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Noise event measures for road traffic

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ABSTRACT
How should noise events in road traffic noise be measured? This paper reports the performance of a set of algorithms that detect noise events in time histories of road traffic noise in the population of acoustic conditions found near roadways. The latter was obtained through simulation of 500 different road traffic noise time histories using a comprehensive range of traffic flow, traffic composition, and propagation distance, conditions in unshielded locations near roadways. The initial set of algorithms tested was developed by systematically expanding on threshold-based algorithms described in the literature, then excluding those that were unreliable. The finding was that the NA50 and NA55 (detecting when road traffic noise exceeded 50 dB and 55 dB respectively), and the NAL50E10 (detecting when the traffic levels exceeded L50 + 10 dB) can all be considered for practical application as event detection indicators. All apply to measurement of indoor events with the windows of the dwelling open. The primary criterion for selection as supplementary indicators (and others in the same clusters that could substitute for them) was their non-monotonic relationship with the LAeq, The traffic and distance conditions under which these event-based measures could potentially be useful supplementary indicators is identified.

1 INTRODUCTION

The temporal pattern of road traffic noise signals is of interest in this paper. Conventional equivalent-energy-based indicators can, in some circumstances, be insensitive to the time history of the traffic noise signal (Wunderli, 2015) – that is to the individual vehicle noise maxima in the road traffic stream. The LAeq, or related energy-based measures, may thus be restricted in ability to assess and manage road traffic in those situations where noise events may represent a problem for humans in terms of sleep disturbance or similar (see Brown (2014) for an overview of concepts and past findings on noise events and human response to surface transport noise, and why event-based measures to supplement energy-based indicators may be required). This paper reports an investigation into how noise events in road traffic should be detected.

Brown et al. (2016) described a suite of algorithms for the detection and counting of the number of noise events (NNEs) in road traffic signals inside dwellings. These were constructed from the literature, and were all based on the traffic noise levels exceeding either fixed or adaptive thresholds - the latter being either the L50 or the LAeq of the signal. They identified 76 different constructions for the detection of events in road traffic noise signals as they would be heard indoors, for each of window-open and window-closed conditions. Level, emergence, and minimum time gap between successive events differentiated the algorithms. Because of the large number of variables, they adopted the following naming convention. For example, LEQE10G03 is an algorithm that detects the NNEs 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 LAeq, with a minimum gap (G) between successive events of 3 s. Likewise, the T55E00G05 detects the NNEs that exceed a threshold of 55 dB (with E=0), and with a minimum gap between successive events of 5 s. All other algorithms can be identified from their name in a similar way. Suffixes OP and CL on the algorithm names indicate whether the indoor event is detected under open-window or closed-window conditions (see Brown et al. (2016) for a discussions of indoor/outdoor locations for event measurement).

Brown et al. (2016) applied these algorithms in a simulation study that modelled the time history of noise levels (for full details of the modelling see de Coensel et al., 2016). After excluding unreliable algorithms and algorithms that resulted in non-functional numbers of events (very low or very high NNEs), 42 indicators remained, and the authors reported the preliminary results of a procedure to reduce redundancy in this large indicator set.

Whether using road traffic noise event measures to supplement conventional noise indicators will prove useful in predicting human response will have to be tested, eventually, through human effects research – that is, by examining if and how levels and events contribute, independently or in combination, to an association between road traffic noise and human response. However, a pre-condition for any such supplementary measure is that it can only add explanatory power if its relationship with LAeq is non-monotonic. For example, if a noise event indicator was linearly related to LAeq, it could not shed any additional light on human response beyond that already estimated from the LAeq itself. To this end, it is noted that I-INCE (2015) suggested, in their partial exploration of supplementary noise indicators for aircraft noise, that a product-moment correlation between LAeq and an events measure must not exceed 0.5 if the supplementary indicator is to be useful.

The approach in this paper is to identify the population of acoustic conditions that can occur in practice.This was obtained by systematically simulating the time history of road traffic noise for 500 different traffic flow/propagation-distance scenarios. These time histories were searched using the set of detection algorithms identified in the data reduction process, to detect and count, noise events.

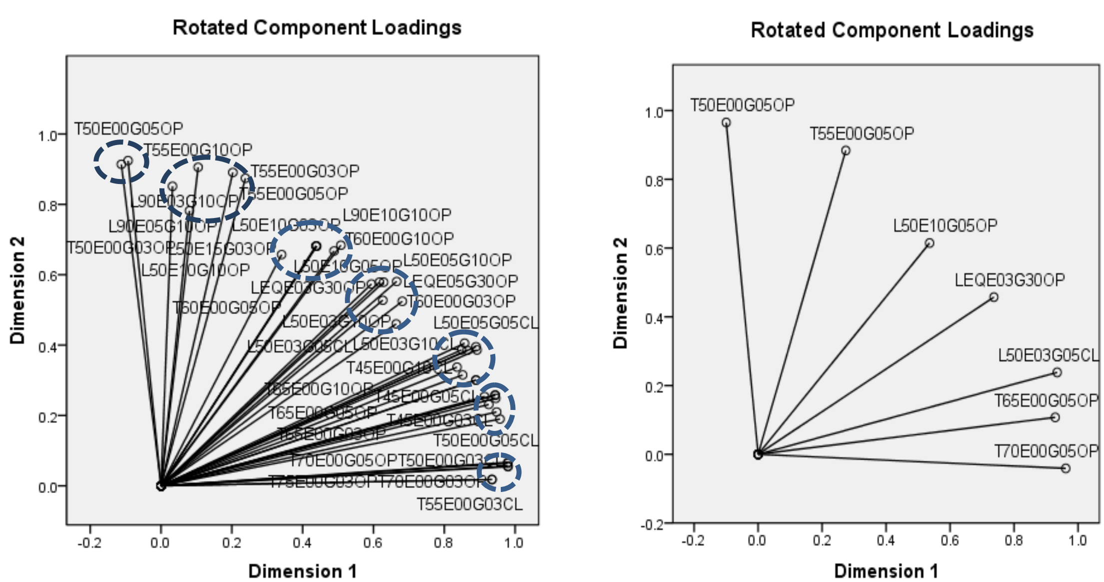
The relationships between the NNE counts and the LAeq are reported below, as are the traffic composition and propagation distance conditions under which the use of supplementary event-detection measures for road traffic noise may be appropriate.

