noise model uses various previously stated fleet abstractions, the number of types of aircraft in the fleet was limited. Therefore, the aircraft noise levels were discrete, which limited the effectiveness of this regulation. Furthermore, due to the multiple parameters (arrival and departure noise level limits), it was not always possible to compare two regulation levels. For purposes of brevity, the regulations are specified using the notation, [*departure_noise_limit*; *arrival_noise_limit*].

The regulation levels (in EPNdB) tested were [91; 97], [91; 98], [91; 100], [93; 97], [93; 98], and [93; 100]. Here, [91: 97] is the most stringent, while [93; 100] is the least stringent regulation.

8 Results

The simulation was run from 2007 to 2015 without noise regulation for the baseline case and for the various types and levels of noise regulations detailed in Section 7.

It is important to note that the selected levels of severity for each type of regulation may not be equivalent. While the rates for the noise taxes were chosen arbitrarily, the most stringent regulatory level for the other regulations reflects the most severe regulation that allowed the resource allocation module to find a solution.

Since the relative severity of all aircraft noise restrictions could not be determined, only the results of the least and most severe regulations were plotted. The scenario without any noise regulations is considered the baseline scenario, and all regulated scenarios were compared to the baseline scenario. Because the network is set up to adapt to the noise regulation, the results may not be compared directly (because the values may correspond to different network structures), but the baseline value provides a reference for evaluation. For convenience, the 'area within the 65 dB DNL contour' is referred to as the 'noise area'.

8.1 Noise at Regulated Airports

An important measure of the effectiveness of any noise regulation is the noise level at the regulated airports. Fig. 5 presents the impact of regulations at ATL (largest regulated airport) in 2011 (mid-way point of the simulation), while Fig. 6 presents the corresponding plot for ATL in 2015 (end point of the simulation).

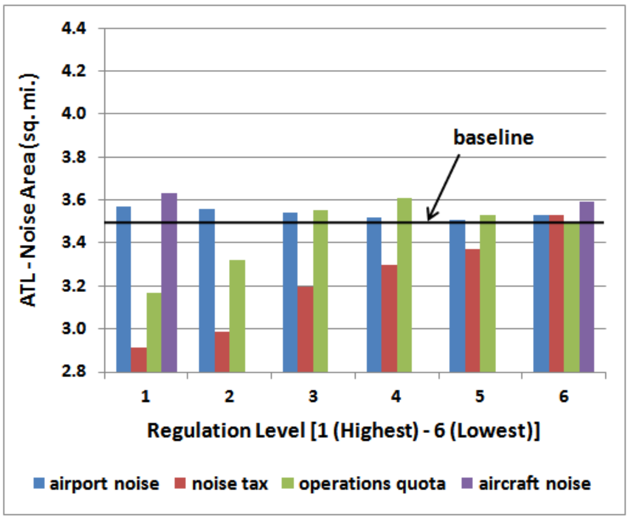

Fig. 5: Impact of regulations at ATL in 2011

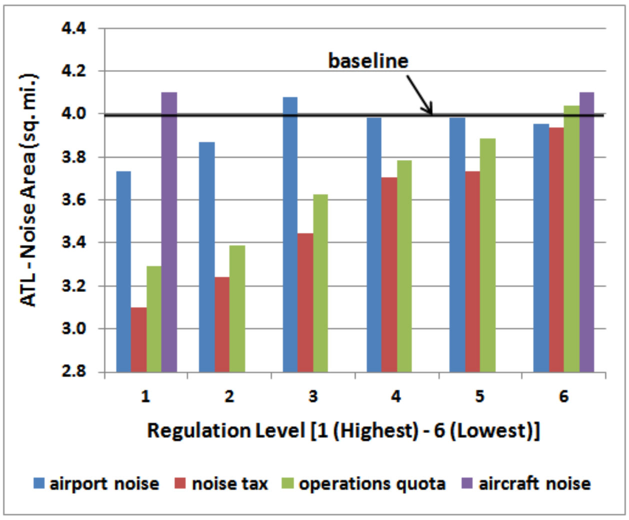

Fig. 6: Impact of regulations at ATL in 2015

At the least stringent level, none of the noise regulations were effective in curbing the noise at the given airport. At the most stringent level, noise taxes and operational quotas were more effective in curbing noise at the targeted airports compared to the other restrictions. The impact of increasing the severity of the regulations was also more evident in noise taxes and operational restrictions. These trends were discernable in both 2011 and 2015.

