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Measurement of noise events in road traffic streams: Initial results from a simulation study

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ABSTRACT

A key question for road traffic noise management is whether prediction of human response to noise, including sleep quality, could be improved over the use of conventional energy equivalent, or percentile, measures, by accounting for noise events in road traffic streams. This paper reports initial results from a noise-events investigation into event-based indicators over an exhaustive set of traffic flow, traffic composition, and propagation distance, conditions in unshielded locations in proximity to roadways. We simulate the time-varying noise level histories at various distances from roadways using a dynamic micro-traffic model and a distribution of sound power levels of individual vehicles. We then develop a comprehensive set of noise event indicators, extrapolated from those suggested in the literature, and use them to count noise events in these simulated time histories. We report the noise-event algorithms that produce realistic, and reliable, counts of noise events for one-hour measurement periods, then reduce redundancy in the indicator set by suggesting a small number of representative event indicators. Later work will report the traffic composition and distance conditions under which noise event measures provide information uncorrelated with conventional road traffic noise indicators - and which thus may prove useful as supplementary indicators to energy-equivalent measures for road traffic noise.

1. INTRODUCTION

A noise event in the sound from a stream of road traffic is a discrete component of the sound signal that stands out, or emerges, from the rest of the signal generated by the traffic stream. It is most often the result of the passage of an individual loud vehicle, or succession of vehicles, or even the passage of a not particularly loud vehicle heard against a quieter background in situations of low traffic flow.

Noise events in transport noise signals are of interest because they may play a role in human response to noise: disturbance to sleep, annoyance, interference with activities, cardiac responses, and effect on children in schools. Brown (2014) has provided an overview of the scattered, but persistent, evidence regarding the effects of noise events in road traffic streams on human response. The presence of events is postulated to result in effects beyond those attributed to the level of road traffic noise exposure itself - the latter measured through conventional indicators such as L_{Aeq} and L_{A10}. The Environmental Noise Directive (Council Directive, 2002) noted the potential use of noise events as supplementary to the standardized energy-based indicators of noise exposure, though there appears to be limited practical application of such supplementary indicators to date. WHO (2009) suggests that events be measured by a combination of number of events and their level, but also noted that as yet there was no generally accepted way to count the number of events. For aircraft noise, measurement of noise events from overflights is standardized (eg Jones and Cadoux, 2009) and counts of events, or measures such as SEL, are relatively straightforward because of the time separation between successive passages. However road traffic can have much shorter vehicle headways resulting in problematic event detection and counting, even at moderate traffic flow rates (Aasvang et al., 2011; Griefahn et al., 2011; Brown, 2013).

This study adopts a rigorous approach to the definition and measurement of noise events from road traffic - something we see as essential given the largely ad-hoc approaches to event measurement in road traffic noise to date. Here we compile and categorize different formulations of event-based indicators relevant for road traffic noise that have appeared in the literature. We systematically test the ability of indicators in this set to detect events in time histories of road traffic noise in the population of acoustic conditions found near roadways.

2. NOISE EVENTS

Estimation of noise event metrics in the sound level signal caused by traffic noise is a two-step procedure. Firstly, individual events in the time history of the traffic noise signal have to be identified using a detection algorithm based on a set of criteria. Secondly, once individual events have been identified, summary indicators can be calculated - most usually the number of noise events (NNE) detected over the period of interest.

2.1 Noise event detection

A wide range of algorithms, protocols, or criteria have been reported in the literature for identifying noise events within a time series of A-weighted sound levels - usually from road, rail or aircraft sources (see Table 1). These algorithms have been built into noise measurement equipment systems (e.g. Murray, 2001) or used in experimentation or field studies (e.g. Taylor et al., 1987). However, there is no agreement as yet regarding appropriate algorithms for event detection in road traffic noise streams, and there has been negligible testing of alternatives.

Three categories of algorithms can be identified. In the first category, the **threshold** for noise event detection is set to a predefined value. Typical values for this threshold have ranged from 45 dB(A) for identifying events in indoor situations with closed windows (Hall et al., 1985) to 80 dB(A) for detecting events in outdoor situations (Lambert et al., 1996; Can et al., 2008). Some authors (Taylor et al., 1987; Fidell et al., 1995; Fidell et al., 2000) have adopted variable thresholds, even within the same study, depending on vehicle flow rates - higher thresholds being used with higher flow rates. In the second category, events are detected when the instantaneous sound level **emerges** by a specified amount above a predefined level (Muller et al., 2004; Mietlicki et al., 2013; Griefahn et al., 2011). However, note that the first category (the threshold algorithms) is, in fact, a subset of the second, but in which the emergence is set to zero. In the third **adaptive** category, events are detected when the instantaneous sound level emerges by a specified amount, typically 3 to 15 dB(A), above another conventional traffic noise indicator such as L_{Aeq} (Wunderli, 2015; Campbell & Isles, 2001), L_{A50} (De Coensel & Botteldooren, 2006; Beaumont & Semidor, 2005), or L_{A90} (Aasvang et al., 2011; Tulen et al., 1986).

