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HOW CAN WE BE SMARTER IN AIRCRAFT NOISE QUANTIFICATION AND MANAGEMENT?

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ABSTRACT
After many years of measurement and modeling, the management of aircraft noise seems as difficult as ever. On some sites, complaints have become more frequent in spite of an overall decrease in aircraft noise. This leads us to question whether we are measuring or modeling the right quantities. Managing aircraft noise is a multi-dimensional problem for which no simple solution has been found. In this paper we explore some of the issues that appear to be significant, such as the accumulation in time of different short-term metrics. Neural network methods provide new insight into the proper quantification of noise from different source types. Training of neural networks for aircraft noise classification presents some special problems, which will be illustrated at the oral presentation.

1 - INTRODUCTION
In spite of the many advances that have been made in measuring, modeling of aircraft noise and optimizing flight operations, the aircraft noise problem seems as difficult as ever. Some sites report more complaints and from greater distance from airports, in spite of the overall reduced aircraft noise level as commonly measured [1]. In many cases, political, economic, psychological, sociological and real estate factors are evident. When due account of these influences is taken, some of the complaint patterns are still puzzling. This leads us to question whether we are really measuring the right sort of quantity and if we are subsequently processing the measurements in the right way to obtain a good correlation with annoyance levels. There is a general international agreement to base noise dosage on A-weighted exposure level, LAE [2]. This metric has served us well under straightforward environmental conditions. LAeq is a simple, easily understood quantity that is related to sound energy, but its very simplicity should be a warning. Most phenomena in real-life are highly nonlinear and it is only in special situations that simple laws apply. Apart from these general considerations, there are other signs that changes in the general viewpoint about noise are occurring, such as:

- The attention to low-frequency sounds, which are suppressed by A-weighting [3];
- The growing research that is taking loudness level seriously [4];
- Mixtures of annoying noise emissions which are not simply additive [5];
- The need to record spectral information and peak statistics in relation to disturbance of human activities [6].

In this paper we consider current practices where improvements could certainly be achieved with available technology. The methods of neural networks and the key issues of training in ascribing noise to aircraft are highlighted. We also advocate the need to collect many other metrics at the same time as conventional data. We also propose that a complex multi-dimensional problem such as noise is a candidate for the application of neural network methodology to help resolve the situation.

2 - THE MEASUREMENT PROCESS
Aircraft noise monitoring systems are set up with measurement microphones placed at strategic sites in the neighborhood of the airport. The choice of these sites is crucial to the value that can be placed on

measurement data. The availability of sites is often severely limited by access, neighboring buildings or terrain, especially in a city environment. The result is frequently a microphone signal that is a dubious representation of the sound field in the neighborhood. Microphones are often placed in schools, where there is easy access and high community concern about noise. But the noise made especially by younger children in the playground, close to a microphone, can be substantial and wrongly attributed to aircraft during fly-over unless special measures are undertaken. If a community is troubled by substantial traffic noise, such as heavy trucks and buses accelerating and breaking, as well as aircraft noise, it is not very smart to place a microphone in such an area and attempt to measure aircraft noise unless some very effective discrimination system is in place. In other cases one finds a microphone placed in a site with noisy machinery. Noise abatement officers who recognize these problems may insist on an audio link, so that they can listen to the sound (at ordinary telephone line quality) and decide whether to include the sound as part of the aircraft noise load or not. But how often and how effectively is this really done? A common practice is to set a threshold which is high enough to exclude all noise except the loudest part of an aircraft fly-over, or to accept much uncertainty about whether the measurements pertain to aircraft or not. Even when great care is taken at the planning stage and detailed preliminary measurements are performed before fixing the permanent noise monitoring sites, the environmental situation can change quite drastically some time after installation. It is unusual to change the permanent sites after commissioning a noise monitoring system.

3 - SOME REMEDIES

The first remedy is to choose sites where the microphone signal is a good representation of the surrounding sound field. When significant non-aircraft noise is unavoidable then an effective discrimination system must be employed. With complex background noise, simple threshold discrimination is not adequate. One must then employ either directional information or recognition by acoustic means. The simplest directional approach, employing an intensity meter, gives the elevation of the incoming sound wave. By tracking this angle in time one can decide that a moving aircraft is responsible for the noise. More directional information is obtainable from a microphone array with appropriate signal processing. Apart from this, there is a need for many more microphones to give a better representation of the sound field in the neighborhood. For most noise abatement services, such an approach is too expensive because of the high cost of outdoor measurement microphones that meet the relevant IEC/ISO standards. There is a definite need for the development of low-cost microphones that quality-wise match the well-proven, outdoor measurement microphones. Failing the availability of multiple microphones, the only recourse is to implement recognition of the nature of the noise source from the single microphone signal [7].

