

A study of the performance of a generalized exceedance algorithm for detecting noise events caused by road traffic

A. L. Brown^a, Bert De Coensel^{b,*}

^a*School of Environment and Science/Cities Research Institute, Griffith University, Brisbane, Australia*

^b*Waves Research Group, Department of Information Technology, Ghent University, Belgium*

Abstract

A key question for road traffic noise management is whether prediction of human response to road traffic noise could be improved by accounting for noise events instead of, or in addition to, energy equivalent or percentile measures of noise exposure. However, there is a critical prior question: how should noise events in road traffic be measured? Even at moderate traffic flow rates, detecting and counting noise events caused by road traffic is not a trivial exercise, and as yet there is no generally accepted noise event detection algorithm. This paper investigates the performance of a generalized exceedance algorithm for detecting noise events, constructed on the basis of the literature on noise events caused by road traffic. For this purpose, a microscopic traffic simulation model, coupled to an emission model that accounts for distributions of sound power levels of individual vehicles, is used to simulate one-hour time histories of the noise level in the proximity of a roadway, for an exhaustive set of traffic flow/composition and propagation distance conditions in unshielded locations. The validity and reliability of the number of noise events detected by the generalized algorithm in these one-hour time histories is then evaluated for a range of algorithm parameter sets. By discarding parameter sets that do not result in an algorithm that returns valid or reliable counts, and by examining redundancy in the remaining ones, a small number of representative parameter sets is identified, which may prove useful in the construction of event-based indicators supplementary to energy-equivalent measures of road traffic noise.

Keywords: Noise event, Detection algorithm, Indicator, Road traffic

PACS: 43.50.Lj, 43.50.Rq

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. The term *noise event* has been used extensively across road, rail and air transport modes (e.g. [1–5]). Synonyms for noise events, and other related terms describing event concepts, are: *maxima* [6], *emergences* [7, 8], *noise peaks* [8], *peak* or *max dB(A) levels* [9], or *peak noise/sound levels* [10–14]. Also used is the non-acoustic term *vehicle passby* [15]. In the literature of noise events, reference to peaks in road traffic noise signals (as in [13, 16]) are to noise events as described above, not to the peak sound pressure. A related concept, but defined instead as an instant of attention focus by an individual on the physical occurrence of a noise event, is the concept of *notice events* [17, 18]. Noise events in traffic noise streams have also been described in inverse, using terms such as *lulls* [19], *noise-free intervals* or *windows* [20].

Noise events in transport noise signals are of interest because of the role they may play in human response to the noise, including disturbance to sleep, annoyance, interference with activities, cardiac responses, and effect on children in schools. Brown [21] has provided an overview of the scattered, but persistent, evidence regarding the effects of noise

*Corresponding author

Email addresses: lex.brown@griffith.edu.au (A. L. Brown), bert.decoensel@ugent.be (Bert De Coensel)

16 events in road traffic streams on human response. The presence of events is postulated to result in effects beyond those
17 attributed to the level of road traffic noise exposure itself—the latter measured through conventional indicators such
18 as L_{Aeq} and L_{A10} . The Environmental Noise Directive [22] notes the potential use of noise events as *supplementary*
19 to the standardized energy-based indicators of noise exposure, though there appears to be limited application of such
20 supplementary indicators to date. The WHO [23] suggests that events be measured by a combination of number of
21 events and their level, but also noted that as yet there was no generally accepted way to count the number of events.
22 For aircraft noise, measurement of noise events from overflights is standardized (e.g. [24]) and counts of events, or
23 measures such as SEL, are relatively straightforward because of the time separation between successive overflights.
24 However, road traffic can have much shorter vehicle headways, resulting in problematic event detection and counting,
25 even at moderate traffic flow rates [25–27]. Apart from their role in potentially explaining human response to certain
26 traffic noise conditions, there is also an interest in road traffic noise events as an intermediate step in the estimation
27 of energy measures of the whole traffic flow noise signal, or in the estimation of uncertainty measures due to the
28 variability of the acoustic sources in time (as in [28]). The latter applications are not considered further in this paper.