In comparison with the baseline, the operational restrictions and noise taxes were more effective in 2015 than in 2011. This can be attributed to a combination of changes in fleet utilization and network topology. Section 8.4 presents the impact on network topology. To study the changes in the fleet servicing a regulated airport, Fig. 7 compares the changes in utilization of the fleet at ATL from 2011 to 2015 of the baseline scenario with the level 2 operations restriction.

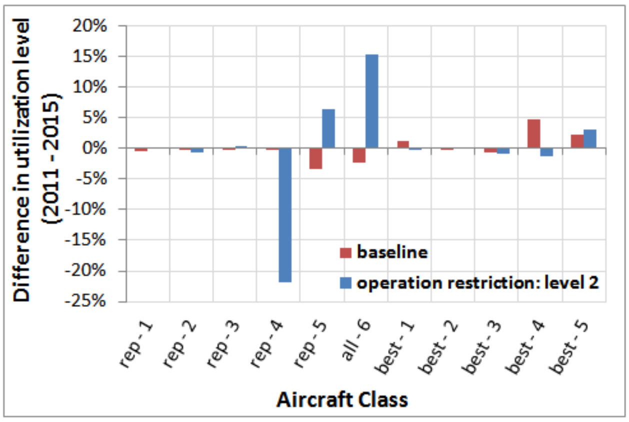

Fig. 7: Difference in fleet utilization

Since the Boeing 777-200 was the representative aircraft, as well as the best-in-class aircraft, in class 6, the operations were grouped together. The baseline scenario showed an increase in the utilization of best-in-class aircraft in classes 1, 4, and 5. It also showed a reduction in the use of all class 6 aircraft, and the representative aircraft in class 5.

On the other hand, the regulation forced the airline to utilize a lot more representative aircraft in classes 5 and 6, while significantly reducing the number of class 4 representative aircraft. While the baseline scenario simply chose newer technology aircraft to reduce DOC, the regulation forces the airline to lower the number of operations at the airport, resulting in an increased use of larger aircraft rather than the most cost-effective. This example illustrates the effect of the restrictions on the airline's operations.

8.2 Noise at Other Airports in the Network

In addition to the noise at the regulated airports, this paper investigated the impact of these regulations on the other airports in the network. Fig. 8 presents the sum of the noise within the 65 dB DNL contour at the 32 unregulated airports in 2011, and Fig. 9 presents the corresponding values in 2015.

