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On the separation of railway noise sources in the urban environment

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Summary

Over recent years, noise pollution has become a common problem for urban centers and its treatment a major environmental policy challenge. Railway contributes in the overall urban noise environment, mainly through the intermittent transient noise of the surface-line urban networks. In contrast to the more prominent and overlapping road traffic noise, its intermittent nature allows for the source separation and identification from other community noises. In close proximity to the railway corridor, railway transit noise usually supersedes the background level for a couple of seconds, unless it is masked by another random transient noise. With the simultaneous vibration monitoring, false-positive peaks in the noise signal time history can be excluded, as railway transit vibrations are many magnitudes higher than ambient vibrations.
In this study, noise & vibration monitoring data was collected from 10,000 train pass-by in various locations in the Athens Tram and Metro Line 1 networks (surface line). By identifying the railway transient noise, a comparison is made between the daily/hourly average sound level, the average sound level only from the trains and the sound level during train pass-by. The vibration signal is used as a trigger-signal to phase out false-positive peaks in the acoustic signal. By applying machine learning techniques to the collected noise & vibration data, a process is investigated that can give reliable results for the railway noise impact even when only the noise signal is used.

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1. Introduction

The urban soundscape contains the noises that are produced by all human activities and, in order to reduce their noise impact on the environment, it is critical for these sources to be firstly identified and secondly accessed for their significance and contribution.
Railway noises poses a significant challenge since:

- it is a high-power source
- it can be very close to sensitive receivers
- it is intermittent in nature
- it is not display periodicity
- it can be present during the night

The above characteristics point to the fact that the railway noise cannot be assessed with standard sound pressure measurements, due to the short pass-by time, and at the same time it cannot be considered negligible, due to its high-power and proximity to sensitive receivers.
By taking advantage of the intermittent nature of pass-by noise, it can be identified and separated from other community noises.

1.1. Simplified model of train pass-by

The main noise source from train operation is the noise produced by wheel-track interaction. In the far-field, the wheel-track interaction noise sources can be modeled as one average linear sound source of finite length. The simplest model will assume that this linear source is traveling on a straight track with constant velocity.
If the attenuation due to the atmosphere, the ground, obstacles, etc. is disregarded, the sound pressure, SP, at a receiver located at distance d from the track is given by:

$$SP = \int_{x1}^{x2} \frac{Q}{2\pi r^2} dx = \frac{Q}{2\pi d}\varphi, \qquad (1)$$

where:

$\varphi(t) = \arctan\frac{ut+\frac{L}{2}}{d} - \arctan\frac{ut-\frac{L}{2}}{d}$ is the angle as depicted in Figure 1,
u is train's velocity,
L is train's length,
d is receiver's distance from track and
Q is the sound power per unit length of the source

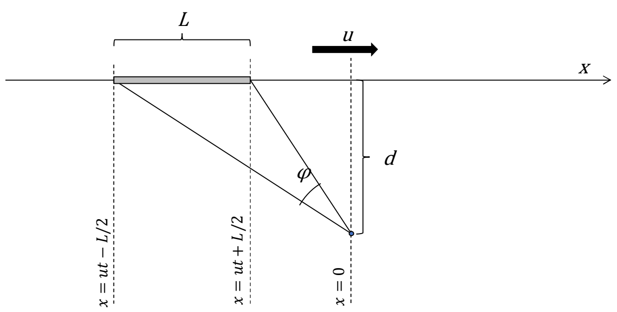

Figure 1, Simplified model of train pass-by

1.2. Calculating sound exposure

Plotting the sound pressure level, SPL, of the moving linear sound source over time (Figure 2), gives a maximum of:

$$L_{max} = 20\log\frac{\frac{Q}{\pi d}\arctan\frac{L}{2d}}{p_{ref}}, \qquad (2)$$

when the linear sound source is centered regarding to the receiver (this moment will be set as $t = 0$ throughout this paper).