2 EXAMINING EVENT-DETECTION ALGORITHMS

This section revisits and refines the preliminary data reduction process applied by Brown et al. (2016) to the 42 prospective detection algorithms. It provides slightly different, but more refined, outcomes, and a more detailed understanding of the effect of different algorithm constructions on the NNEs detected.

2.1 Identifying redundancy

Examining redundancy between algorithms using bivariate correlations was not possible as many of the indicators exhibit non-linear inter-relationships. Principle component analysis similarly requires linearity between variables and was not appropriate. Instead, the SPSS 23 CATPCA (Categorical Principal Component Analysis) procedure was utilized as it allows data reduction between variables with nonlinear relationships. The data set analysed consisted of NNEs returned from all 42 algorithms (25 open-window, 17 closed-window), for each of the 500 traffic flow/distance scenarios. A two-dimension solution of the CATPCA analysis explained 83.3% of the total variance in the indicator variables, and the component loadings of the 42 indicators (Varimax rotated) on these dimensions are shown in Figure 1(a). Seven clusters of indicators that have similar loadings on both dimensions are identified by broken circles in Figure 1(a). Identification of the number and configuration of clusters in the figure was based on a visual scan.



(a) (b)

Figure 1: Component loadings(a) on two dimensions from the CATPCA analyses of 42 indicator variables. and (b) on the seven indicators chosen as representative of those in the seven clusters.

The nature of the CATPCA analysis is that each cluster will encompass much of the redundancy between algorithms. All variables identified within each cluster are listed in Table 1. Bivariate scatterplots were then used to examine selected relationships between variables within clusters, particularly between similar algorithms differentiated by just one dimension in their formulation (e.g. open vs closed windows).

Table 1: The variables that constitute the seven clusters in Figure 1. The variable selected to represent the others within a cluster is shown in bold type.

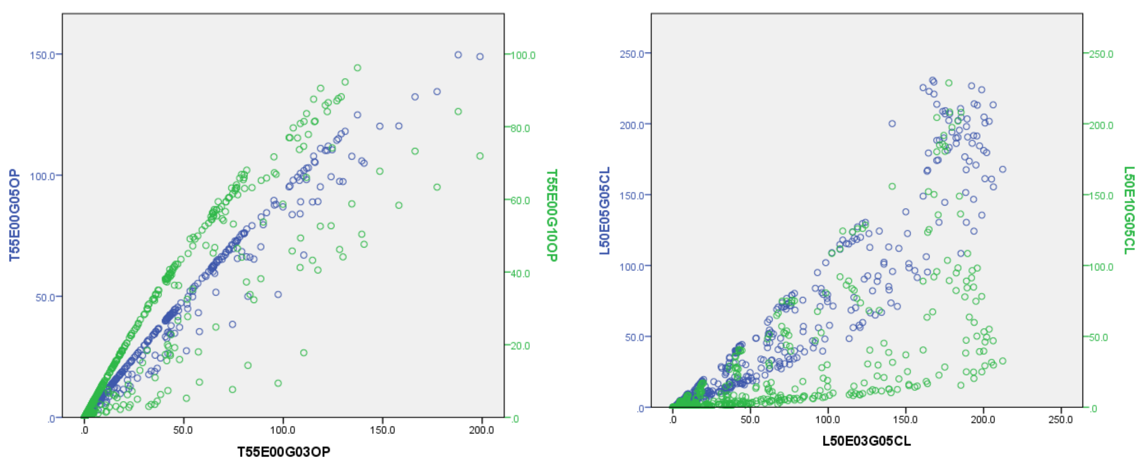
Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
T50E00G03OP	T55E00G03OP	T60E00G10OP	T60E00G03OP	T45E00G10CL	T45E00G03CL	T50E00G03CL
T50E00G05OP	**T55E00G05OP**	L50E10G03OP	T60E00G05OP	T65E00G10OP	T45E00G05CL	T50E00G05CL
	T55E00G10OP	**L50E10G05OP**	L50E03G10OP	**L50E03G05CL**	T65E00G03OP	T55E00G03CL
	L90E03G10OP	L50E10G10OP	L50E05G10OP	L50E03G10CL	**T65E00G05OP**	T70E00G03OP
	L90E05G10OP	L50E15G03OP	L90E03G10CL	L50E05G05CL	L90E10G03CL	**T70E00G05OP**
		L90E10G10OP	**LEQE03G30O**	L50E05G10CL	L90E10G05CL	
			LEQE05G30OP	L50E10G03CL	L90E10G10CL	
				L50E10G05CL		
				L90E05G10CL		

2.1.1 Open-window vs closed-window algorithms

Clusters 5 to 7 in Table 1 include fixed-threshold algorithms for both open and closed window conditions. Given the 20dB difference between open and closed windows used in the modelling, it is unsurprising that the 45, 50 and 55dB closed-window fixed-threshold variables were found to have a strong linear relationships with the 65, 70 and 75dB open-window fixed-threshold variables respectively. Thus the closed-window algorithms do not provide NNE information dissociated from that generated by open-window algorithms.