29 This study applies a rigorous approach to the exploratory definition and measurement of noise events from road
30 traffic—something essential given the largely ad-hoc approaches to event measurement in road traffic noise streams to
31 date. In Section 2 we compile and categorize different formulations of event-based indicators relevant for road traffic
32 noise that have appeared in the literature; formalize a general conceptualization of road traffic noise events based on
33 these; systematically extend the set of event indicators to cover all relevant and realistic exceedance dimensions; and
34 develop a formal approach to the detection of these events in time histories of road traffic noise. We then examine,
35 through a modelling study, the behaviour of this generalized event detection algorithm across acoustic conditions
36 generated from a wide range of traffic parameter and propagation distance conditions found near roadways. The
37 conditions we utilize are, effectively, the population of acoustic conditions that can exist near roadways where there is
38 direct propagation of sound from traffic sources to receivers (that is, excluding only situations with roadside barriers or
39 shielding by urban infrastructure). We also examine the limits on the likely repeatability of measurement of different
40 noise event measures in practice, and the sensitivity of counts of noise events to the parameters of the event detection
41 algorithms that define them. Finally, the wide range of parameter value combinations of the generalized noise event
42 detection algorithm, based on exceedance, is narrowed to a smaller, hence more manageable in future work, valid,
43 reliable set.

44 The research methodology of the modelling study is outlined in Section 3, and the results are analyzed in Section 4
45 and Section 5. The intent of this paper is to rigorously and comprehensively report counts of noise events arising from
46 different possible algorithm definitions for detecting noise events in road traffic, the interrelationships between these
47 alternatives, and any practical limitations on their use. Our focus is on alternative ways in which noise events in
48 road traffic noise might be measured, and on the sensitivity of the number of noise events to different traffic and
49 distance conditions for the different formulations of a noise event. Increasing the rigour and the understanding of the
50 occurrence and measurement of road traffic noise events in this way is a prerequisite to future studies that may seek
51 to develop relationships between the level and number of noise events in road traffic streams, and human responses to
52 events in terms of annoyance and sleep disturbance—and to attempts to limit or manage exposure to events.

53 2. Noise events

54 Estimation of noise event metrics in the sound level signal caused by traffic noise requires a two-step procedure.
55 Firstly, individual events in the time history of the traffic noise signal have to be identified using a detection algorithm
56 based on a set of criteria, for example the instantaneous sound level exceeding a predefined threshold. Secondly, once
57 individual events are identified, summary indicators can be calculated, such as the total number or total duration of all
58 noise events over the period of interest. Sections 2.1 and 2.2 focus on the first stage of identifying noise events based
59 on detection algorithms used in literature over the past decades. These are reviewed, and a generalized noise event
60 detection algorithm is proposed. With events detected by a specific algorithm, noise event metrics for the period of
61 interest can then be calculated. Section 2.3 summarizes different noise event metrics that have been proposed in the
62 same body of literature—though in this paper, the focus is primarily on the number of noise events.

63 2.1. Noise event detection in literature

64 A wide range of algorithms, protocols, or criteria, have been reported in the literature for identifying noise events
 65 within a time series of A-weighted sound levels—usually from road, rail or aircraft sources. These algorithms have
 66 been built into noise measurement equipment systems (e.g. [29]), used in experimentation or field studies (e.g. [30]),
 67 or sometimes just postulated as possible approaches to event detection. To date, there is no agreement regarding
 68 the appropriate algorithm for event detection in road traffic noise streams. This study makes no a priori assumptions
 69 regarding identification of a noise event. Although noise event detection algorithms have typically been constructed *ad*
 70 *hoc*, a general commonality among algorithms is that they utilize exceedance of some threshold of the instantaneous
 71 sound level of the traffic noise signal. Three main categories of algorithms can be identified, which differ in how this
 72 threshold is constructed.