There is also considerable use of other noise event statistics apart from NNEs. These include Total Duration of Events, Duration of Noise Free Intervals, Unexpectancy, etc. We will consider these alternative noise-event measures in a later paper.

Table 1. Various noise event detection algorithms for transport noise found in the literature (L_β=Threshold; E= Emergence; τ_e=min. event duration; τ_G= min. delay between events)

Reference	**Source type**	**Application**	**Envelope**	L_β	E	τ_e	τ_G
Ribeiro *et al.* (2013)	road/rail/air	outdoor	$L_{\mathrm{Aeq,1s}}$	55 dB(A)	0 dB(A)	–	–
Murray (2001)	road	outdoor	L_{AF} @ 250 ms	65 dB(A)	0 dB(A)	≤25s	≥3s
Fidell *et al.* (2000)	air	indoor	L_{AF} @ 500 ms	site-specific	0 dB(A)	≥2s	–
Sato *et al.* (1999)	road	outdoor	not specified	75 dB(A)	0 dB(A)	–	–
Lambert *et al.* (1996)	rail	outdoor	not specified	70/80 dB(A)	0 dB(A)	–	–
Hall *et al.* (1985)	road/rail/air	indoor	L_{AS} @ 1 s	45/50/55/60/65 dB(A)	0 dB(A)	≥30s	–
Taylor *et al.* (1987)	road/air	outdoor	not specified	55/60/65/70/75 dB(A)	0 dB(A)	–	–
Can *et al.* (2008)	road	outdoor	$L_{\mathrm{Aeq,1s}}$	75/80 dB(A)	0 dB(A)	–	–
Fidell *et al.* (2008)	air	indoor/outdoor	L_{AF} @ 1 s	50/60/70 dB(A)	0 dB(A)	≥2s	–
Müller *et al.* (2004)	air	indoor/outdoor	L_{AS} @ 125 ms	not specified	4 dB(A)	–	–
Mietlicki *et al.* (2013)	road	outdoor	not specified	not specified	10 dB(A)	–	–
Griefahn *et al.* (2011)	road/rail	indoor	not specified	not specified	10 dB(A)	–	–
Wunderli et al. (2015)	road/rail/air	outdoor	$L_{\mathrm{Aeq,1s}}$	$L_{\mathrm{Aeq,T}}$	3 dB(A)	–	–
Cambell and Isles (2001)	road	outdoor	$L_{\mathrm{Aeq,250ms}}$	L_{Aeq}	15 dB(A)	–	–
De Coensel *et al.* (2006)	road/rail/air	outdoor	L_{AS} @ 1s	$L_{\mathrm{A50,30s}}$	3 dB(A)	≥3s	–
Beaumont and Semidor (2005)	road/rail	outdoor	$L_{\mathrm{Aeq,30s}}$	$L_{\mathrm{A50,10min}}$	5/10/15 dB(A)	–	–
Aasvang *et al.* (2011)	road/rail	indoor/outdoor	L_{AF} @ 1 s	$L_{\mathrm{A90,5min}}$	10 dB(A)	≥2s, ≤40s	≥5s
Tule *et al.* (1986)	road	indoor	$L_{\mathrm{Aeq,1s}}$	$L_{\mathrm{A90,10min}}$	10 dB(A)	–	≥15s

Apart from the threshold, emergence and adaptive criteria, most authors report additional decision rules within the algorithms that accept or reject a noise event. One rule is the duration of the exceedance. For example, events could be required to last for at least 2 to 3 s before they are counted (Fidell et al., 1995; Fidell et al. 2000; De Coensel & Botteldooren, 2006; Aasvang et al. 2011). Hall et al. (1985) used much longer minimum event durations of 30 s, but their detection algorithm was directed mainly towards air and railway traffic. In Murray et al. (2001) and Aasvang et al. (2011), a maximum duration was set on the length of an event. A further criterion is the minimum time between events. Inclusion of a minimum time gap implements an elementary hysteresis effect into the detection algorithm (Murray et al., 2001; Aasvang et al., 2011; Tulen et al., 1986). This overcomes the problem of multiple event registrations of a single event which has irregular rise or decay patterns, and it responds to the (untested) notion that multiple sequential events, within a short period, are likely to be perceived as a single event, or that the disturbances caused by the multiple events might be experienced as one.