2.1.2 Effect of time gaps between successive events

Each cluster in Table 1 includes algorithms that differ in formulation only in terms of the minimum time gap between successive events. Figure 2(a) shows a scatterplot of the NNEs detected by the 55dB fixed-threshold algorithm with open windows, with three different time gaps. As could be expected, increasing the minimum gap between successive events results in fewer events being detected, The figure shows that, while pairs of these algorithms are strongly related, the longer gap is also associated with some drop-out in event detection for some traffic and distance scenarios, resulting in a smaller NNEs. For otherwise similarly formulated algorithms, different time gaps will tend to produce different, but correlated, NNEs. Redundancy in the set of algorithms can thus be reduced, where there are similar algorithms differentiated by time gap, by utilizing just one of the time gaps. We have chosen to retain the mid gap-size (5s) algorithms, filtering out those with longer or shorter gaps within the same cluster.



(a) (b)

Figure 2: Scatterplots illustrating largely linear relationships between the NNEs for (a) the open-window 55dB fixed-threshold algorithms with different minimum time gaps (3, 5 and 10s) between events and (b) an adaptive algorithm with varying emergences (3, 5 and 10dB) above L50 (closed windows, 5s gap).

2.1.3 Effect of different emergence requirements in adaptive threshold algorithms

An example of the effect of increasing the emergence required above an adaptive threshold is illustrated in Figure 2(b). It shows the NNEs detected by three different closed-window algorithms, differentiated only by different emergences of 3, 5 or 10dB above L50 (closed windows). As could be anticipated, the greater the required emergence, the fewer noise events are detected – but, again, the counts of events by the different algorithms are related.

2.1.4 Relationships between other algorithms within clusters

Figure 3 shows relationships between the NNEs detected by various other pairs of algorithms from within the same clusters. This includes between fixed-threshold and adaptive-threshold algorithms, and between adaptive algorithms that use different noise indices (L50, L90, LEQ) as thresholds. From the 500 data points on each of the plots in Figure 3 (each being one traffic and distance scenario) it can be seen that the NNEs detected can be very different based on different algorithms, and that the patterns tend to be different with each pair - some with considerable scatter and with many outliers. However, based on visual assessment, the patterns in each of the five plots in Figure 3 confirm that there is a discernible relationship between most of the pairs of algorithms shown, and of sufficient strength of association to explain why the CATPCA analysis allocated each of the pairs to the same cluster of variables – and hence one of the algorithms can represent the cluster.

2.1.5 Algorithms selected as representative of the clusters

Based on these examinations of the inter-relationships between variables within the seven clusters, a single algorithm has been selected as representative of those in the cluster. These are in bold type in Table 1. The choice of representative algorithms was based on: open-window fixed thresholds chosen over closed-window fixed thresholds; algorithms based on 5 s time gaps between successive events chosen over algorithms with longer or shorter time gaps; adaptive algorithms with the smallest emergence chosen above those with larger emergence thresholds; and finally, where choice still remained, algorithm types most commonly represented within that cluster – or in the case of Cluster 4, an algorithm type (emergence above an adaptive threshold based on LAeq) not included in any other cluster.

This data reduction to seven algorithms does not imply that the algorithms in Table 1 that have not been selected are not appropriate to use in future practice – any of them could be used as the representative algorithm as they all meet the requirements of reliable and valid measures of noise events.