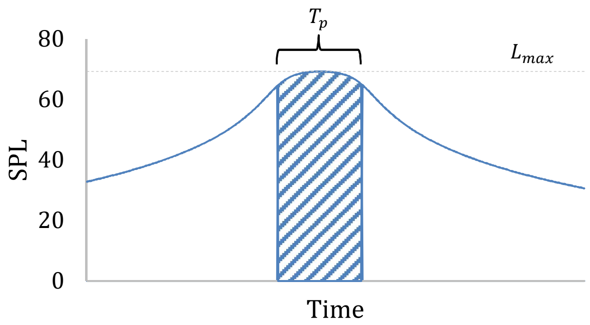

Figure 2, SPL over time

Theoretically the linear source produces sound pressure to the receiver even when it is very far away. However, if we integrate equation (1) to get the sound exposure, the resulting integral, from t = -∞ to t = +∞, is finite and sound exposure level, SEL, equals to:

$$SEL = 20\log\frac{\lim_{T\to\infty}\int_{-T}^{+T}\frac{Q}{2\pi d}\varphi(t)dt}{p_{ref}} =$$

$$= 20\log\frac{QL/2ud}{p_{ref}} \qquad (3)$$

It is however obvious that, in real life, a finite time interval must be applied in order to measure sound exposure from a real train pass-by. A characteristic time interval, that can easily be replicated, is train pass-by time, T_p, which is defined as the duration when any part of the train is opposite to the measuring position [1].

In Figure 2 the train pass-by time, T_p, is marked as the hatched area at the center of the graph. The A-weighted equivalent continuous sound pressure level on the pass-by time, L_{pAeq,T_p}, as defined in EN ISO 3095 [1], equals to:

$$L_{pAeq,T_p} = 20\log\frac{\frac{1}{Tp}\sum\int_{-Tp/2}^{+Tp/2}\frac{w_i Q_i}{2\pi d}\varphi(t)\,dt}{p_{ref}}, \qquad (4)$$

where:
$T_p = L/u$ is the train pass-by time
w_i is the A-weighted factor per frequency band
Q_i is the sound power per frequency band

The introduction of measured data in the above formulas yields the results shown in Table I. It is evident that for short trains and/or long distances from the track, the sound exposure of the receiver might be severely underestimated, if the noise impact assessment is based on L_{pAeq,T_p}.
It is thus evident that such a measuring method is not suitable for environmental assessment. The acoustic energy contained in preceding and succeeding 'trails' (Figure 2) cannot be neglected.

Table I. Comparison of SEL for $T = T_p$ and $T \to \infty$

Input Data	L_{max} [dB]	SEL_{T_p} [dB]	SEL [dB]	0.1 dB accuracy
Q = 10 W/m L = 120 m u = 60 km/h d = 12 m	79.2	90.9	91.5	$SPL - L_{max}$ -58.6 dB
Q = 5 W/m L = 120 m u = 60 km/h d = 12 m	73.2	84.8	85.5	$SPL - L_{max}$ -58.6 dB
Q = 10 W/m L = 120 m u = 100 km/h d = 12 m	79.2	86.4	87.0	$SPL - L_{max}$ -58.6 dB
Q = 10 W/m L = 30 m u = 60 km/h d = 12 m	75.5	76.8	79.4	$SPL - L_{max}$ -66.9 dB
Q = 10 W/m L = 60 m u = 60 km/h d = 12 m	77.9	84.2	85.5	$SPL - L_{max}$ -63.4 dB
Q = 10 W/m L = 120 m u = 60 km/h d = 7.5 m	83.7	95.2	95.6	$SPL - L_{max}$ -54.9 dB
Q = 10 W/m L = 120 m u = 60 km/h d = 30 m	69.4	81.9	83.5	$SPL - L_{max}$ -64.7 dB

In order to calculate a sufficient time interval that is necessary to accurately estimate sound exposure, one has to investigate how the sound exposure evolves as the time interval of the exposure, T, is growing, starting from $T = 0$ for $t = 0$ and equally expanding towards past and future. To reach the $T \to \infty$ limit, as defined in equation (3), to an accuracy of 0.1 dB, the 'effective' measuring interval needs to be expanded to include sound pressure levels more than -50 dB from L_{max} (Table I), which is not possible in real life due to background noise.

