3aNSb6. A multi-objective evolutionary optimization approach to procedural flight-noise mitigation

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Exposure to noise is a significant problem for communities that exist near airports. The distribution of noise exposure can be positively affected by changes in the procedures that aircraft follow in the vicinity of an airport (e.g. rate of ascent, ground track, etc.). When considering such changes, a decision maker often has to weigh the objective of lower noise impact against 'more practical' considerations such as fuel consumption and time-of-flight. This study presents a method of numerical optimization which seeks to find the optimal-tradeoff set (Pareto front) of flight procedures given information about an airport and the surrounding population and geography. This front will only include procedures such that an aggregate noise metric cannot be improved without detriment to a more practical objective. A contemporary multi-objective evolutionary algorithm is used as the basis of the optimization effort. Results from a simulated military airfield near Asheville, NC are shown. Ways in which decision makers are empowered by having access to a Pareto front are discussed.
INTRODUCTION

“Encroachment” is the word that military airbase operations officers use to describe the creep of residential zones towards the boundaries of their facilities over time. As the geographic and social center of the many communities which find employment there, it is only natural that encroachment towards an airbase occurs. This phenomenon is observable at many facilities, especially along the eastern seaboard of the United States where high population density and community noise problems from other sources are commonplace.

While general aviation and commercial aircraft have become quieter over time (largely due to the action of the federal government in response to community disquiet,) military aircraft have followed an opposite trend. When posed with a tradeoff, military decision makers seem to not find it difficult to decide between performance and something less tangible or pressing (e.g. noise generation and it’s impact on the population surrounding an airbase). Also, the laws which govern military aircraft noise are made to fit the current state of the art [3], whereas the state of the art commercial and civilian aircraft are made to fit the noise laws [4].

The problem of more people living closer to louder aircraft has created an accelerating problem of noise exposure near military airfields in America. This document contains current information on a search for a reliable algorithmic method of suggesting modifications to flight procedures. It is hoped that this effort can have a positive impact on some of the issues that can be linked to transient noise exposure [5, 6].

A Posteriori Multi-objective Optimization

Computational multi-objective optimization is the algorithmic process of generating solutions to problems in which there are multiple goals that may or may not oppose each other. “A posteriori” optimization indicates that no decision is made between the goals before the algorithm is run. The form of a solution returned by the algorithm is a collection of individual answers which form an optimal tradeoff set. In this set, one goal cannot be improved upon without detriment to at least one other goal.

![Figure 1: Hypothetical a posteriori multi-objective optimization problem. The tradeoff between time and cost in the manufacturing of a product is an example that many have encountered.](image)

A hypothetical multi-objective optimization problem (MOP), shown in Figure 1, is that of the tradeoff between the cost of a product, and the time taken for it’s production. An infinite amount of money is needed to produce something in 0-time. Also, if one never expends any resources, nothing will be produced. In this case the tradeoff set is continuous and well-behaved (hyperbolic, in fact). Accordingly, it will not be difficult for a producer to make an informed decision as to where on the set they would like to operate. However, there may be features of this set (discontinuities, multi-modality, etc.) which, if unknown, will lead to poor decisions by the producer. In more complicated cases, the revelation of tradeoff information can lead to great strides in the pursuit of production efficiency.
An excellent introduction to the topic of multi-objective optimization (specifically, the use of evolutionary algorithms for solving MOPs) is Cello-Coello [7], which also contains references to a large set of illustrative case studies.

Procedural flight-noise mitigation is clearly a multi-objective problem. An implicit and un-engineered balance has been struck for decades now between the desires of those who control flight procedures at military installations, and the desires of those who have the (great) capacity to be annoyed by the operations of military aircraft. If planes were not annoying in some way, they would routinely be routed directly over residential communities on training missions. Likewise, if procedures existed which led to 0-noise effect on the surrounding community without adverse consequence for those operating the aircraft, there would not be 60 years of research into community flight-noise impact. The fact that neither of these conditions exist indicates that there are conflicting objectives in the overall problem of designing flight procedures, with noise being only one.

There are many factors which may oppose the objective of minimizing noise: fuel burn, time-of-flight, emissions, etc. This study uses only one objective to oppose noise: that of the length of a flight procedure (in feet) which is added in an attempt to alleviate noise. While not directly related to any of the above objectives, this representative objective produces conceptual correlation with all of them.

By searching for and observing the behavior of the optimal tradeoff set between procedure length and the generated noise impact, a decision maker can understand how much a change in one objective will impact another. In this way, the greatest real-world efficacy of a noise optimization tool is achieved only when noise is taken into consideration as an objective equal to other possibly conflicting objectives.