2.2 Event detection algorithms tested in this study

2.2.1 Building a set of threshold, emergence, and adaptive indicators

The set of detection algorithms tested in this study was obtained by varying two main parameters: the detection threshold and the minimum time gap τ_G between events. For the detection threshold, both the fixed and adaptive indicator types were used. Fixed thresholds vary from 45 dB(A) to 75 dB(A) in steps of 5 dB(A) (in an earlier pilot study, higher limits of 80, 85 and 90 dB(A) were considered, but such high thresholds did not lead to results that were repeatable and/or sensitive to changes in traffic parameter or distance conditions). The adaptive thresholds considered were L_{Aeq}, L_{A50} or L_{A90} as background level L_β, and 3, 5, 10 and 15 dB(A) as minimum emergences E above L_β. Four alternatives were used for all these indicators in terms of the minimum time gap between events. This was set, respectively, to 3, 5, 10 or 30 s. No lower limit was set on the duration of events since the simulated sound level time histories were road traffic noise, and there was no need to filter out occasional spikes of non-traffic flow related events such as door slams. This resulted in 76 (19 combinations of L_β and E, with 4 values of minimum time gap for each) different noise event detection algorithms. These are listed in Table 2, showing the naming convention adopted for each of the indicators (for example, the variable LEQE10G03 is the outcome from an algorithm that detects the Number of Noise Events (NNE) in one hour in a time series of A-weighted road traffic levels utilizing an adaptive protocol requiring an emergence (E) of 10 dB above LEQ, with a minimum gap between successive events of 3 s).

Table 2. Naming convention for the 76 different noise event indicators.

	Emergence E	Threshold T	Minimum time gap G between two events				Examples of Threshold & Emergence Indicators equivalent to Fixed Threshold Indicators				
			3s	5s	10s	30s					
Fixed thresholds	0 dB	45 dB	T45E00G03	T45E00G05	T45E00G10	T45E00G30					
	0 dB	50 dB	T50E00G03	T50E00G05	T50E00G10	T50E00G30	T45E05				
	0 dB	55 dB	T55E00G03	T55E00G05	T55E00G10	T55E00G30	T45E10	T50E05			
	0 dB	60 dB	T60E00G03	T60E00G05	T60E00G10	T60E00G30	T45E15	T50E10	T55E05		
	0 dB	65 dB	T65E00G03	T65E00G05	T65E00G10	T65E00G30		T50E15	T55E10	T60E05	
	0 dB	70 dB	T70E00G03	T70E00G05	T70E00G10	T70E00G30			T55E15	T60E10	T65E05
	0 dB	75 dB	T75E00G03	T75E00G05	T75E00G10	T75E00G30				T60E15	T65E10
Adaptive thresholds	3 dB	LAeq+3	LEQE03G03	LEQE03G05	LEQE03G10	LEQE03G30					
	5 dB	LAeq+5	LEQE05G03	LEQE05G05	LEQE05G10	LEQE05G30					
	10 dB	LAeq+10	LEQE10G03	LEQE10G05	LEQE10G10	LEQE10G30					
	15 dB	LAeq+15	LEQE15G03	LEQE15G05	LEQE15G10	LEQE15G30					
	3 dB	LA50+3	L50E03G03	L50E03G05	L50E03G10	L50E03G30					
	5 dB	LA50+5	L50E05G03	L50E05G05	L50E05G10	L50E05G30					
	10 dB	LA50+10	L50E10G03	L50E10G05	L50E10G10	L50E10G30					
	15 dB	LA50+15	L50E15G03	L50E15G05	L50E15G10	L50E15G30					
	3 dB	LA90+3	L90E03G03	L90E03G05	L90E03G10	L90E03G30					
	5 dB	LA90+5	L90E05G03	L90E05G05	L90E05G10	L90E05G30					
	10 dB	LA90+10	L90E10G03	L90E10G05	L90E10G10	L90E10G30					
	15 dB	LA90+15	L90E15G03	L90E15G05	L90E15G10	L90E15G30					

Separately, we illustrate, in the five right-hand columns of Table 2, the redundancy in using emergence criteria in association with fixed threshold criteria. For example, an emergence E=5 above L_β=45 is an identical detection algorithm to an emergence E=0 above L_β=50. Thus the T45E05 algorithm would produce an identical NNEs outcome to the algorithm T50E00. The redundant indicators do not need to be considered further in this paper.

They are mentioned here for completeness, as other authors have elsewhere utilized emergence-algorithms as well as fixed-threshold-algorithms.

2.2.2 Windows open or closed

Sleep researchers tend to utilize noise events in road traffic as heard indoors, while others have identified noise events in sound level time histories heard outdoors. For consistency with sleep disturbance work, we detect events based on the time histories of road traffic noise as experienced by people inside their dwellings. These sound level time histories are those which are initially incident on the facade of the dwellings, but then further shaped by the building attenuation, the state of window closure, and the sounds generated internally in the dwelling. We recognize, of course, that façade attenuation is frequency dependent, but for present purposes a consideration of A-weighted attenuations will be sufficient. Accordingly, we measure noise events in road traffic streams as experienced indoors, but we do this separately under two conditions. The first condition is for fully open windows. For this condition, the letters 'OP' are appended to each of the detection algorithms named in Table 2. The second condition is fully closed windows – with 'CL' appended to each of the algorithm names. An outside to inside attenuation of 5 dB(A) was applied for the windows open condition. For closed windows, a building envelope attenuation of 25 dB(A) was used (effects of using a different attenuation assumption can be examined later). Additionally, to simulate the indoor time history, it was assumed that internal sources in the dwelling generated a steady level of 35 dB(A) which would be experienced, by residents indoors, simultaneously with the externally-generated road traffic time histories.

