# Predicting environmental noise using neural networks

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**ABSTRACT**

Advancements in acoustic instrumentation and data acquisition enables the analysis of a substantial amount of data collected during long term noise monitoring programmes. Generally, variations of environmental noise at a particular location are random. However, recent research and analysis based on a substantial amount of data collected in urban areas showed the presence of patterns or major cycles in the time histories of noise levels. This paves a way to exploring the concept of a generic time history and predictions of future noise.
Neural networks represent an attractive tool to explore and predict future noise levels based on previous measured values. This paper considers opportunities for predicting noise levels using this tool. The networks were trained on noise data acquired in a variety of urban and suburban noise environments, such as road, rail and industrial noise sources. Different modelling approaches are considered for attempts to forecast a noise level time history. Future use of this technique in environmental noise monitoring could open opportunities for expecting or preventing non- compliance.

## 1 INTRODUCTION

Monitoring programs that are based on cloud technologies significantly simplify acquisition of big volumes of data. Post processing of noise levels from long term monitoring programmes shows the existence of cycles in relation to outdoor noise levels (Gajardo et al.,2015; Lenchine,2017; Morillas,Ortiz-Caraballo and Gajardo, 2015) which paves a way for deriving generic variations of sound pressure levels (SPLs) and other statistics to characterise noise at a monitoring location. The data can also be used for training of neural networks to predict noise levels or clusterisation of the data.

This paper considers various approaches to predict variations of SPLs in urban environments. Data collected at a number of monitoring locations where noise is controlled by a range of sources has been chosen for this purpose. Simple feed-forward neural networks were chosen to run predictions of the noise levels. Different strategies were considered for the task.

## 2 INPUT DATA AND PREDICTION OUTPUT

Environmental noise can be characterised by a significant number of acoustic descriptors. Different standards and guidelines recommend a variety of monitoring and compliance parameters for different noise sources. However, A-weighted SPLs are utilised more frequently in environmental noise monitoring tasks and compliance checking procedures. Therefore, prediction of A-weighted SPLs acquired over 15 minute intervals is considered in this paper.

A full set of available data includes many descriptors and 1/3 octave data. Previous work (Song, Lenchine,2017) shows that 1/3 octave magnitudes of urban noise within the same octave band are highly correlated. Therefore, analyzing data with better resolution than 1/1 octave is deemed not necessary. An original set of data includes time, octave magnitudes from 16 Hz to 16 kHz and unweighted, C-weighted and A-weighted equivalent sound pressure levels. The prediction output was calculated as the difference between A-weighted SPLs for the current/last time *i-th* interval and next one:

$$\Delta L_{A,i} = L_{A,i+1} - L_{A,i}. \tag{1}$$

### 2.1 Reduction of input data

The full set of inputs represents a very large volume of data to process, which includes 15 entries for each time interval. Not all of them may be necessary and some entries may even be detrimental for training the neural network (Haykin, 2009; Venetsanopoulos, Karayiannis, 2010). Another obvious reason for further reduction of the number of inputs is the fact that some of the octave magnitudes may have a negligible influence on A- weighted SPLs. However, a negligible influence does not necessarily mean that the input is insignificant for predicting SPLs.

Principal component analysis is one of the widely used techniques to reduce the number of inputs (Jolliffe,2002; Vidal, Ma and Sastry, 2016). It is assumed that some of the inputs in the data set are close to the principal components and provide noticeable contribution to the output variance. Further analysis of possible combination of the inputs was concentrated on choosing the maximum possible number of inputs where relative explicit variance exceeded 1%. It can be interpreted as a requirement that the final set of inputs can be decomposed into the principal components where the least contribution to the cumulative variance of an individual input is still somewhat noticeable. If there are a few possible final combinations, then the variant with greater relative variance for the last input is chosen.

## 3 PREDICTING A-WEIGHTED SPL

### 3.1 Set of input data

Large volumes of 15 minute data acquired from over a year of environmental noise monitoring were analysed. Noise at each monitoring location was controlled by a particular noise source. Location 1 was significantly affected by freight rail operations, while monitoring location 2 was close to passenger rails with diesel powered trains. Noise at locations 3 and 4 was controlled by an industry which operated over 24/7 and road traffic respectively.