It is therefore proposed to assess the sound exposure of the pass-by using correction factors to the sound exposure based on T_p as the integrating time interval. For the simplified model, it turns out that parameters Q and u do not affect the 'effective' measuring interval needed to accurately calculate sound exposure; the parameter that affect the result is the ratio of the train's length to the receiver's distance from track:

$$SEL = SEL_{T_p} + C_{L/d}, \qquad (5)$$

where:

$$C_{L/d} = 20\log\frac{2\pi}{2\arctan L/d + \frac{\ln(1+(L/d)^2)}{L/d}}$$

2. Influence of background noise

In practice it is impossible to measure true sound exposure produced from railway transits using simple sound pressure level measurements, due to background noise. If the background noise level is high enough, then the sound exposure is overestimated when the background noise level is higher than the sound level of the 'effective' measuring interval.

2.1. Background noise masks source

It was shown that the sound exposure is underestimated if the calculation interval is not long enough. ISO 3095 suggests calculating the sound exposure, referred as 'Single Event Level' (noted as 'SEL' in the document), by computing the sound pressure level during the time interval starting when the noise level is -10 dB compared to the level when the front of the train is opposite of the measurement position and ending when the noise level is -10 dB compared to the level when the back of the train is opposite of the measurement position. The purpose of the 'Single Event Level' index is to be used for type testing and periodic monitoring testing of rail vehicles, where the measurements are executed in controlled environment and at 7.5 meters from the track [1]. It was shown in the previous section that -10 dB might not be enough under certain circumstances, especially for measuring positions far away from the track. Besides, in urban environments it is not always possible to satisfy the 10 dB difference from background noise, therefore this method is not favorable.

Returning to the simplified model, background noise can be modeled as a constant sound pressure level L_b. The overall sound pressure level at the receiver is then given by:

$$SPL_{overall} = 10\log\left(10^{\frac{SPL}{10}} + 10^{\frac{Lb}{10}}\right) \qquad (6)$$

Hence the sound exposure can be calculated from the overall sound pressure level as:

$$SEL_T = 10\log\int_T 10^{\frac{SPL_{overall}}{10}} dt - L_b - 10\log T \; (7)$$

Of course, in practice background noise is not constant so there is an error introduced if equation (7) is used with an average value for L_b. When L_b is estimated from the 95th or 99th percentile of the measurement values before and after the pass-by, the resulting sound exposure level of the pass-by, when equation (7) is applied, will be towards the conservative side (background noise influence will not be overestimated).

2.2. Identify railway transits from other 'peaks' in time history

The other major issue from the influence of the background noise is that the time history may contain other peaks that don't correspond to the sound source under investigation. This is often the case when investigating railway noise in urban environments since it is very common to have road traffic noise coming from vehicle circulation from roads closer to the receiver than the railway corridor.

For railway noise surveys, a very effective method to identify train transits is by simultaneously measure noise and vibration. It is highly improbable, in urban environments, that any other source of transient vibrations will be present at the magnitude of railway vibrations. Hence, false-positive peaks in the noise signal time history can be excluded (Figure 3).

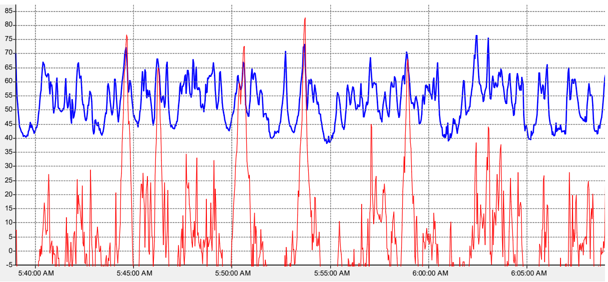

Figure 3, superimposed noise and vibration signals: 30' time history of noise (**thick line**) and vibration (thin line) signals. Train pass-by can be clearly identified in vibration signal while noise signal includes other peaks as well

Another parameter that makes the identification of train transient sources from the vibration signal very efficient is that the 'effective' sound exposure period is very related to the 'effective' vibration exposure period (Figure 3). Thus, especially when acquiring statistical values over long-term monitoring sessions, there is no need for post-processing each pass-by to adjust the sound exposure interval according to background noise; it can be estimated from the automatically detected vibration exposure.

3. Case study: Athens Tram and Metro Line 1

It is a common practice for railway operators to monitor noise and vibration emissions for environmental purposes and compliance. The monitoring program for Athens Tram and Metro Line 1 includes train pass-by identification, in order to isolate railway noise from other noise sources. The technique using the vibration signal as the trigger for identification, as shown in 2.2, has been performed in over 10.000 train pass-by.