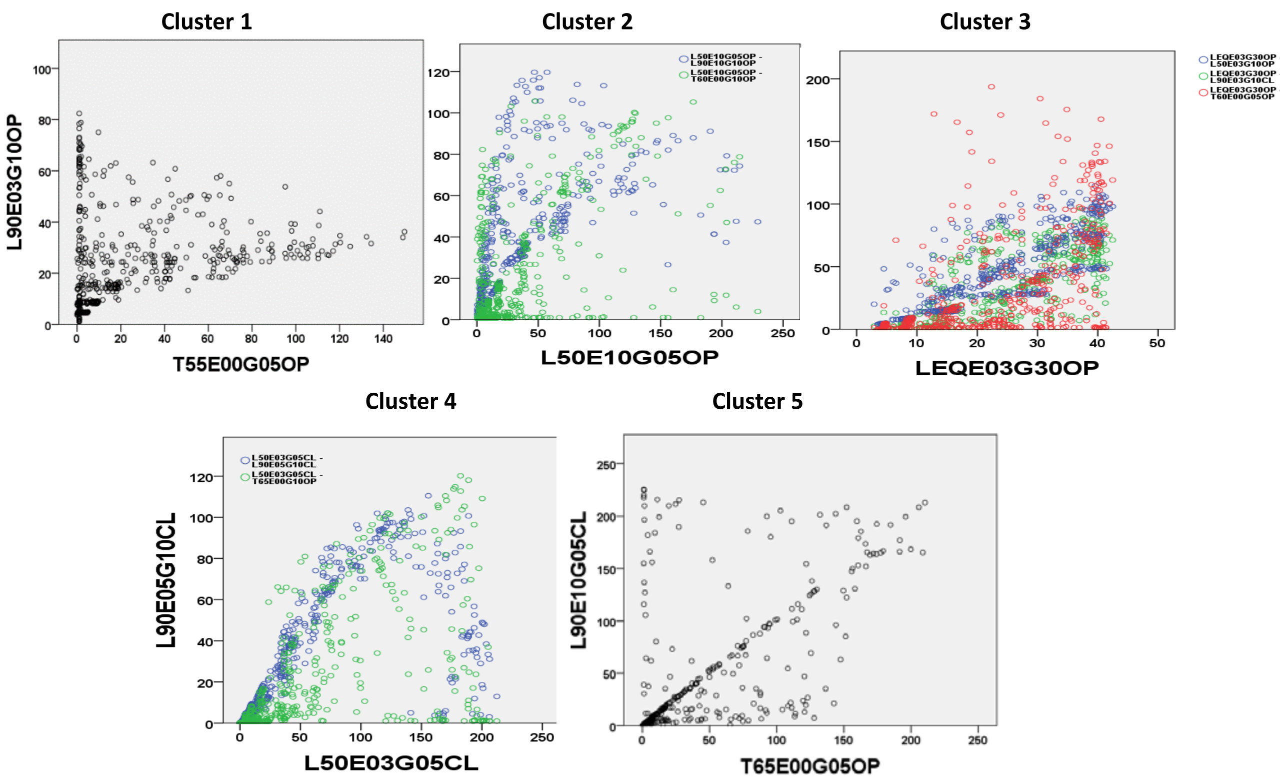


Figure 3: Scatterplots illustrating the relationships between the NNEs detected by pairs of algorithms within the clusters in Table 1.

The CATPCA procedure was run again, using only the seven representative algorithms as variables. The outcome is the two dimension solution, Varimax rotated, shown in Figure 1(b). The two dimensions account for 84.9% of the total variance in the seven representative variables. The variables are widely separated on the two dimensions.

Interpretation of the dimensions of the CATPCA solution is improved by including supplementary variables in the analysis (Figure 4). Three traffic and propagation variables (the total traffic flow QTOTAL; the percentage of heavy vehicles PERCENTH; and DISTANCE of the receptor from the roadway) and two acoustic measures (the outside LAeq, LAeqOUT, and the standard deviation of the outside noise levels over one hour, sigmaOUT) were used. Supplementary variables do not enter the analysis but they facilitate interpretation. From Figure 4, Dimension 1 can be interpreted as the overall level of noise. Dimension 2 is orthogonal to Dimension 1 and thus largely unrelated to level, but as SigmaOUT loads reasonably highly, it can be partially interpreted as the variability of the traffic noise signal outside.

This interpretation of Dimensions 1 and 2 facilitates interpretation of the various clusters. Clusters 1 and 2 (represented by the 50 and 55dB fixed-threshold algorithms, open windows) are associated with higher variability of the road traffic noise signal than they are with the overall level of traffic noise. Clusters 5, 6 and 7 (represented by the L50+3dB adaptive threshold, closed window; and by the 65 and 70dB fixed thresholds, open windows) are associated with high overall levels rather than the variability of the signal. Clusters 3 and 4 (both adaptive thresholds) are interim between these, being associated with both level and variability of the road traffic noise signal. This suggests that the NNEs detected by different algorithms will be differentially associated with overall level of the traffic noise and with the variability of the road traffic signal.

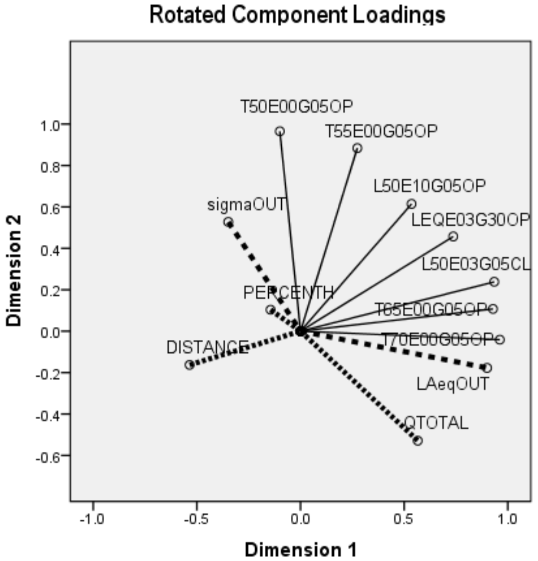


Figure 4 CATPCA with supplementary variables

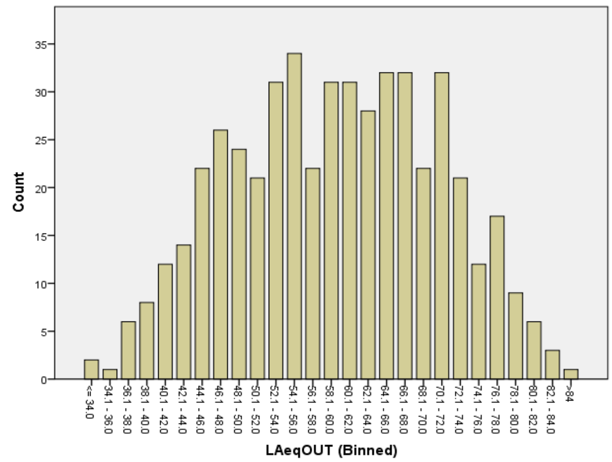


Figure 5. Distribution of free-field LAeq,1h for 500 traffic flow/distance scenarios. The count is the number of scenarios with a particular LAeq (in 2 dB bands).