Evolutionary Algorithms

The class of optimization algorithms used for this work fall under the category of evolutionary algorithms (EAs). These algorithms were inspired by the observed process of biological evolution [8]. They maintain a population of candidate solutions which evolve through generations (algorithm iterations). Every generation, new solutions are proposed by combining extant features of the current population. The different schemes used for selecting which population members survive through successive generations are largely what distinguish different EAs from one another.

EAs have the capability for global search, that is, they are not necessarily limited in the answer they return by the starting conditions of an optimization run. They are also predisposed to have the capacity to solving a posteriori MOPs, as they maintain a population which can converge to an entire optimal tradeoff set at once. EAs applied to MOPs are known simply as “multi-objective optimization evolutionary algorithms” (MOEAs).

Gradient-based methods, the other major class of optimization algorithms, will take less time to converge but will not have the global search property necessary for this problem. They also typically lack the ability to maintain a diverse set of solutions, so that each member of the optimal tradeoff set would have to be generated by a separate optimization run.

Problem Definition

This section gives an overview of the way in which procedural flight noise mitigation is formulated as an MOP so that it can be evaluated by an MOEA. Problem formulation is a critical component of this study: if the problem posed to the computer is too broad, an untenable amount of time will be needed to generate a solution. If it is too restricted, the tradeoff set may be restricted as well. For the defense of the methods presented here, see [1].
The Noise Objective

The noise impact prediction model used is NoiseMap, which has been in use by the US Navy for approximately half of a century and is now in version 7 [9]. This study will model a hypothetical single daytime departure of a Boeing F/A-18E/F Super Hornet from runway ‘34’ (340° heading, approximately north) of the Asheville Regional Airport (call sign ‘AVL’, in North Carolina). US Census data is used to create the population distribution of Asheville, NC and it’s surrounding settlements. Figures 2 and 3 show a satellite view of the Asheville region and the region as seen by NoiseMap (through the US Census data) respectively.

**FIGURE 2:** A satellite view of the Asheville, NC area including Weaverville to the north, Hendersonville to the south, Black Mountain to the east, and Canton to the west. The red box indicates the location of AVL.

**FIGURE 3:** The population distribution retrieved from US Census data that is used for the noise objective. Each point is approximately the centroid of a Census block, and the color of the point indicates the population belonging to that block (ascending from blue to red). The Easting and Northing units originate at the beginning of the AVL runway (south end).

NoiseMap calculates the SEL exposure values between a proposed flight procedure and each of the Census blocks. This necessitates a means of aggregation of these SEL values into a single noise-exposure metric. For this project, an aggregate metric is proposed which calculates a power-sum over the blocks. It is called LOUDPeople \( (L_P) \), endearingly named by it's creators:

\[
L_P = \sum_i \text{Population}_i \cdot 2^{\left[\frac{\text{SEL}_i - 100}{10}\right]} \quad \text{for } i \in \text{Census Blocks} \quad (1)
\]

First introduced in [2] and developed more thoroughly in [1], the \( L_P \) metric is asserted here relatively without defense. Recently, a similar power-sum construction was used by Miedema et al. as a basis for solving the “noise and number” problem [10] in which the parameters of their model were fit to empirical data in an effort which wound up verifying that the 10 dB nighttime penalty of the DNL metric is justified by human response (among other findings). In the \( L_P \) case, no equivalent data exist, so there can be no defense of the constants used in this procedure (e.g. the 2 as the base of the exponent in Eq. 1). However, it is comforting to know that the general method of aggregation used here has been shown in the past to produce equitable results across human populations. It is also interesting to note that if the base of the exponent was 10 instead of 2, \( L_P \) would be equivalent to summing the incident acoustic pressures-squared over the population.
The Length Objective

The length objective is defined as the distance (in feet) which the aircraft flies “out of its way” in an attempt to reduce noise impact (measured in ft). The aircraft will depart from AVL heading roughly north and will then be allowed to turn twice before returning to a northern heading to exit the region.

This objective calculates the minimum possible distance that the aircraft will have to fly to accomplish this goal, and then subtracts that from the total track length of the given procedure. If the aircraft does not turn, this objective would be minimal (approximately 0 ft: the aircraft will have to turn at least once to get onto the final heading). If the aircraft turns and flies south before turning around again and proceeding north, this objective will be very high.

The Algorithm

The MOEA used employs a strategy for deciding the set of members which persist through generations called $\varepsilon$-dominance (both $\varepsilon$-dominance and traditional dominance are discussed below). Accordingly, it is named “$\varepsilon$-Dominated Multi-Objective Evolutionary Algorithm” ($\varepsilon$-MOEA) [11]. It has been shown to have performance characteristics on test problems which are highly competitive within its class [11, 12].