3.1. Measurement procedure

The time history data acquisition, in 1 second intervals, was done with the use of two signal analyzers in synch. The first was inputting the sound pressure level at a height of 4m and the second was recording the vibration acceleration on the vertical axis. Both sensors were placed at a distance of 2m from the façade of the sensitive receiver.
Using the technique presented in 2.2, the train pass-by were identified from the vibration signal and the rest of the time period was considered as background noise. Based on the above, the sound exposure for each event and the background noise are calculated.

The individual events are summed up to calculate the sound exposure from all train pass-by, thus the railway noise to the overall noise level can be compared.

3.2. Discussion

The results from a 24-hour sample period are shown in Table II in next page. From the data presented it is evident that the use of the overall measurements can substantially overestimate the contribution of the railway to the environmental noise. In particular, the deviation of the overall from the railway noise is 8.6 to 10.8 dB for the three rating periods (day, evening, night) which corresponds to a deviation of 9.7 dB for the weighted 24-hour L_{DEN} index.
It is also important to point out that while the background noise is exceeded during pass-by, the overall exposure of railway is below that from the other noise sources that comprise the background noise.
In general, the day and the night average sound level are widely employed in legislation, regulations and guidelines. The presented technique can be applied for long term monitoring without the need of manual intervention for masking out background noise. Hence, without much effort, long term noise annoyance indexes can be calculated with less uncertainty than using techniques to extrapolate short term measurements of the sound exposure level from a representative sample of records for the various environmental and traffic flow conditions [2].

Table II. Train pass-by per hour analysis

Time period	$L_{eq,1h}$ [dB(A)]	$L_{eq,pass\ by}$ [dB(A)]	*Duration* (# of pass-by)	L_b [dB(A)]	$L_{Aeq,1h,only\ train}$ [dB(A)]	*Assessment according to EU Directive 49/2002*
07:00-08:00	70.6	72.1	00:05:23 (11)	68.1	61.2	
08:00-09:00	70.1	71.8	00:05:45 (12)	67.0	61.2	
09:00-10:00	67.0	68.8	00:05:50 (12)	66.8	58.7	
10:00-11:00	67.2	67.7	00:06:41 (15)	67.2	58.2	
11:00-12:00	68.0	69.5	00:07:24 (16)	67.8	60.4	
12:00-13:00	66.7	69.0	00:07:53 (16)	66.3	60.2	L_{day} [07:00 – 19:00] Overall: 68.7 dB(A) Only trains: 60.1 dB(A)
13:00-14:00	68.3	69.3	00:06:43 (13)	68.1	59.8	
14:00-15:00	68.8	71.7	00:06:34 (14)	68.3	59.4	
15:00-16:00	67.8	69.3	00:06:38 (13)	67.6	59.7	
16:00-17:00	68.5	70.9	00:07:59 (17)	67.9	62.1	
17:00-18:00	71.0	68.1	00:07:48 (17)	71.3	59.2	
18:00-19:00	68.3	71.2	00:06:42 (15)	67.8	59.0	
19:00-20:00	68.8	69.1	00:07:34 (16)	68.7	60.1	
20:00-21:00	67.4	67.3	00:07:29 (13)	67.4	58.3	$L_{evening}$ [19:00 – 23:00] Overall: 67.9 dB(A) Only trains: 58.9 dB(A)
21:00-22:00	67.8	68.4	00:05:35 (10)	67.8	58.1	
22:00-23:00	67.4	68.9	00:06:10 (14)	67.2	59.0	
23:00-00:00	65.6	67.2	00:03:41 (8)	65.5	55.1	
00:00-01:00	63.9	67.5	00:03:13 (7)	63.6	52.5	
01:00-02:00	62.8	66.5	00:03:02 (7)	62.5	51.3	
02:00-03:00	64.2	67.8	00:01:45 (4)	64.0	50.1	L_{nig} [23:00 – 07:00] Overall: 63.4 dB(A) Only trains: 52.6 dB(A)
03:00-04:00	61.9	-	00:00:00 (0)	61.9	-	
04:00-05:00	63.0	-	00:00:00 (0)	63.0	-	
05:00-06:00	59.0	65.2	00:03:40 (8)	57.9	52.2	
06:00-07:00	63.7	69.5	00:04:41 (10)	62.6	57.4	

4. Identify train events without vibration signal

The train pass-by identification can be considered a pattern recognition problem. Machine learning techniques can be used to the collected noise & vibration data in order to identify train pass-by; in this study a technique from neural network theory was applied.