3 NNEs DETECTED ACROSS ACOUSTIC CONDITIONS IN PROXIMITY TO ROADWAYS

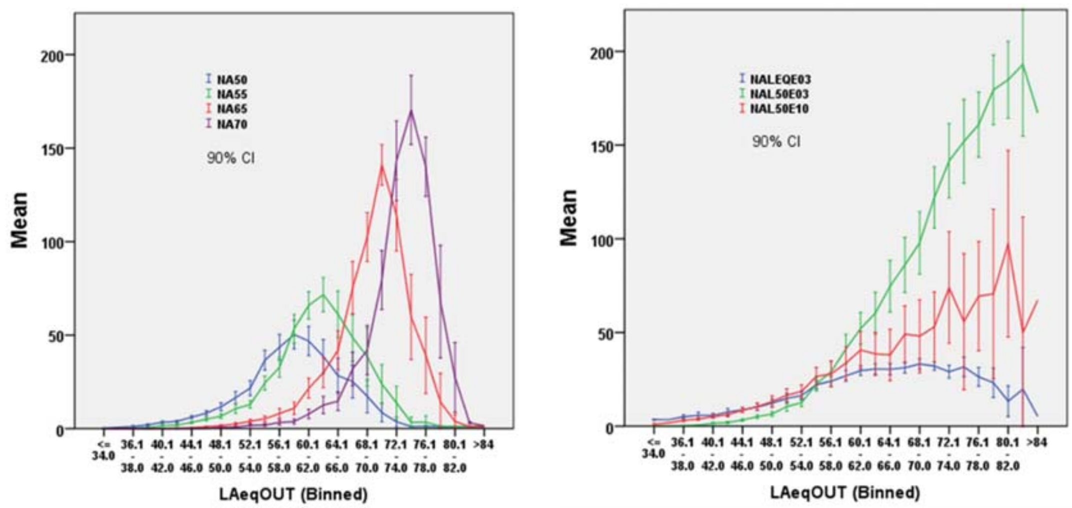
This investigation first generated a population of acoustic conditions near roadways by systematically simulating the time history of road traffic noise for 500 different traffic flow/propagation-distance conditions (2 speeds x 10 flow rates x 5 traffic mixes x 5 distances: speeds 60, 100 km/h; traffic flows 5, 10, 20, 50, 100, 200, 500, 1 000, 2 000, 5 000 veh/h; proportions of heavy vehicles 0, 10, 20, 50, 100 % heavy vehicles; distances 7.5, 15, 30, 60, 120 m. The patterns of time history of noise signals for each of these conditions were then searched with the seven algorithms, detecting and counting noise events (NNEs). The LAeq was also calculated. The LAeq is as would be measured free-field, outside the dwelling. Figure 5 illustrates the population of LAeq,1h generated by the 500 modelled scenarios, but plotted in 2 dB bands. The range was from just under 34 dB to near 84 dB. Counts in any one band may result from very different scenarios: either, for example, from very high traffic flows at a considerable distance, or from lower flow rates but at a close distance.

Six of the event indicators identified the NNEs as detected inside a dwelling with windows open; one event indicator counted NNEs as detected inside a dwelling but with windows of the dwelling closed. For convenience in presenting results, a simpler name is adopted in the remainder of this paper for the NNE counts from each of the representative detection algorithms. Outputs from the four algorithms which counted the number of events based on exceedance of fixed thresholds of 50, 55, 65 and 70 dB (open windows) are now termed NA50 (Number of events above 50 dB), NA55, NA65 and NA70. NNE outputs from the adaptive threshold algorithms based on exceedance of the inside L50 (by 3 dB and 10 dB) and are now termed NAL50E03 and NAL50E10. The NAL50E03 was different to the other four in that it was based on indoor levels with windows closed – as compared to windows open conditions for all other algorithms. The seventh algorithm was the adaptive thresholds requiring the inside LAeq to be exceeded by 3 dB and NNEs detected is NALEQE03.

The results of applying the seven detection algorithms to the time histories of road traffic noise generated by the 500 traffic/distance conditions are shown in Figures 6. The figures plot the mean NNEs detected by each algorithm against the LAeq for the same scenario. The mean is calculated for those scenarios which result in an

LAeq,1h within each of the 2 dB bands of exposure. The vertical bars on the algorithms are the intervals that contain 90% of the NNEs detected by that algorithm within that 2 dB band of LAeq. The source of this variation in NNEs is not ‘error’ - it reflects that different scenarios that generate the same LAeq may be associated with a range of different NNEs.

The NNEs detected by each of the fixed exceedance open-window algorithms have a Gaussian distribution on LAeq (Figure 6(a)). The NNEs detected by the L50-based adaptive threshold algorithms (Figure 6(b)) have very different relationships with LAeq, with the mean NNEs tending to increase monotonically with LAeq but with a large spread in NNEs about the mean. The LAeq-based adaptive threshold algorithm has a distribution more like those of the fixed threshold algorithms, but much flatter and with a lower NNEs detected.



(a) (b)

Figure 6. Mean NNEs for each 2 dB band of LAeq (outside) for 500 traffic/distance scenarios (a) fixed threshold NA50, NA55, NA65, NA70; (b) Adaptive thresholds algorithms: NAL50E03, NAL50E10 and NALEQE03,

Visual examination of Figures 6 (a) and (b) shows non-monotonic relationships between LAeq and the mean NNEs detected by the four fixed threshold algorithms and by the NALEQE03 algorithm. The mean NNEs of both the L50-based adaptive thresholds in Figure 6 (b) increase consistently with LAeq up to the levels of 80/82 dB, thus these two algorithms nominally fail the non-monotonicity test required for an event-based indicator to supplement the energy-based indicator. However, the spread of the NNEs about the mean NNEs for the NAL50E10 algorithm is so large, as indicated by the vertical bars, that particular values of NNE in individual scenarios could be associated with many different values of LAeq.