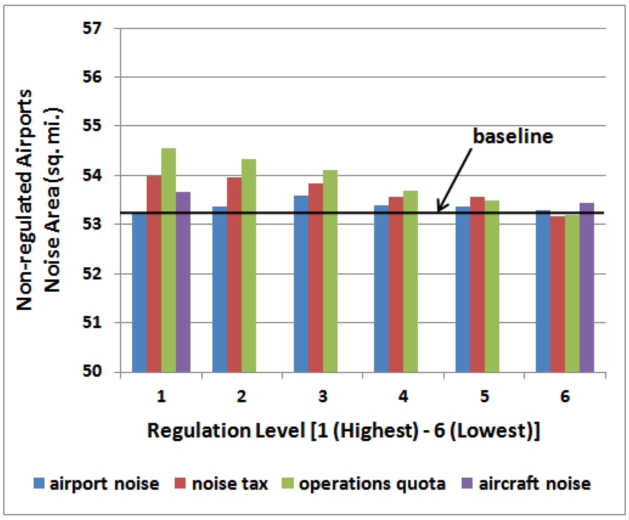

Fig. 8: Noise at non-regulated airports in 2011

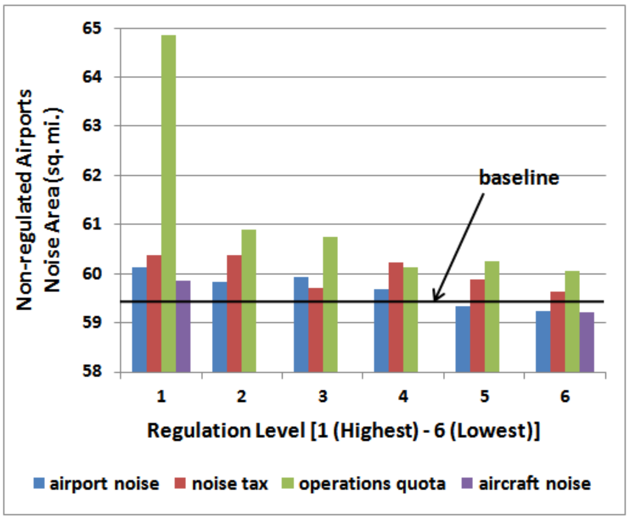

Fig. 9: Noise at non-regulated airports in 2015

While operational quotas had the most detrimental effect on the noise at non-regulated airports in 2011, their adverse impact on noise at these airports increased exponentially in 2015. This suggests that it was harder for airlines to cope with operational quotas in subsequent years. A larger proportion of noisier aircraft were allocated to the non-regulated airports due to the absence of noise regulations. Thus, the non-regulated airports bore the brunt of this sub-optimal allocation.

In contrast to operational quotas, the impact of noise taxes on noise at the non-regulated airports remained consistent in the 2011 and 2015 scenarios. Airport and aircraft noise restrictions did not have a large adverse impact on these non-regulated airports in either scenario.

In 2011, there appeared to be a correlation between the extent of the regulations and the impact on the noise at the non-regulated airports for noise taxes and operational quotas. This trend continued and was more visible in 2015, even for airport noise regulations.

8.3 Direct Operating Cost

While noise regulations are important, they should not be prohibitively expensive for airlines. The impact on the airline DOC measures the relative burden imposed on the airline by these regulations. Fig. 10 presents the DOC for the airline in 2011 under various noise regulations, while Fig. 11 presents the values for the 2015 scenario.

Because noise regulations result in a sub-optimal allocation of resources, most of the regulated cases showed a higher DOC compared to the baseline. This difference was larger in 2015 compared to 2011. Because the noise taxes directly impact the airline's DOC, the noise tax scenarios had the highest penalty on the DOC in both 2011 and 2015. Operational quotas had the second largest impact on the airline DOC.

Thus, the two noise regulations that were most effective in reducing the airport noise were also the most severe on an airline's operating cost. Moreover, for the noise tax and operational quota scenarios, there was a direct correlation between the extent of regulation and the increase in DOC.

Because the simulation's objective was to minimize the DOC, the fleet allocation is an important part of the simulation. Fig. 12 compares the difference in aircraft utilization under the severest regulations of each kind with the baseline values in 2015.