The algorithm maintains two sets of solutions at all times, a constant size Population which uses traditional dominance rules, and a variable sized Archive which uses $\varepsilon$-dominance to produce a finite-sized tradeoff set. To generate new solutions, members of the Population and Archive are combined using various “genetic operators” [8]. These new members are evaluated by the objective functions and then checked for admission into both solution sets. Figure 4 shows a diagram of this process. The algorithm executes this loop for a set number of OF evaluations, after which the Archive is returned as the result.

![Diagram of the flow of $\varepsilon$-MOEA](image1)

![Diagram of dominance conditions](image2)
It is important to understand the concept of dominance, as it is crucial to the operation of this algorithm: If a solution is evaluated to be better in all objectives than another, it is said to “dominate” that solution. If it is worse than the other in all objectives, it is said to be “dominated.” If a solution is better than another in some objectives, but not all, the two are said to be “non-dominant.” $\epsilon$-dominance is a special case whereby the objective space is broken up into small rectilinear blocks and dominance is assessed based on block-membership instead of by the raw objective function value of a solution. These dominance conditions are shown geometrically in Figure 5. The mutually non-$\epsilon$-dominated set that is contained in the Archive at the end of an $\epsilon$-MOEA run is returned as the answer to the MOP.

The only modification made to the basic $\epsilon$-MOEA algorithm as described in [11] is that the number of offspring which are evaluated at any one time is increased. This is done in order to limit the number of times that NoiseMap is started, as a significant amount of time is spent to launch the program. For a more complete discussion and a defense of this modification see [1].

**RESULTS**

An initial goal of this research was to produce an algorithm which can fully solve the NoiseMap MOP problem in 12 hours on a contemporary desktop computer. A 3.0 GHz machine was used for this study, on which 12 hours corresponds roughly to 10,000 function evaluations. While this amount of time is shown to be enough to reveal overall characteristics of a problem, it is generally not enough to produce sufficient convergence (at least with the methods used) [1]. The result presented here is generated using 10 12-hour runs.

The tradeoff sets are presented as flight-tracks overlaid on the population distribution, as well as in the objective function space in Figures 6 and 7 (resp.). This set represents 77 independent flight procedures which form a mutually non-dominated set in the objective function space. The set generally breaks up into 5 main groups marked with the letters A-E in the figures. These markings show the mapping between the two figures, and it can be seen that jumps in the objective space correspond to jumps between groups of tracks.

An interesting feature of Figure 7 is that the groups A and B are contained in the interval of [0, 5,000] ft of the length objective. If an extant procedure belonged to group A, and migration to a more exotic group (C-E) was not possible, these results show that it would still be possible to realize a noise reduction of nearly half (by the $L_P$ metric) by adding less than a mile to the procedure.

An instructive way of interpreting these results is that the optimization has revealed the “best way to use more length.” A member of the optimal set is known: proceed directly north. This solution represents the least-length procedure, and will therefore always be a part of the returned set. If allowed more length, this result reveals the best way to use that length in order to mitigate the noise impact of the departure. There are surprising jumps between the competing groups which are not necessarily intuitive, and this result reveals not only which groups to jump between, but also when it is advantageous to jump instead of adding length within a group.

It is also important to note that this result implies that there is a maximum usable length when solving this problem (approximately 7 miles). If more length than necessary is brought to bear, the aircraft does not leaving the region expeditiously, and winds up creating more aggregate noise than it would if it were to find a more efficient path. If this was not true, one would see an asymptotic trend at the top of Fig. 7 instead of an abrupt end, as increasing length would always lead to a decrease in $L_P$.

Lastly, it is important to note that if a procedure is being used that is not a member of this set, two things are immediately understood: 1. That there is a solution which does better on
**FIGURE 6:** Returned solutions visualized as flight tracks over the Asheville, NC population distribution. The black lines represent the ground tracks of aircraft departing AVL and attempting to exit the airspace on a north-heading. The tracks form groups as indicated by the letters A-E. These labels map between this figure and the equivalent representation in the objective function space in Fig. 7.

**FIGURE 7:** Returned solutions visualized in the objective function space (also known as the “Pareto front” [7]). There are 77 points here, each of which corresponds to a track in Fig. 6.
noise for the same length. 2. That there is a solution that does better in length for the same
noise. The utility of the former is obvious to the noise control engineer, however the latter can
also be helpful, even if only as a “bargaining chip.”

Though these results are the aggregation of 10 runs, it is interesting to note that they were
produced by two sets of 8 and 2 independent optimization runs. Though these were executed
serially for this study, it is possible to parallelize these runs using a master-slave paradigm [7]
to achieve an execution time of 1 day instead of 5 (in fact, 19 hours for this case).

CONCLUSION

It has been shown that the concept of multi-objective procedural flight noise mitigation has
the potential to aid decision makers who have to weigh noise impact as one facet of the larger
problem of routing aircraft. It has also been shown that a well-formulated problem can be solved
within a reasonable amount of time using contemporary and commonly available computational
facilities.

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