The NA50 and NA55, and the NAL50E10, have low correlations with LAeq, (Table 2) indicating that these measures can provide useful supplementary information beyond that of the LAeq. The NA65 and NA70, and the other two adaptive algorithms, NAL50E03 and NALEQE03, have high rank order correlations with LAeq, suggesting they would not be useful as supplementary indicators. Only NA50 and NA55, and the NAL50E10, meet the I-INCE (2015) criterion that a product-moment correlation between LAeq and a supplementary events measure must not exceed 0.5.

Table 2. Correlations between LAeq outside, and NNEs inside. Open windows condition for all detection algorithms, except closed for NAL50E03. n = 500.

`		NA50	NA55	NA65	NA70	NAL50E03	NAL50E10	NALEQE03
Spearman’s rank correlation coefficient	LAeqOUT	- .244	.123	.787	.868	.917	.384	.633
(Pearson correlation)		(.003)	(.216)	(.573)	(.628)	(.824)	(.454)	(.611)

The NA50 and the NA55 fixed-threshold algorithms, and the adaptive-threshold NAL50E10 are primary candidates for further consideration as event-counting indicators. The correlation of adaptive threshold based on exceedance of LAeq by 3 dB (the NALEQE03) with LAeq is modest, but it is examined further below because of its very different construction.

The different algorithms have distinctly different ranges of LAeq over which they detect events. This accords with the interpretation in the CATPCA analysis that several groups of fixed-threshold algorithms are associated with lower overall levels of road traffic noise and that some are associated with high overall levels. The adaptive-threshold algorithms detect events across the full range of LAeq, but with far fewer at levels below 50 dB. Anecdotally, events in road traffic streams are seen to be an issue in terms of human response at lower levels of road traffic noise – for example at night when traffic flows and overall levels are lower, with noisier vehicles heard above these lower levels. If this is correct it would suggest that it may be appropriate to adopt algorithms (NA50, NA55) that detect events in traffic noise signals at least at the low end of the LAeq scale.

3.1 Relationship of NNEs Detected and LAeq: Identification of Algorithms that Meet the Requirements of a Supplementary Indicator

A more detailed examination of the relationships between NNEs detected and the LAeq across the 500 traffic/distance scenarios is possible from Figure 7. These panels plot the NNEs as they would be detected inside a dwelling with open windows for all traffic flows modelled - with separate panels for each combination of traffic speed and distance from the roadway - against the outside LAeq. The LAeq is, as would be expected: linearly related to the log of traffic flow; slightly lower at the lower vehicle speed of 60km/h than of 100km/h; and decreases with increasing distance from the source roadway. For clarity, the effects of variation in the percentages of heavy vehicles on the indicators is not shown – and both the LAeq and the NNEs plotted are the arithmetic means for the five different traffic composition scenarios modelled. (The level dependence on the percentage of heavy vehicles in the traffic stream would be only a small vertical translation in the LAeq line, and the effect of traffic composition on NNEs is examined in more detail in the next section). Figure 7 confirms the observation above that NA50 and NA55 both have distinct non-monotonic relationships with LAeq, and are potential supplementary indicators. They detect events from the lowest traffic flows up to traffic flows of 1,000 to 2,000 vehicles per hour, with no events detected at higher flow rates. Both indicators also detect events at all the distances modelled, with decreasing numbers of events as the distance from the roadway increases.

Figure 7 also confirms the observation above that NAL50E10 also has a non-monotonic relationships with LAeq, and thus a potential supplementary indicator. It detects events across the full range of traffic flows, with the maximum number occurring at flow rates of 500 to 2,000 veh/h. But unlike the NA50 and NA55, the maxima occur at lower flow rates as distance from the roadways increases. The NNEs also decrease with distance. The NALEQ03 is different in that it has a much flatter distribution, with events being detected across the full range of traffic flows, but in much smaller numbers than for any of the other algorithms - and with some events being detected even at the highest flow rates.

The conclusion from examination of Figures 7 is that the NA50, the NA55 and the NAL50E10 can all be considered for practical application as event detection indicators, with the primary difference being that the NAL50E10 detects the maximum NNEs at higher traffic flow rates, but with the maxima occuring at increasingly lower flow rates as the distance from the roadway increases. All detect noise events heard indoors with the windows of the dwelling open.

4 TRAFFIC AND DISTANCE SCENARIOS AND EVENT DETECTION

The traffic and distance conditions that generate the different values of NA50 and NAL50, are shown in Figures 8 and 9.

In Figure 8 it can be seen that, at the closer distances to the roadway, events above 50 dB are detected at the very lowest traffic flows, increasing to a maximum NA50 around 200 veh/h. then decreasing rapidly to zero at between 500 and 1,000 veh/h. The increase in the NA50 as traffic flow increases from the lowest flows is indicative that every passing vehicle triggers the NA50 algorithm – irrespective of the mix of light and heavy vehicles on the roadway. Above 200 veh/h when all vehicles are cars - but at about 100 veh/h when there are 100% heavy vehicles - the NA50 peaks then starts to decrease, and this is explained by the smaller vehicles headways at these flow rates resulting in the “filling in” of the traffic noise signals as the gap between successive vehicles decreases (Brown, 2013). This results, at about 1,000 veh/h and for low proportions of heavy vehicles, in the NA50 detecting zero events because the indoor traffic noise signal (with windows open) never drops below the detection level of 50 dB. This transition occurs at lower vehicle flow rates with increasing percentages of heavy vehicles in the mix. At higher flow rates, zero events are detected as the level stays above the threshold.