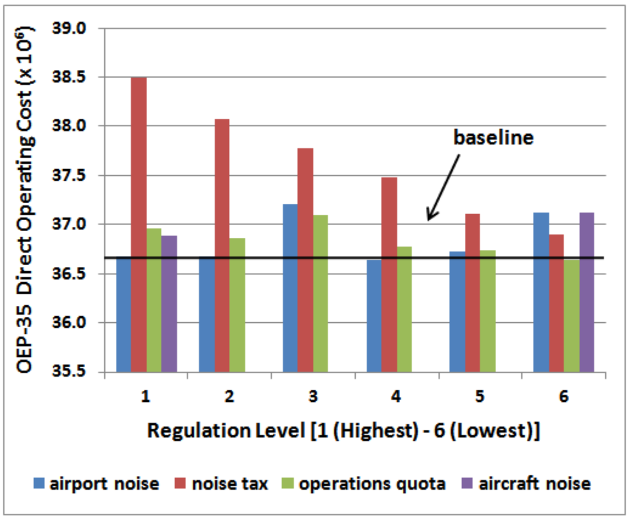

Fig. 10: DOC for OEP-35 airports in 2011

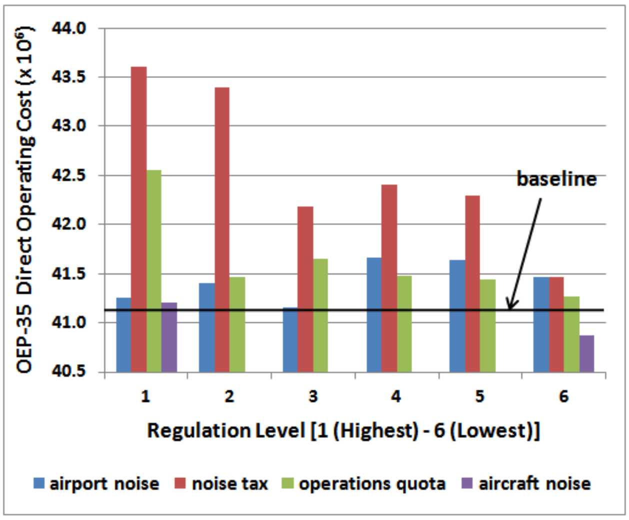

Fig. 11: DOC for OEP-35 airports in 2015

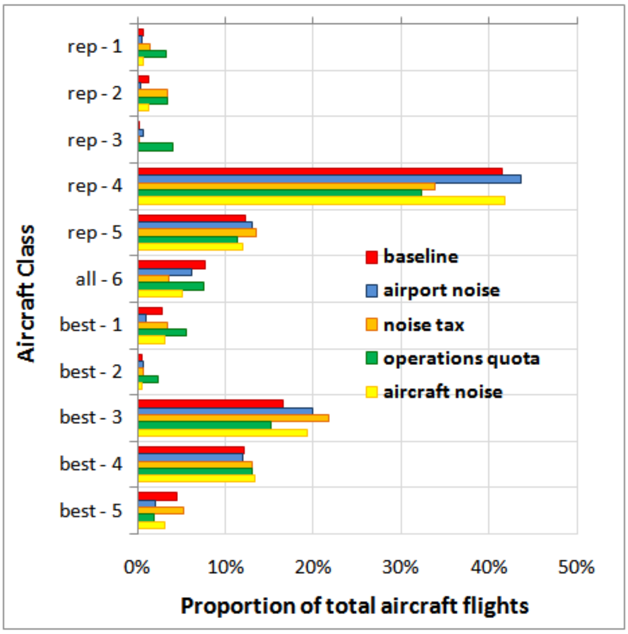

Fig. 12: Aircraft utilization in 2015

The airport noise restriction increased the utilization of the representative aircraft in class 4 and the best-in-class aircraft in class 3, because these aircraft have lower contributions to airport noise per passenger. Since noise taxes penalize the airline on the basis of certification noise levels, under this constraint the simulation lowered the utilization of the class 4 representative aircraft, and increased the use of the best-in-class aircraft in class 3 and the class 2 representative aircraft.

Interestingly, the operations quota restriction increased the use of all class 1 and 2 aircraft. Since the simulation forced the airline to use all the larger aircraft to service the regulated airport (to minimize operations), the airline required many smaller aircraft to satisfy the demand at other non-regulated airports. This also explains the increased noise at non-regulated airports. The aircraft noise restrictions did not produce any significant fleet-level utilization trends.

8.4 Network Topology

Network topology is the network structure created by the links connecting the nodes of the network. For each time-step of the simulation, the network forecasting algorithm adds and removes links in the network. Because noise is included as an externality, the noise regulations have an influence on the network topology of the airline. The degree of a node is the number of other nodes in the network connected to it. Over time, airline networks gravitate towards a scale-free structure. The degree distribution plot facilitates the study of the impact of noise regulations on the tendency to form scale-free networks.

Fig. 13 presents a degree distribution of the network in 2011 for the most severe regulations, and Fig. 14 presents the equivalent distribution in 2015.

The baseline network is similar to a scale-free network structure [3], but it is not a true scale-free network due to the limited size and high inter-connectivity between the nodes. The 2015 baseline network had a steeper slope and a shorter tail compared to the 2011 baseline network.

In all regulated 2011 scenarios, except aircraft noise, the number of nodes with degree 34 decreased, and number of nodes with degree 33 and 32 increased. This pattern was again repeated with the number of nodes of degree 31 decreasing, and number of nodes with degree 30 increasing.