Thus there are 76 different NNE indicators developed for testing in this study, for each of the open and closed window conditions.

3. METHODOLOGY

This study used a modelling approach to establish the population of acoustic conditions that exist near roadways. Modelling ensured that the traffic parameters of the source roadways and the propagation distances could span an appropriate range of values, and that each of these could be varied independently - something that would be largely impractical using field-measured data. As will be described in Section 4, modelling simulated the time histories of sound levels generated for 500 different traffic flow and source-receiver distance scenarios. The 76 noise event algorithms shown in Table 2 detected the NNEs, for each of window-open and window-closed conditions, for each of the 500 traffic flow/distance scenarios.

Various aspects of the performance of the set of noise event algorithms in detecting NNEs were then examined (Section 5). This included reliability of NNE detection (did the algorithm produce consistent counts of NNEs when applied to identical conditions?); the validity, or reasonableness, of the numbers of events detected for each indicator across the 500 scenarios; and, finally, redundancy between the different indicators within the large set of indicators examined (were different indicators producing results identical to each other?). The outcome reported in this paper is a small set of valid, reliable, indicators in which redundancy between different indicators has been reduced. This set will be examined further in a subsequent stage of this project.

4. SIMULATION MODELLING AND EVENT DETECTION

4.1 Simulation of instantaneous sound level

The instantaneous sound level in free field caused by road traffic was simulated using the road traffic noise pattern simulation model described in De Coensel et al. (2016). This model, called Noysim2, combines a microscopic simulation of road traffic with an instantaneous vehicle noise emission and a point-to-point sound propagation model. Aimsun (www.aimsun.com) is a commercially available microscopic road traffic simulation model used to simulate the traffic. In particular, given a road network, vehicle fleet properties and aggregated traffic demand data, the movement of individual vehicles is simulated, and the instantaneous position, speed and acceleration of each vehicle at each time step during a predefined simulation period is provided.

Subsequently, the instantaneous emission of all sources is calculated using a noise emission model that includes distributions of vehicle sound power levels (De Coensel et al., 2016). This model is based on the Imagine road traffic noise emission model (Peeters and van Blokland, 2007), to which a per-vehicle correction is added that accounts for the distribution in sound power emitted by individual vehicles within different categories. Correction distributions were constructed based on a large set of roadside measurements (Brown and Tomerini, 2011). Using individualized vehicle emission laws, this road traffic emission model accounts for the influence of vehicles that are producing more/less noise than the average vehicle. The output of the Noysim2 road traffic noise simulation model consists of the time history of the instantaneous sound level at the location of the receiver, calculated in ⅓-octave bands using the ISO 9613 sound propagation model. As only broadband road traffic noise exposure is considered in this work, all sources have a similar emission spectrum. Spectral aspects are therefore neglected in first order. More details about the Noysim2 model and its operation can be found in De Coensel et al. (2016).

4.2 Noise exposure scenarios representing the population of acoustic conditions near roadways

The modelling is based on a receiver adjacent to a straight dual-lane roadway carrying uninterrupted traffic. A wide range of road traffic noise exposure scenarios were modelled, even for this simple geometry, by varying traffic flow parameters and the distance between the receiver and the road:

- Speed limits: 60, 100 km/h
- Traffic flow rates: 5, 10, 20, 50, 100, 200, 500, 1000, 2000, 5000 veh/h
- Proportion of heavy vehs: 0, 10, 20, 50, 100 %
- Distance from roadway: 7.5, 15, 30, 60, 120 m.

The total number of unique traffic parameter and distance scenarios which determined the population of acoustic conditions likely to be found near roadways is thus 2 x 10 x 5 x 5 = 500 scenarios.

A simplified geometry is appropriate given the purpose of this study, but more complex road network configurations could later be modelled by the same system, where multiple roadway links, roadway intersections, and signalized controls on traffic could be introduced. The analysis here is restricted to uninterrupted flow road traffic streams, in contrast to situations where traffic is congested or is known to be controlled by traffic signals or other devices (e.g. Can et al., 2008). A rigorous investigation into different algorithms for the detection of noise events from freely flowing road traffic streams is a prerequisite to any later application to interrupted traffic flow. The duration of each simulation was set at one hour, with a time step of 125ms. This time step allows for a good temporal resolution of the simulations, and equals the shortest sample interval found in the literature overview. The 1h choice of simulation duration was a compromise between simulation variability and real-life measurement pragmatics. On the one hand, variability between simulation runs can be expected due to the stochastic nature of the simulation, with variability reducing with increased simulation duration. On the other hand, eventual field measurements, based on an event detection protocol measuring NNEs as noise limits, requires practical limits, and a 1h period for this seems appropriate. The actual 1h simulation runs included an additional warm-up period of 5 minutes. The simulation for each unique scenario was repeated 30 times, generating a total of 15,000 simulation runs (30 x 500) of 1h time histories of road traffic noise levels near the roadway.