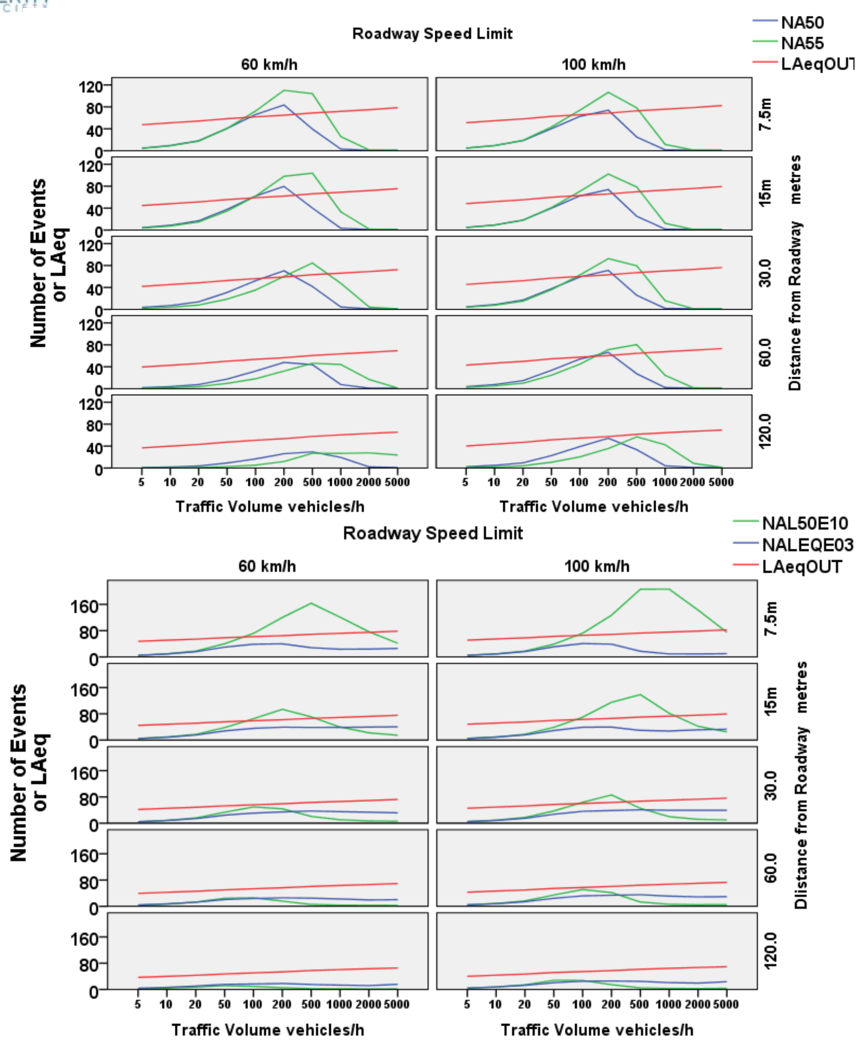


Figure 7. Comparison of outdoor LAeq with: NA50, NA55, NAL50E10 and NALEQ03.

At 100km/h the distributions are largely similar to those for 60 km/h but the maxima NNEs are lower for the flows with lower proportions of heavy vehicles – presumably because at the higher speeds the emissions of the light vehicles have increased more than do those of the heavy vehicles, resulting in earlier "infill" in the gaps between vehicles. While it appears counter-intuitive, more events are detected by NA50 at all but the lowest flow rates when there are fewer heavy vehicles in the traffic stream

The NA50 is lower with increasing distance from the roadway. At the largest distance modelled (120 m) the NA50 no longer detects events at flow rates below about 100 veh/h unless the proportion of heavy vehicles in the mix is very high – presumably because most cars do not produce high enough levels at these distances to trigger an event.

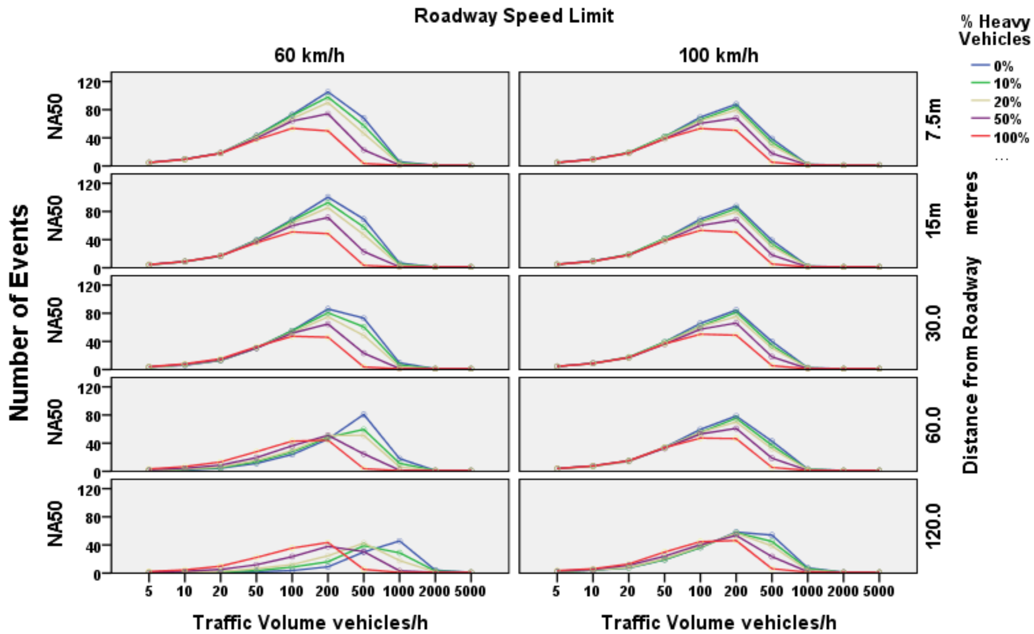


Figure 8. NNEs detected exceeding an indoor level of 50 dB (NA50), with windows open.