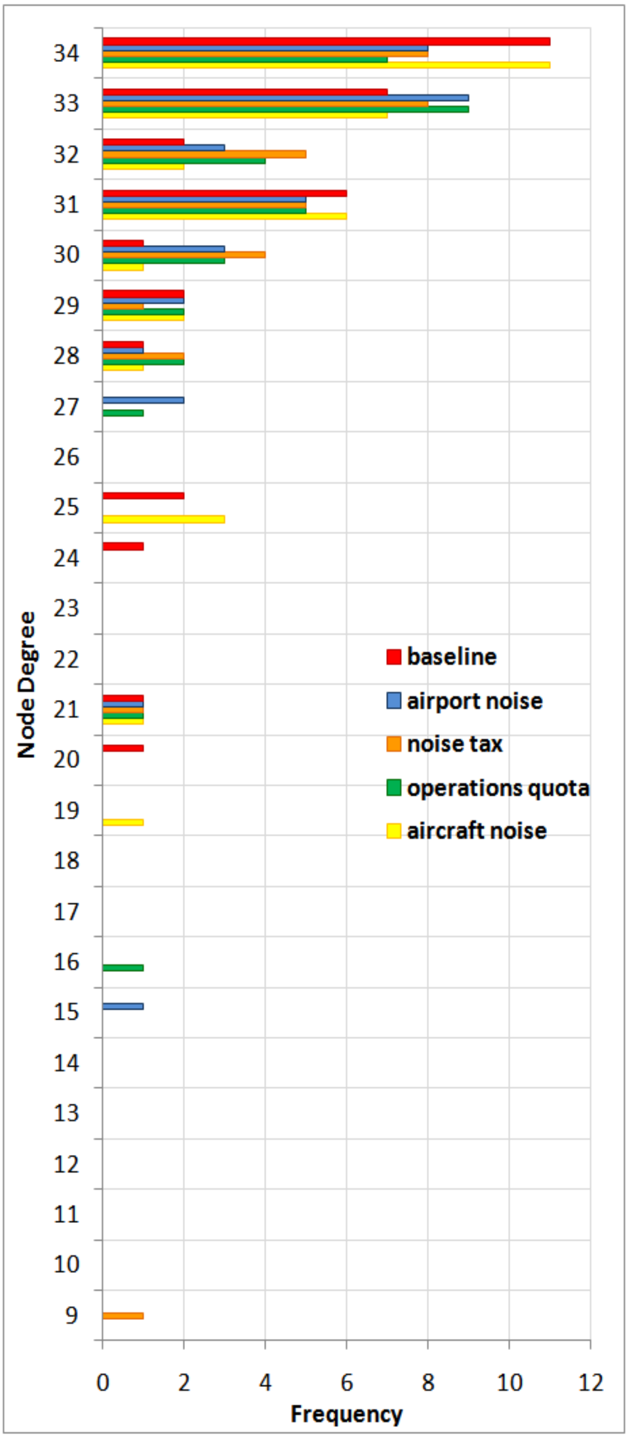

Fig. 13: Network structure in 2011

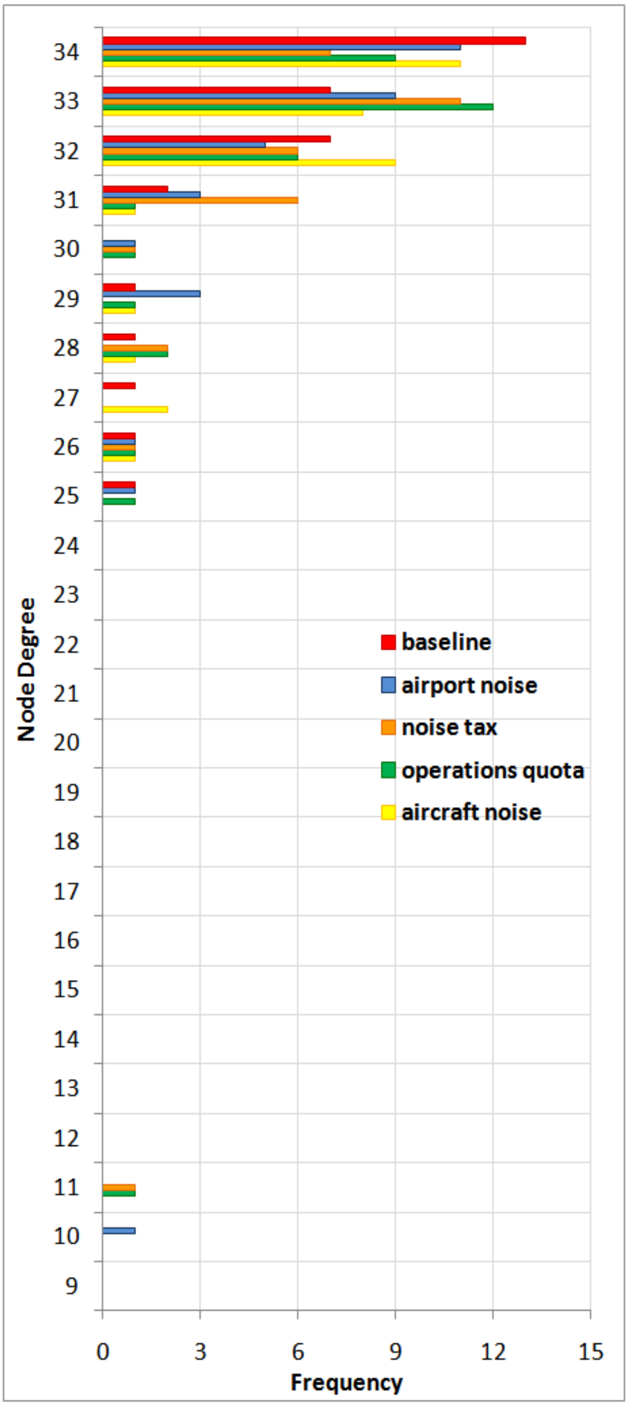

Fig. 14: Network structure in 2015

This pattern indicates that including noise as an externality in the fitness function lowered the fitness of the airports with heavier traffic, and increased the probability of linking of nodes with lower traffic. Thus, these noise regulations opposed the trend towards a scale-free network structure.

This trend was also evident in the 2015 scenario, even for aircraft noise regulations. Airport noise and noise tax regulations have a larger impact on the network than the other regulations in 2015.

All regulatory scenarios showed one airport with a low node degree value compared to the others. On analysis, the anomalous airport was identified as MIA. MIA was consistently dropping links under noise regulations compared to the baseline. This decrease was accompanied by a corresponding increase in the connectivity of STL. Table 3 presents the node degree values for both airports for each scenario in 2011 and 2015.

Table 3: Node degree: MIA and STL

	2011		2015	
	MIA	STL	MIA	STL
baseline	20	25	25	8
airport noise	15	28	10	29
noise tax	9	28	11	28
operations quota	16	28	11	26
aircraft noise	19	25	8	26

In comparison to the baseline, the noise regulations forced the simulation to assign sub-optimal aircraft to non-regulated airports. As explained in Section 8.2, this often increased the noise at the non-regulated airports. Since noise was included as an externality in the network forecasting model, the higher noise lowered the fitness values of the non-regulated airports. Non-regulated airports that had low fitness values to start with (e.g. MIA has a low fitness value due to low demand and low clustering coefficient) were most affected. As the simulation progressed, the impact on MIA was compounded. Other airports in the network, such as STL, were the unintended beneficiaries of the noise regulations.

9 Conclusion

In the near future, many airports will consider enacting noise regulations due to the increasing demand for air transportation, and the growing awareness of the ill-effects of airport noise. In addition to the local benefit, it is important to consider the system-level effects of these regulations.