The inputs used for predicting variations of $L_{Aeq}$ are summarised in Table 1. It should be noted that time, equivalent SPL unweighted and A-weighted are common for all of the monitoring locations as well as the number of final inputs for monitoring locations affected by transport noise. Octave data used for predictions always contains low to mid frequency components. Octaves with central frequencies from 2kHz to 4 kHz were not selected as the predictive inputs. Perhaps this is connected with high correlation of the octave magnitudes with unweighted or A-weighted equivalent levels. Very low frequency octaves were also deemed to be non-essential for the prediction task.

Table 1: Inputs used for training neural networks

| Monitoring location | Inputs | Minimum relative variance,% |
|---|---|---|
| Location 1 | Time,$L_{eq}$, $L_{Aeq}$, Octaves:125Hz,250Hz,8kHz,16kHz | 1.4 |
| Location 2 | Time,$L_{eq}$, $L_{Aeq}$, Octaves:63Hz, 125Hz,250Hz,16kHz | 1.2 |
| Location 3 | Time,$L_{eq}$, $L_{Aeq}$, Octaves: 63Hz, 125Hz,250Hz,500Hz,1kHz | 1.1 |
| Location 4 | Time,$L_{eq}$, $L_{Aeq}$, Octaves: 63Hz,125Hz,4kHz,16kHz | 1.3 |

### 3.2 Neural network architecture and prediction strategies

It was decided to initially concentrate on simple neural networks. Predictions were made using a feedforward neural network with both 1 and 2 hidden layers. Relevant theorems state that a single hidden layer neural network is sufficient to simulate any continuous function with desirable accuracy and a two hidden layer network can reproduce any dependence (Haykin, 2009; Hagan et al.,2014).

Sigmoig and hyperbolic tangent functions were used as trigger functions for the neurons. Important questions of optimal architecture for a neural network are still not resolved. However, there are many recommendations that can be used for choosing the number of neurons in each of the hidden layers. Some strategies suggest that the optimal number of neurons depends on the number of inputs or outputs or both. Some researchers also recommend taking into account the number of data entries used for training purposes of the neural network. The latter approach can be too impractical if a significant volume of data is utilised to train a neural network. Recommendations of a previous study (Sheela, Deepa, 2013) were used for exploring networks with a different number of neurons which depends only on the number of inputs. Typically, increasing the number of neurons in a hidden layer by more than 3-4 times the number of inputs did not bring any noticeable benefits.

The strategy of a recursive update of the training set of data with prediction of only one step was proven to be more accurate. Multi-step predictions were proven to provide unsatisfactory results, perhaps due to the accumulation of error. Predicted $\Delta L_{Aeq}$ deviation tended asymptotically to zero for long time predictions. An example is noted in Figure 1 (computed over 15 min intervals).

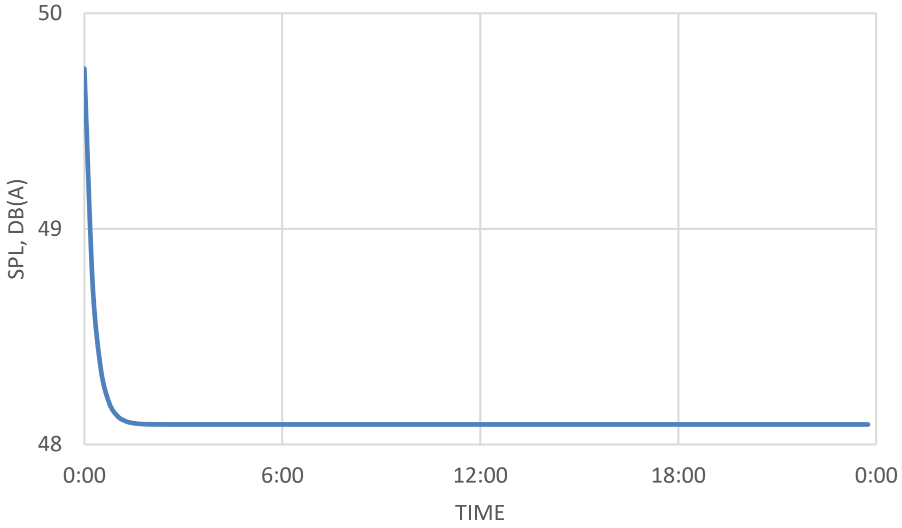


Figure 1: Example of noise prediction based on a trained network without recursive update

Single step predictions with recursive updates of the neural network (based on real data) for each of the consequent calculations is found to be a more accurate way. Figure 2 shows a prediction of the $L_{Aeq}$ deviation versus real day data. At the first glance it seems like a reasonable accuracy of predictions during particular periods, however relative error of the predictions is quite substantial and can scarcely be utilised for practical purposes.