4.3 Event detection

Figure 1 provides illustrations of the application of the complete sound level simulation and event detection methodology, for one (of the available 500) scenarios and for four event detection algorithms (T60E00G03OP and LEQE05G03OP; T60E00G03CL and LEQE05G03CL). In the figure, the outdoor sound level time history is shown in a solid grey line, whereas the indoor sound level time history is shown in a solid black line, for both open and closed windows (only the first 10 minutes of the simulation are shown). The figure illustrates the detection of noise events, as vertical grey bars, by two different detection algorithms. One algorithm uses a fixed threshold of 60 dB(A) (detecting NNE of 1 or 0 for open and closed window conditions in panels (a) and (b) respectively); the other uses an adaptive threshold of LAeq + 5 dB(A) (detecting NNE of 4 or 1 events for open and close window conditions in panels (c) and (d) respectively).

Table 3 shows the mean NNEs detected by each of the 152 algorithms in Table 2 (76 open-window and 76 closed-window) in the time histories of road traffic noise generated by the 500 traffic flow/distance scenarios that represent the population of acoustic conditions found near roadways. It can be seen that the different indicators varied widely in the NNEs detected, with a few detecting zero noise events, and others detecting up to a mean of 77 noise events per hour across the 500 scenarios.

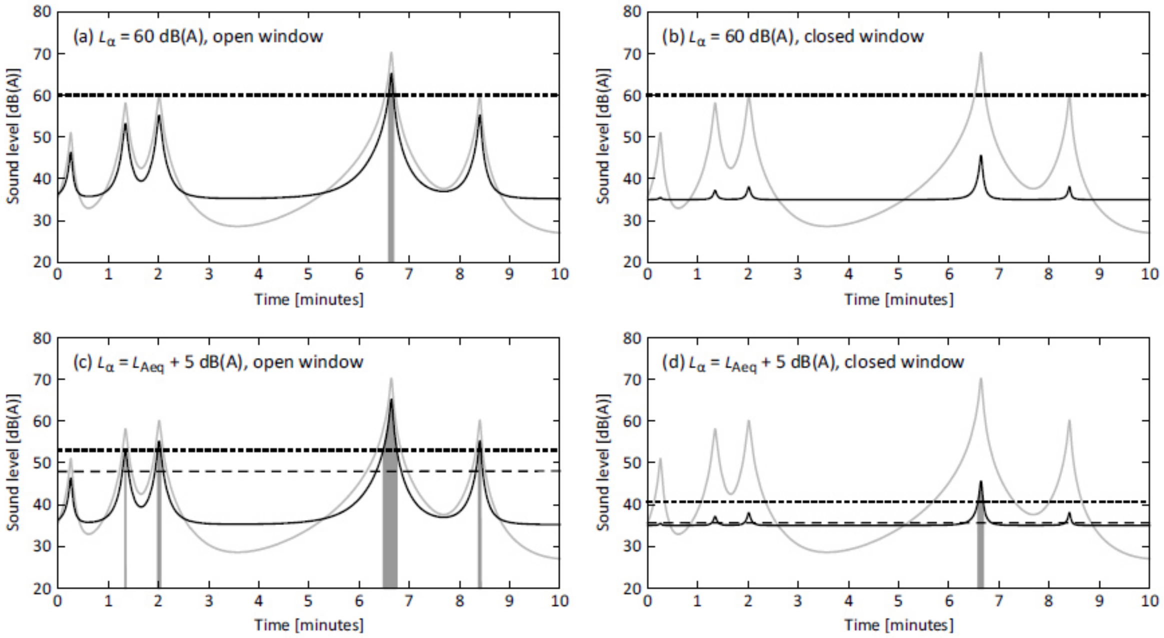


Figure 1: Simulated time history of the free-field outdoor sound levels (solid grey lines) at a distance of 30 m from a two-lane road with a speed limit of 60 km/h and 20% heavy vehicles. Events are detected in the indoor sound level time histories (solid black lines) when the detection levels (heavy dashed lines) for each of the algorithms (a) to (d) are exceeded. Detected events are shown as vertical shaded bars.

Table 3: Mean/standard deviation of NNEs per hour detected by each algorithm when applied to the 500 scenarios. For example, the indicator T45E00G03OP (see Table 2) detected a mean NNEs of 16 events per hour across the 500 scenarios, with the NNEs about this mean having a standard deviation of 18 NNEs. The numbers in parentheses show the standard deviation in the NNEs detected in the 30 simulation replications of any one scenario, pooled across the 500 scenarios (See 5.1). The darker cells indicate algorithms with low reliability (see 5.1); the lighter cells algorithms that may not detect a sufficient number of events (see 5.2).