This study investigated four types of noise regulations - airport noise limits, noise taxes, operational quotas, and aircraft noise restrictions - using a system-of-systems approach. The simulation model used a network forecasting algorithm, a resource allocation module, and a noise model to study the impact of implementing these noise regulations on the system.

Noise taxes and operations quotas were the most effective at regulating noise at the targeted airports. Airport and aircraft noise restrictions prevented further increase in noise, but did not lower the noise significantly. Non-regulated airports in the network were most affected by operational quotas, but this regulatory approach did not increase DOC prohibitively. On the other hand, noise taxes significantly increased the airline's DOC, but had a smaller impact on the non-regulated airports.

Although airport and aircraft noise restrictions did not lower the noise at the regulated airports, they prevented any significant increase in the noise area at these airports. Moreover, airport and aircraft noise restrictions did not significantly impact either the noise at the non-regulated airports, or the direct operating cost of airlines. Thus, these restrictions may be a reasonable middle ground.

Noise taxes and aircraft noise restrictions may be more effective if they were based on the actual noise contribution, rather than certification noise levels. Many airports currently employ a combination of noise regulations, and such customized measures may be needed to address the individual needs of each airport.

As seen in section 8.4, noise regulations can affect other airports in the network in unintended ways. In addition to the extent of the regulations, the proportion of the network that is regulated is bound to affect all aspects of the system. All airports in the network will be affected by noise regulations at any airport in the network, and it is important to analyze these intricate interactions using a systems approach. While noise regulations are important, it is critical for the sustainable growth of aviation that these regulations are studied in a framework, such as the one presented in this paper, before implementation.

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