4 - THE NEURAL NETWORK APPROACH TO SOURCE RECOGNITION

The basic idea is to determine from a single microphones signal whether the dominant noise is from aircraft or from other sources in each one-second interval. An artificial neural network (ANN), which has been previously trained to discriminate between aircraft and other noise sources, is implemented as part of the software of an otherwise normal noise monitoring unit [7]. Several researchers have concentrated on deciding whether a complete noise event is due to aircraft or not [8,9]. But in a busy city, a noise event is often due to a mixture of causes and therefore it is more sensible to adopt a one-second-decision process and to accumulate the noise dosages from each source type at each one-second interval [7]. The dimension and number of layers of the ANN is limited by the computing capacity of the noise-monitoring terminal. However, off-line simulation of the effectiveness of networks of varying complexity shows that a quite modest three-layer network with 25 to 31 inputs performs almost as well as considerably more complex structures. The input of the ANN is spectral information, which can be third octave outputs processed either according to a time constant, or an average value, or a peak value (over 0.1, 0.5, or 1 sec). Or, one can take the pre-processing a step further and use specific loudness, or a smoothed differential power spectrum as input to the ANN. Regardless of the form of input or the complexity of the ANN, the strategy of its training is very critical.

5 - TRAINING

To train an ANN one must have an agreed reference of correct data. A human listener establishes this by assigning each one-second of recorded data to one of the three classes: jet, propeller aircraft, or background. A subset (about 1/3 of the total) of this data series is used for training. The remainder is used for testing performance after training. The ANN employs the standard back-propagation procedure, but with special measures to judge its degree of success. For each of the three classes, the ratio of the number of correctly judged intervals to the total number of intervals in the class is computed. The

minimum of this set of numbers over all classes is taken as the measure of success, and it is this number which the training procedure endeavors to maximize. The traditional approach in which the squared error of the total series is minimized does not work if there is a large discrepancy between the sizes of the classes. The class with the largest number of elements is likely to end up nearly 100% correct, and the smallest class nearly 100% wrong. A fourth class is necessary: the class for which the ANN is unable to make a decision. Since there are only four classes, one can use a binary logic decision process with a small region in which for each bit, logic 0 or 1 is uncertain. In practice the uncertain class turns out to be very small.
Training can often be speeded up by beginning with a small subset of the training data, provided it is representative of the three classes similarly to the full set. The set of coefficients obtained from this step is used as a starting set for the main training session. There are in fact many aspects of training, choice of input-data and pre-processing to consider, which go well beyond the scope of this paper.

6 - METRICS

We now have available instrumentation that can record and process sound signals in almost any desirable manner. We ought to be doing better than simply recording LAeq or LAmax of events or over daily periods. Recent work shows that loudness level over time [4] is a much better indicator of annoyance than LAeq, when noise from different types of sources is present. Also, loudness level (phon), rather than loudness (sone), accumulated over time, is a much better measure to use [4]. This finding is consistent with the results in [7], where accumulated loudness level made sense but accumulated loudness led to the strange result, in conflict with all other evidence, that background noise had a greater impact than aircraft noise.
Nevertheless, some annoying low-frequency sounds seem to need additional factors such as roughness to characterize them [10]. And for some noise patterns there seems to be a need for measures of peak event values or rate of rise of level to accord with the annoyance experienced [6]. A possible approach would be to record a total daily level variation such as

$$\sum_{i=0}^{n} |L_{i+1} - L_i| \qquad \text{or} \qquad 10\mathrm{lg}\left\{\sum_{i=0}^{n} \left|10^{0.1L_{i+1}} - 10^{0.1L_i}\right|\right.$$

where L_i is the level at the ith time interval. Or, one could go further and employ a total variation over frequency and time:

$$\sum_{j=0}^{m}\sum_{i=0}^{n} |L_{j,i+1} - L_{j,i}| \qquad \text{or} \qquad 10\mathrm{lg}\left\{\sum_{j=0}^{m}\sum_{i=0}^{n} \left|10^{0.1L_{j,i+1}} - 10^{0.1L_{j,i}}\right|\right.$$

where $L_{j,i}$ is the level of the jth third octave at the ith time interval. Many other metrics could be devised and implemented in practice.

7 - CONCLUDING REMARKS

Researchers from various disciplines are investigating aspects of the multi-dimensional community noise problem. A problem as complex and as difficult to grasp in all its aspects as this is, is an ideal candidate for neural network methods. It amounts to collecting all the short-term metrics and human reactions over time, and literally throwing this huge data set at a large neural network to find some interconnections. Fanciful as this may seem, less plausible problems have been successfully tackled in this way. In the neural network world, we don't expect to find nicely formulated deterministic laws or neat statistical descriptions. Instead, we find a set of coefficients, which together with a network topology determine relationships, effect decisions or predictions, or match patterns. This is a far-reaching view of what "smart" systems are about and the time is now ripe to exploit the full power of these new methods.

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