	Emergence E	**Threshold T**	**Open Window**				**Closed Window**			
			G=03	**G=05**	**G=10**	**G=30**	**G=03**	**G=05**	**G=10**	**G=30**
Fixed thresholds	**0 dB**	**45 dB**	16/18 (2.9)	15/17 (2.7)	14/15 (2.4)	9/9 (1.8)	43/66 (5.0)	34/50 (4.2)	23/31 (3.4)	10/13 (2.2)
	0 dB	**50 dB**	22/26 (3.7)	21/24 (3.4)	18/20 (2.9)	11/11 (2.0)	37/71 (4.5)	28/52 (3.9)	18/31 (3.0)	8/13 (2.1)
	0 dB	**55 dB**	31/38 (4.5)	28/33 (4.1)	21/25 (3.3)	11/12 (2.1)	24/63 (3.5)	19/46 (3.1)	13/28 (2.5)	6/11 (1.8)
	0 dB	**60 dB**	40/54 (4.7)	33/43 (4.2)	23/28 (3.5)	11/13 (2.2)	10/41 (2.5)	9/31 (2.3)	6/20 (1.9)	4/9 (1.4)
	0 dB	**65 dB**	43/67 (5.0)	34/49 (4.2)	22/31 (3.3)	10/13 (2.2)	3/14 (1.4)	2/12 (1.3)	2/10 (1.2)	2/5 (1.0)
	0 dB	**70 dB**	37/72 (4.5)	28/52 (3.9)	18/31 (3.0)	8/13 (2.1)	1/3 (0.7)	1/3 (0.7)	0/3 (0.6)	0/2 (0.6)
	0 dB	**75 dB**	24/63 (3.5)	19/46 (3.1)	13/28 (2.5)	6/11 (1.8)	0/1 (0.3)	0/1 (0.3)	0/1 (0.3)	0/11 (0.3)
Adaptive thresholds	**3 dB**	**LAeq+3**	61/70 (9.6)	54/56 (8.0)	43/35 (6.0)	23/12 (3.8)	54/71 (8.6)	48/58 (7.1)	37/37 (5.1)	19/14 (3.3)
	5 dB	**LAeq+5**	42/50 (8.3)	39/44 (7.3)	34/32 (5.6)	21/13 (3.6)	35/51 (7.2)	33/44 (6.2)	28/33 (4.7)	16/14 (3.0)
	10 dB	**LAeq+10**	15/18 (4.4)	15/17 (4.2)	14/15 (3.9)	12/11 (2.9)	10/17 (3.4)	10/16 (3.2)	10/15 (3.0)	8/11 (2.3)
	15 dB	**LAeq+15**	5/6 (2.1)	5/6 (2.1)	5/6 (2.0)	4/5 (1.9)	3/5 (1.5)	3/5 (1.4)	3/5 (1.4)	2/4 (1.3)
	3 dB	**LA50+3**	77/86 (6.2)	63/59 (5.3)	43/31 (4.3)	19/11 (2.6)	72/89 (5.7)	59/62 (4.9)	40/34 (4.0)	18/13 (2.6)
	5 dB	**LA50+5**	66/80 (5.7)	56/59 (5.1)	41/33 (4.2)	20/11 (2.7)	57/82 (5.1)	48/62 (4.6)	35/37 (3.8)	16/14 (2.6)
	10 dB	**LA50+10**	37/52 (4.1)	34/44 (4.0)	29/32 (3.5)	17/13 (2.6)	25/47 (3.4)	23/42 (3.3)	19/30 (2.9)	11/14 (2.3)
	15 dB	**LA50+15**	20/31 (2.8)	19/29 (2.8)	17/24 (2.7)	12/13 (2.2)	9/22 (2.1)	9/21 (2.1)	8/18 (2.0)	6/11 (1.8)
	3 dB	**LA90+3**	53/49 (7.5)	41/33 (6.0)	25/18 (4.1)	10/7 (2.1)	65/61 (6.6)	0/44 (5.4)	33/28 (4.0)	14/12 (2.4)
	5 dB	**LA90+5**	65/86 (8.2)	51/43 (6.7)	33/23 (4.7)	14/10 (2.5)	67/68 (6.4)	51/54 (5.3)	33/32 (4.1)	15/13 (2.5)
	10 dB	**LA90+10**	61/79 (7.0)	51/56 (6.1)	36/31 (4.8)	17/11 (2.8)	44/80 (4.9)	37/59 (4.3)	26/35 (3.6)	12/14 (2.4)
	15 dB	**LA90+15**	41/60 (5.6)	37/49 (5.1)	29/33 (4.2)	16/13 (2.7)	20/47 (3.5)	17/40 (3.2)	14/28 (2.8)	8/12 (2.0)

Some observations regarding the results in Table 3 are:

- For the fixed-threshold algorithms in open-window conditions, the NNEs detected (and their spread) increases with increasing threshold, reaching a maximum where the threshold is 65 dB(A), then decreases with higher thresholds. The fixed-threshold algorithms in closed-window conditions show maximum NNEs detected occur at a much lower threshold, 45 dB(A).
- For the adaptive-thresholds, NNEs decrease with increasing emergence above the threshold, except where the adaptive threshold is the LA90, when emergences of 5 and 10 dB(A) detect more events than emergences of 3 or 15 dB(A).
- As the time gap before recognizing a subsequent event increases from 3 to 30 s, the NNEs detected decreases in all algorithm formulations.
- NNEs are higher in the closed-window condition than in the open window condition for detection algorithms based on fixed thresholds of 45 and 50 dB(A). For all other fixed thresholds, and all the adaptive thresholds, the NNEs are higher in the open-window condition.