73 In the first category of algorithms, the *threshold* for noise event detection is set to a predefined, fixed, value. Typical
 74 values for this threshold range from 45 dB(A) for identifying events in indoor situations with closed windows [31] to
 75 80 dB(A) for detecting events in outdoor situations [8, 32]. Some authors [1, 30, 33] have adopted variable thresholds,
 76 even within the same study, depending on vehicle flow rates (higher thresholds being used with higher flow rates).
 77 In the second category of algorithms, events are detected when the instantaneous sound level *emerges* by a specified
 78 amount above a predefined background level [26, 34, 35]. The first category of algorithms can be seen as a subset
 79 of the second category, in which the emergence is set to zero. In the third category, events are detected when the
 80 instantaneous sound level emerges by a specified amount, typically 3 to 15 dB(A), above another conventional traffic
 81 noise indicator, such as L_{Aeq} [36, 37], L_{A50} [7, 38] or L_{A90} [25, 39], this way used as an *adaptive* threshold.

82 In their suggested event algorithms, most authors have implemented additional decision rules as to whether to
 83 retain or reject exceedances above the threshold as noise events. A first criterion commonly encountered is based on
 84 the duration of the exceedance. For example, events may have to last for at least 2 to 3 s, before they are counted [1,
 85 25, 33, 38]. In [31], a much longer minimum event duration of 30 s is used, but their detection algorithm is mainly
 86 directed towards air and railway traffic noise events. In [29] and [25], in addition, a maximum duration is set on the
 87 length of an event. Another criterion is based on the time between events. A minimum time gap between noise events
 88 can be set to implement an elementary hysteresis effect into the detection algorithm [25, 29, 39]. This overcomes
 89 the problem of multiple event registrations of a single event with irregular rise or decay pattern, and it responds to
 90 the (untested) notion that multiple events in short sequence are likely to be perceived as a single event, or that the
 91 disturbances caused by multiple events might be experienced as one disturbance.

92 Table 1 summarizes the parameters for a number of transportation noise event detection algorithms found in
 93 literature. This table is not meant to be comprehensive, but gives an idea of the ranges of parameters that have been
 94 used in literature, and this has guided the research methodology that will be presented in Section 3 below. For each
 95 reference, Table 1 indicates the type of noise source that the algorithm has been designed for, and the situation in
 96 which it has been applied (noise events detected indoor or outdoor). Typically, the instantaneous A-weighted sound
 97 level envelope of the noise signal is used as the time series, but various time weighting (S/F) and sampling rates can
 98 be found (see [27]). Often not all details were reported as to the basis on which noise events were detected. Note that
 99 here, only detection algorithms that are based solely on (the time history of) the sound signal are discussed. There are
 100 other approaches, such as those in which event time periods are set *a priori* based on data from an external database,
 101 e.g. for airplane overflights, those in which there is human intervention in selecting events, or those that apply more
 102 general pattern recognition techniques to identify outliers (e.g. [40]). These approaches are outside the scope of this
 103 work.

104 2.2. A generalized noise event detection algorithm

105 Based on the overview of the literature in Section 2.1, a generalized noise event detection algorithm based on
 106 exceedance is proposed. The approach is illustrated in Figure 1, in which an example of a sound level time history
 107 $L_A(t)$ is shown. The onset of the i th noise event at time $t_{1,i}$ is detected when the instantaneous level exceeds a threshold
 108 L_α . This threshold itself consists of a background level L_β and an emergence E ,

$$L_\alpha = L_\beta + E \quad (1)$$

109 and may vary in time (e.g. when the background level L_β is set to an adaptive value such as L_{A50} , calculated over a
 110 limited period of time). The end $t_{2,i}$ of the noise event is reached when the sound level drops below the threshold L_ω .

Table 1: Various noise event detection algorithms for transportation noise found in literature (L_β = threshold level; E = emergence; τ_e = event duration; τ_g = time between events).