4.1. Machine learning implementation

Neural networks can recognize, classify, convert and learn patterns [3]. Pattern recognition refers to the categorization of input data into classes by recognizing significant features or attributes of the data. In traditional pattern recognition theory, a pattern is a dimensional feature vector or a point in n-dimension space. In the neural network approach, a pattern is represented by a set of nodes along their activation levels [4].

According to the interconnection theme, a network can be either feedforward or recurrent and its connections either symmetrical or asymmetrical [5]. Here we employ a feedforward neural network, whose connections all point in one direction, from the input to the output layer. Figure 4 exhibits a typical feedforward neural network [6]:

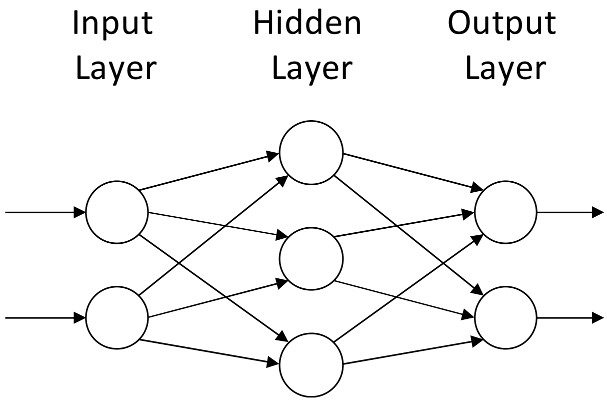

Figure 4, Typical diagram of a feedforward network

For the training of the network a variant of the back propagation algorithm was used, resilient back propagation (Rprop). Rprop is a learning heuristic for supervised learning in feedforward artificial neural networks. This is a first-order optimization algorithm, created by Martin Riedmiller and Heinrich Braun in 1992 [7]. Rprop is one of the fastest weight update mechanisms along with the cascade correlation algorithm and the Levenberg-Marquardt algorithm.

4.2. Train pass-by learning and prediction

For the learning and prediction of the train data, a three-layer feedforward neural network was implemented using the library Encog3 (www.heatonresearch.com/encog) [8].
For Athens Tram and Metro Line 1 networks, the input and hidden layer had 25 nodes each. The usual Sigmoid activation function was employed. The weights were initialized with random values. The output layer had only one node. After training with resilient propagation plus (+), for around 1400 seconds, the network's error rate in contrast to simple resilient propagation displayed steady monotone decrease, showing fast convergence.
When the algorithm was tested for a 10-day noise dataset with already identified train events, the algorithm managed to identify all actual pass-by, but it also outputted 28% false-positive events. However, when applying a high-pass duration filter to the output data, the final results contain only 6% false-positive events and 1% missing actual events. The sound level accuracy of the predicted pass-by is ±0.5 dB compared to the measured values.
Hence it is concluded that a 30-minute dataset, which includes about 10 events, is enough for an adequate train identification. For such small training interval, the training dataset can be manually acquired on site very easily and the computational power needed to assemble the neural network can be done in an average modern computer.

4.3. Further development

This methodology can be further developed, evaluated and tested under different conditions (geometry, traffic flow density, networks where different vehicle types operate simultaneously, etc.) in order to assess the algorithm's stability and performance in other scenarios.

5. Conclusions

This study presents methods that can be used to identify railway noise and separate it from other community noises in urban environments. It is not possible in practice to accurately measure sound exposure for individual train pass-by due to background noise. A correction factor, depending on the ratio of the train's length to the receiver's distance from track, is proposed to be used when using train pass-by time to calculate sound exposure.
Community noise in urban environments contains intermittent noises that don't correspond to train transit noise. This study presents two simple and straightforward approaches to identify and separate railway noise from other sources, one using vibration signal as a trigger-signal and one using a machine learning algorithm that distinguishes the peaks in the time history and predicts train transits, upon feeding it with a short training sample with identified pass-by. The above methods have been tested with data acquired from Athens Tram and Metro Line 1 urban railway networks.

Acknowledgement

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