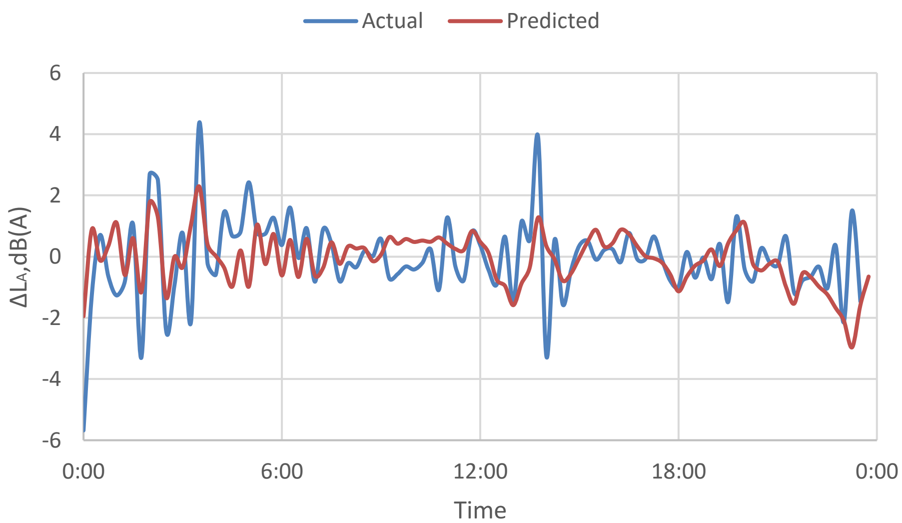


Figure 2: An example of a day SPL variation prediction using recursive update

### 3.3 Trend prediction

It makes sense to explore another approach for predicting variations of A-weighted SPLs. Instead of predicting exact numbers, the output can be considered as a binary consequence where -1 corresponds to a negative predicted deviation and +1 to a positive deviation. Then the task can be considered as a prediction of the trend rather than a particular number. The corresponding models were retrained using binary output.

Further optimisation of inputs and configuration of neural networks should be considered. However, for the purposes of this paper, calculations show that it is possible to achieve a 60% - 70% rate of successful predictions with substantially reduced number of inputs and just a single hidden layer. The average success rate of trend predictions is shown in Table 2 together with inputs used for the neural networks. It is interesting to note that octave magnitudes were superfluous for trend predictions. In some cases, even time information was considered excessive for training purposes of the neural network. The achieved rate of successful predictions is perhaps not significant enough for use in practical noise exceedance warning systems, however consequent improvement of the neural networks may make this application possible in the future.

Table 2: Success rate for SPL trend predictions

| Monitoring location | Inputs | Correct prediction rate, % |
|---|---|---|
| Location 1 | Time, $L_{eq}$, $L_{Aeq}$ | 68.4 |
| Location 2 | Time, $L_{eq}$, $L_{Aeq}$ | 65.2 |
| Location 3 | $L_{eq}$, $L_{Aeq}$ | 62.5 |
| Location 4 | Time, $L_{eq}$, $L_{Aeq}$ | 62.3 |

## 4 CONCLUSIONS

This paper has explored opportunities for predicting variations in A-weighted SPL using sets of data that were acquired during long term noise monitoring programs. Principal component analysis was engaged to reduce the number of inputs required for the predictions. It showed that equivalent non-weighted and A-weighted SPLs together with temporal information are important for all of the monitoring locations explored, whereas input octave magnitudes slightly differ.

Predictions of A-weighted SPL variations using single and double hidden layer neural network configuration do not show reasonable accuracy of predictions. Another attempt of the neural network utilization was made for predicting binary results such as positive or negative trends in the SPL variations. It required a reduced amount of inputs and resulted in a 60-70% prediction success rate. This is not sufficient for practical applications. More advanced neural networks together with another set of input data needs to be further explored in order to increase the rate of correct predictions.

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