Reference	Source type	Application	Envelope	L_β	E	τ_e	τ_g
Ribeiro et al. [41]	road/rail/air	outdoor	$L_{Aeq,1s}$	55 dB(A)	0 dB(A)	–	–
Murray [29]	road	outdoor	L_{AF} @ 250 ms	65 dB(A)	0 dB(A)	≤ 25 s	≥ 3 s
Fidell et al. [33]	air	indoor	L_{AF} @ 500 ms	site-specific	0 dB(A)	≥ 2 s	–
Sato et al. [42]	road	outdoor	not specified	75 dB(A)	0 dB(A)	–	–
Lambert et al. [32]	rail	outdoor	not specified	70/80 dB(A)	0 dB(A)	–	–
Hall et al. [31]	road/rail/air	indoor	L_{AS} @ 1 s	45/50/55/60/65 dB(A)	0 dB(A)	≥ 30 s	–
Taylor et al. [30]	road/air	outdoor	not specified	55/60/65/70/75 dB(A)	0 dB(A)	–	–
Can et al. [8]	road	outdoor	$L_{Aeq,1s}$	75/80 dB(A)	0 dB(A)	–	–
Fidell et al. [1]	air	indoor/outdoor	L_{AF} @ 1 s	50/60/70 dB(A)	0 dB(A)	≥ 2 s	–
Müller et al. [34]	air	indoor/outdoor	L_{AS} @ 125 ms	not specified	4 dB(A)	–	–
Mietlicki et al. [35]	road	outdoor	not specified	not specified	10 dB(A)	–	–
Griefahn et al. [26]	road/rail	indoor	not specified	not specified	10 dB(A)	–	–
Wunderli et al. [36]	road/rail/air	outdoor	$L_{Aeq,1s}$	$L_{Aeq,T}$	3 dB(A)	–	–
Campbell and Isles [37]	road	outdoor	$L_{Aeq,250ms}$	L_{Aeq}	15 dB(A)	–	–
De Coensel and Botteldooren [38]	road/rail/air	outdoor	L_{AS} @ 1 s	$L_{A50,30s}$	3 dB(A)	≥ 3 s	–
Beaumont and Semidor [7]	road/rail	outdoor	$L_{Aeq,30s}$	$L_{A50,10min}$	5/10/15 dB(A)	–	–
Aasvang et al. [25]	road/rail	indoor/outdoor	L_{AF} @ 1 s	$L_{A90,5min}$	10 dB(A)	≥ 2 s, ≤ 40 s	≥ 5 s
Tulen et al. [39]	road	indoor	$L_{Aeq,1s}$	$L_{A90,10min}$	10 dB(A)	–	≥ 15 s

111 Other characteristics of the i th noise event are its duration $\tau_{e,i} = t_{2,i} - t_{1,i}$, the time gap (or noise free interval) since
 112 the previous noise event $\tau_{g,i} = t_{1,i} - t_{2,i-1}$, the maximum sound level $L_{Amax,i}$, the time $t_{max,i}$ when this maximum sound
 113 level within the event is reached, and its event sound exposure level

$$SEL_{e,i} = 10 \log_{10} \left(\int_{t_{1,i}}^{t_{2,i}} 10^{L_A(t)/10} dt \right) \quad (2)$$

114 These additional characteristics can be used to retain/reject particular events. Table 1 shows the values for the param-
 115 eters L_β and E , and the ranges for the parameters τ_e and τ_g used in the references.

116 2.3. Summary metrics based on detected noise events

117 Once individual noise events are detected, summary indicators can be calculated over a given period of interest.
 118 Table 2 gives an overview of some summary metrics that others have proposed (again, this list is not meant to be
 119 exhaustive). According to Marks et al. [43], summary metrics can be categorized into those that characterize the
 120 *microstructure* or the *macrostructure* of the sound signal time history. The former characterize the properties of
 121 individual events whereas the latter characterize the succession of noise events. These categories are separated in
 122 Table 2 by a horizontal line. In practice, for road traffic noise, both categories depend on quite different physical
 123 drivers. The acoustical microstructure of noise events depends mainly on vehicle type and source strength of the
 124 vehicles on the roadway, on the speed at which they are travelling, and on the distance from the roadway sources to
 125 the receiver. By contrast, the acoustical macrostructure depends mainly on the volume of traffic on the roadway.