While some of these observations are intuitively obvious, others are not, suggesting that there are complex interactions between the parameters utilized in any particular detection algorithm and the time history of road traffic noise levels generated by particular traffic parameter, distance, and background level conditions. Some preliminary analyses, not reported here, show some of these interactions to be non-linear, even non-monotonic. This will be examined and reported on in later work.

5. REDUCING THE SET OF EVENT-DETECTION ALGORITHMS

Selection of appropriate noise event detection algorithms for road traffic noise from the large set of alternatives will eventually have to be assessed through human effects research – that is, by examining if and how different noise event measures of a road traffic signal correlate with human outcomes (sleep disturbance, annoyance, etc.). However, there are also *a priori* criteria that any event detection algorithm must meet in terms of reliability of the NNEs detected by the algorithm, and in terms of validity.

5.1 Reliability

The reliability of the indicators can be assessed by examining variation in the NNEs detected across the 30 replications of the one-hour simulations for each scenario. The numbers in parentheses in each cell of Table 3 show the standard deviation in the NNEs detected in the 30 replications, with the standard deviations pooled across the 500 scenarios. The standard deviations ranged from 0.3 events to 9.6 events across the indicator set. As an initial cut, a standard deviation of 5 or less is suggested as being sufficiently reliable for practical NNE measurement (for a standard deviation of 5, some 90% of replicated NNE detections would be within +/-8 events of the true value; for a standard deviation of 3, some 90% of replicated NNE detections would be within +/-5 events of the true value). In Table 3, those indicators that are regarded as insufficiently reliable for use are shown with darker shading. Notably, this has excluded several of the adaptive-threshold indicators.

5.2 Validity

A valid noise event detection algorithm needs to detect road traffic noise events in signals generated by most (not necessarily all) traffic flow and distance scenarios, and it must also result in variation in the NNEs as the traffic flow/distance scenarios change. Table 3 shows that these conditions are met for most of the indicators. Some indicators detect a mean NNEs value of 10 or less across the 500 scenarios, but many detect means of 20 to 60 events. Low mean value of NNEs also tend to be associated with low variation in the NNEs (as illustrated by the means/standard deviations reported in the cells of Table 3). Standard deviations in NNEs of 20 to 80 events are associated with those indicators with mean NNEs across the scenarios of greater than about 20 events.

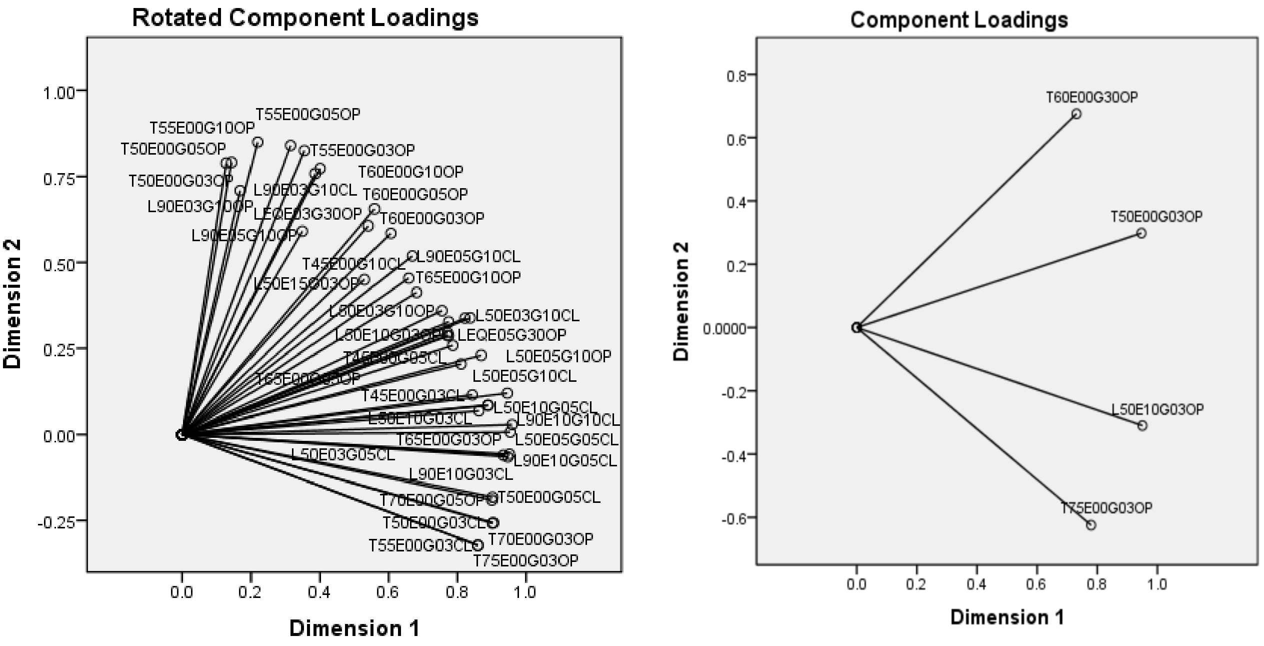
Again, the appropriate NNEs per hour detected within any noise signal can only be determined through human effects research (correlating human response to events with the NNEs detected) – but in the absence of such information, it seems reasonable to carry forward for further analysis those indicators that detect a mean NNEs per hour, across all traffic and distance scenarios, of greater than 20 events per hour. The indicators that do not meet this criterion are indicated in Table 3 by light cell shading. Notably, a high proportion of closed-window indicators; most indicators that require a minimum time between events of 30 s before detection; and various adaptive-thresholds indicators with 15 dB emergences; did not detect a sufficient number of events to meet this criterion. That closed-window indicators largely do not meet this criterion is suggestive that there may be difficulties in detecting noise events indoors when windows are closed.