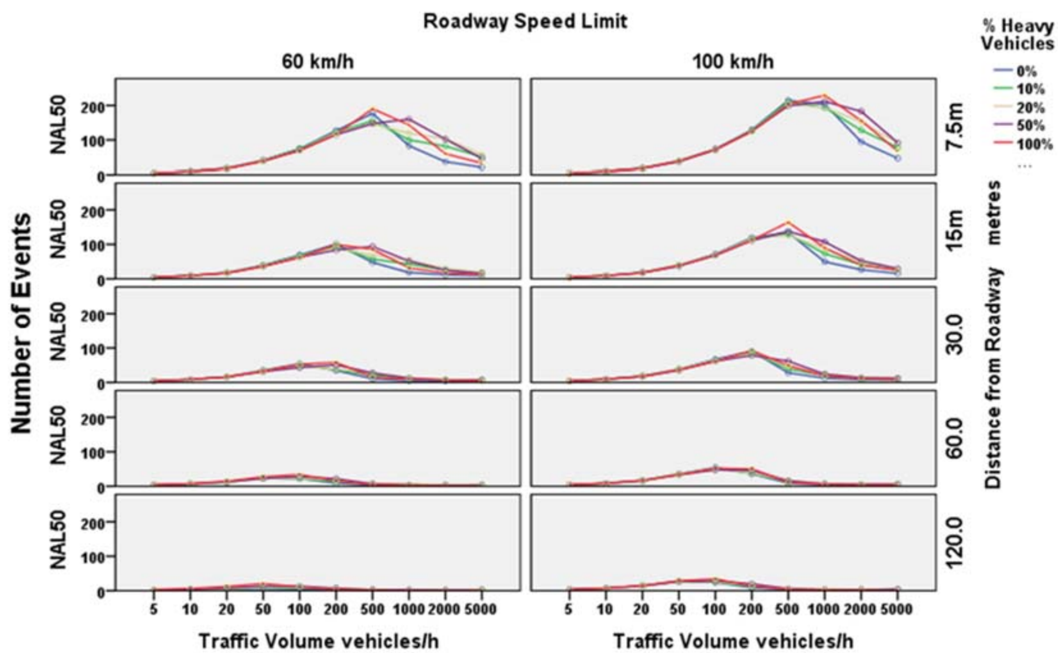


Figure 9. NNEs detected exceeding the indoor L50 by 10 dB (NAL50 algorithm) with windows open.

The equivalent results for the NA55 are not shown, but tend to follow the same pattern as the NA50 across most of the scenarios, but with a somewhat greater number of events detected at any given scenario, and with the distributions of NNEs translated to slightly higher traffic volumes.

Figure 9 shows that the adaptive threshold NAL50 tends to detect a higher number of noise events than either NA50 or NA55 for most traffic/distance scenarios. Events are detected across all traffic flow rates, from very low flows to the highest, but with very flat Gaussian distribution with some negative skewness for all distance/vehicle speed conditions. The maxima of the NNEs detected is much lower, and occurs at lower traffic flow rates (in contrast to NNEs detected by the fixed threshold algorithms) with increasing distance from the roadway. This would appear to be due to the adaptive characteristic of this algorithm, with the L50 dropping with increasing distance from the roadway, but with the maxima from individual vehicles dropping even more because these levels attenuate according to point source spreading. As a result, the NAL50 decreases with distance. It is not intuitively obvious why this effect of distance is so strongly dependent on traffic flow. Speed has very little effect on NNEs detected by the NAL50, though there are slightly more events at 100 km/h than at 60 km/h, and it is also largely independent of traffic mix (apart from at the higher traffic volumes and closer distances).

5 SUMMARY

This paper has reported further progress on a project to determine algorithms for the detection of noise events in streams of road traffic noise. Use of noise event measures to supplement conventional noise indicators such as LAeq for management of road traffic noise will, in the end, have to be tested through human effects research – that is, by examining if and how levels and events contribute, independently or in combination, to an association between road traffic noise and human response. While there are ongoing suggestions, both from sleep research and from other studies of human effects of noise, that human response may also depend on noise events in road traffic noise exposure as well as level, there is no agreement as yet as to how noise events should be measured.

Earlier work described a suite of algorithms for the detection and counting of the number of noise events (NNEs) in road traffic signals inside dwellings, all based on the traffic noise levels exceeding either fixed or adaptive thresholds - the latter being either the L50 or the LAeq of the signal. There is a large number of alternative constructions of these threshold-based algorithms, even after those that are unreliable or produce unreasonable numbers of events are identified.

This paper reports the performance of a parsimonious set of these algorithms in the detection of events in time histories of road traffic noise in a population of acoustic conditions found near roadways. The latter was obtained through simulation of 500 different traffic flow/propagation-distance conditions. The finding was that the NA50 and NA55 (detecting when the road traffic noise exceeded 50 dB and 55 dB respectively), and the NAL50E10 (detecting when the traffic levels exceeded L50 + 10 dB) can all be considered for practical application as event detection indicators. All three apply to measurement of indoor events with the windows of the dwelling open. This finding is based on the pre-condition, for any such supplementary measure, that its relationship with LAeq is non-monotonic.

ACKNOWLEDGEMENTS

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