126 By far the most commonly used macroscopic metric is simply the number N (also noted as NNE) of noise events
 127 over a period of interest with duration T . This number can be normalized to a particular time unit, such as the number
 128 of events per hour, and can be counted in bins according to the maximum level of the noise event. Referring to the
 129 notion of the threshold that is used to detect noise events, this metric is also sometimes called the “number above
 130 threshold” NA . A second metric is the total (cumulative) duration T_e of noise events, sometimes called “time above
 131 threshold” TA . A related metric is the mask index MI , defined as the fraction of time that noise events are detected [8].
 132 In contrast, one may also consider the noise free intervals as the relevant metric (see e.g. Roberts et al. [19]), and define
 133 the total and average duration of noise free intervals (or the “time below threshold” TB).

134 Examples of microscopic metrics are the average and worst case maximum level of noise events, the average rise
 135 time of noise events, or the total sound exposure level of noise events, defined in Table 2. Two additional metrics
 136 are the intermittency ratio IR [36] and the unexpectancy U [44]. The intermittency ratio is defined as the ratio of the

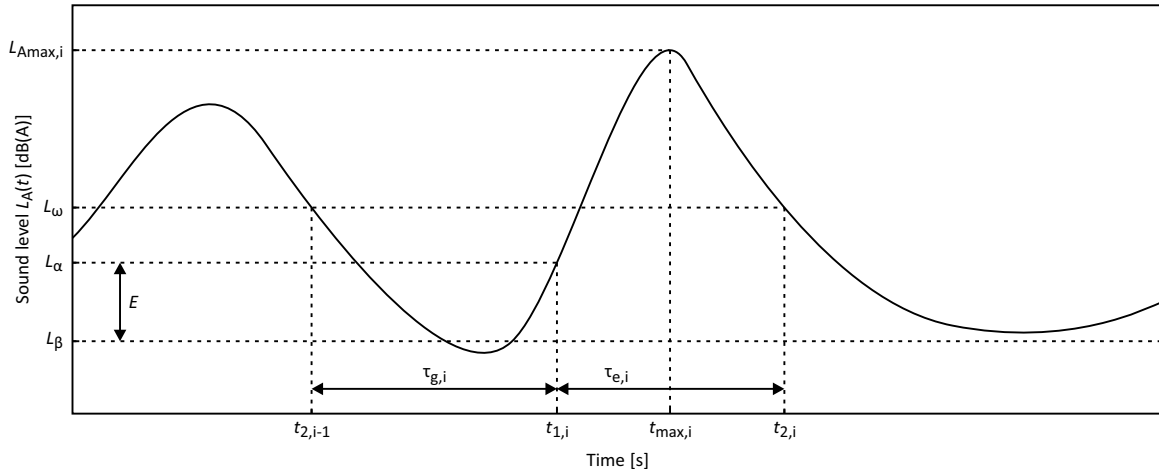


Figure 1: Parameters of the generalized sound event detection algorithm.

137 event-based sound energy to the total sound energy in the traffic noise signal. The possibility of calculating energy-
 138 equivalent sound level metrics on only that part of the sound signal above some threshold has been suggested several
 139 times in the past [18, 45]. The unexpectancy is defined as a linear combination of the variance of the maximum
 140 levels of the sequence of events and the variance of the temporal gap between successive events, with a and b being
 141 constants (no values are given in [44]). The rationale behind this metric is the hypothesis that when events are regular
 142 in succession, such as with trains passing by, they are much more predictable, whereas for irregular events such as
 143 originating from air or road traffic, they are not expected.

144 In this paper, only the macrostructure summary metric, number of noise events, will be considered.

145 3. Methodology

146 The overall methodology involves testing how different formulations of event detection perform across the popu-
 147 lation of acoustic conditions that exist near roadways. A modelling approach was adopted as this provides the ability
 148 to test the generalized algorithm against time histories of traffic noise generated for all likely situations. In these,
 149 traffic flow variables, and the propagation distance from roadway to receiver, covered a full range of realistic values,
 150 and these could be varied independently—something that would be largely impractical using data gathered in field
 151 measurement studies. The modelling study follows a two-stage approach. Firstly, the time history of instantaneous
 152 sound level is simulated for a large set of road traffic noise exposure scenarios (Sections 3.1, 3.2 and 3.3). Secondly,
 153 an extensive set of alternative parameter values of the generalized exceedance algorithm (Section 3.4) is utilized to
 154 detect and count noise events in these time histories. Analysis focuses on the repeatability of the counts of events
 155 when using different parameter values in the exceedance algorithm, and on examining, and reducing, redundancy in
 156 the results obtained from the many alternative formulations of event detection.