5.3 Dimension reduction

Excluding those cells that are shaded either dark or light in Table 3 because the indicators failed the criteria in Sections 5.1 and 5.2, 42 indicators remain (25 open-window, 17 closed-window). Given the systematic way in which the indicator set was formulated, many of these will still be highly intercorrelated – that is, they will detect similar NNEs when applied to any particular traffic noise time history. The following analysis uses a statistical data reduction procedure to reduce the redundancy in these remaining variables to achieve a smaller, more manageable, subset of indicators without major loss of information. Our data set consisted of NNE counts according to the algorithms for each of these 42 indicator variables, for each of the 500 traffic flow/distance scenarios.

Because the indicators are likely to have non-linear relationships, examination of redundancies between indicators through bivariate correlation analysis was not possible. For the same reason, standard principal component analysis was not appropriate, and the SPSS 20 CATPCA procedure was utilized (Categorical Principal Component Analysis) as it allows for nonlinear relationships between variables.

The two-dimension solution of the CATPCA analysis explained 75% of the total variance in the indicator variables, and the component loadings of each of the 42 indicators (Varimax rotated) on the two dimensions are shown in Figure 2(a). The interpretation of these dimensions is not of interest here, as the sole purpose of the analysis was to reduce redundancy between the indicator variables. This was achieved, visually from Figure 2(a), by selecting one indicator from the groups of indicators that have similar loadings on the two dimensions. The indicator chosen to represent each group was one that had good reliability and spread of NNEs across the 500 scenarios (based on the data in the cells of Table 3). Where there was nothing to choose between candidate variables, the indicator that was open-window, and that used a minimum gap between events of 3 s, was selected. The following four indicator variables were chosen as representative of groupings of the original 42 variables: T50E00G03OP, T65E00G03OP, T75E00G03OP and L50E10G03OP. Other than the fact that each of these four



(a) (b)

Figure 2: Component loadings on two unnamed dimensions from CATPCA procedures of (a) the 42 indicator variables selected from Table 3 and (b) the four indicators chosen to represent groupings of the 42 variables.

variables was representative of a cluster of variables in Figure 2 (a), the actual selection is arbitrary to the extent that others could be considered equally representative (this may need to be reconsidered as this project develops). For illustrative purposes, the CATPCA procedure was run again, using only these four representative indicators. The unrotated result is shown in Figure 2 (b). The two (unnamed) dimensions of the analysis account for 99% of the total variance in the four representative variables, and the four variables are widely separated, loading differently on the two dimensions. These four variables will be carried forward in further analysis.

6. SUMMARY

This paper has reported progress on a study to ascertain appropriate algorithms for the measurement of noise events in time histories of sound levels from road traffic streams. A set of potential algorithms was developed from the literature based on thresholds at predefined levels and on emergences above adaptive thresholds. Level, emergence, and minimum time gap between successive events differentiated the algorithms. We developed 76 variables with different event-detection algorithms for each of window-open and window-closed conditions.

We then systematically tested the ability of these indicators to detect events in time histories of road traffic noise in the population of acoustic conditions found near roadways. This population of acoustic conditions had been simulated based on 500 different traffic flow/propagation-distance conditions.

The analysis reported here was an initial exploration of the validity and reliability of the different indicators derived from those in the literature. Some 20% of the indicators were considered unreliable in that they did not produce consistent counts of NNEs when applied to 30 replications with the same source parameter/distance conditions. Approximately 50% of the indicators did not estimate a reasonable number, or range, of NNEs when applied across the 500 acoustic condition scenarios. The remaining 42 indicator variables were reliable and generated what were regarded as valid counts of NNEs. These were then examined for redundancy in terms of different indicators producing identical NNE counts. The outcome of the dimension-reduction procedure was to select four indicator variables that were, collectively, representative of the groupings of the original 42 variables.

This small set of alternative noise-event indicator variables will be carried forward for subsequent analysis in this project to examine more of the characteristics of noise event indicators in road traffic streams. In particular, they will be used to examine the traffic composition and propagation distance conditions under which noise-event measures may provide information about road traffic noise levels and time histories that is uncorrelated with conventional road traffic noise indicators – and thus may provide useful supplementary information pertinent to human response. This is work in progress and will be reported elsewhere.

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