157 3.1. Simulation of instantaneous sound level

158 The instantaneous sound level in free field caused by road traffic is simulated using the road traffic noise pattern
 159 simulation model described in De Coensel et al. [46]. This model, called Noysim2, combines a microscopic simulation
 160 of road traffic with an instantaneous vehicle noise emission and a point-to-point sound propagation model. Aimsun, a
 161 commercially available microscopic road traffic simulation model (distributed by TSS Transport Simulation Systems),
 162 is used to simulate the traffic. In particular, given a road network, vehicle fleet properties and aggregated traffic demand
 163 data, the movement of individual vehicles is simulated, and the instantaneous position, speed and acceleration of each
 164 vehicle at each timestep during a predefined simulation period is provided.

165 Subsequently, the instantaneous emission of all sources is calculated using a noise emission model that includes
 166 distributions of vehicle sound power levels [46]. This model is based on the Imagine road traffic noise emission

Table 2: Overview of macrostructure and microstructure summary metrics of noise events.

Description	Formula
Total number of noise events	N
Total duration of noise events	$T_e = \sum_{i=1}^N \tau_{e,i}$
Average duration of noise events	$\overline{T_e} = \frac{T_e}{N}$
Mask index [8]	$MI = \frac{T_e}{T}$
Total duration of noise free intervals	$T_g = \sum_{i=1}^N \tau_{g,i}$
Average duration of noise free intervals	$\overline{T_g} = \frac{T_g}{N}$
Average maximum level of noise events	$\overline{L_{Amax}} = \frac{1}{N} \sum_{i=1}^N L_{Amax,i}$
Worst case maximum level of noise events	$\max_i \{L_{Amax,i}\}$
Average rise time of noise events	$\frac{1}{N} \sum_{i=1}^N \frac{L_{Amax,i} - L_\alpha}{t_{max,i} - t_{1,i}}$
Total sound exposure level of noise events	$SEL_e = 10 \log_{10} \sum_{i=1}^N 10^{SEL_{e,i}/10}$
Intermittency ratio [36]	$IR = \frac{100}{T} \frac{10^{SEL_e/10}}{10^{L_{Aeq,T}/10}}$
Unexpectancy [44]	$U = a \cdot \var_{i} \{L_{Amax,i}\} + b \cdot \log_{10} \left(\frac{\var_j \{\tau_{g,j}\}}{T} \right)$

167 model [47], to which a per-vehicle correction is added that accounts for the distribution in sound power emitted
 168 by individual vehicles within different categories. Correction distributions were constructed based on a large set
 169 of roadside measurements [48]. Using individualized vehicle emission laws, this road traffic noise emission model
 170 accounts for the influence of vehicles that are producing more/less noise than the average vehicle.

171 Finally, the output of the Noysim2 road traffic noise simulation model consists of the time history of the instanta-
 172 neous sound level at the location of the receiver, calculated in 1/3-octave bands using the ISO 9613 sound propagation
 173 model [49]. As only broadband road traffic noise exposure is considered in this work, all sources have a similar emis-
 174 sion spectrum. Spectral aspects are therefore neglected in first order, and only the A-weighted instantaneous sound
 175 level at the receiver is considered. Psychoacoustic effects such as frequency masking, and the differential effect on the
 176 frequency spectrum of transmission of the road traffic noise signals through building envelope components, are thus
 177 outside the scope of this work. More details about the Noysim2 model and its operation can be found in De Coensel
 178 et al. [46].

179 3.2. Noise exposure scenarios

180 The modelling is based on a receiver adjacent to a straight dual-lane roadway carrying uninterrupted traffic. This
 181 is a setting encountered in rural areas, but also in urban areas away from intersections or signal controls. A wide range
 182 of road traffic noise exposure scenarios were modelled, even for this simple geometry, by varying traffic flow variables
 183 and the distance between the receiver and the road. Figure 2 shows a schematic drawing of the setting, together with
 184 the values used in the construction of the scenarios.

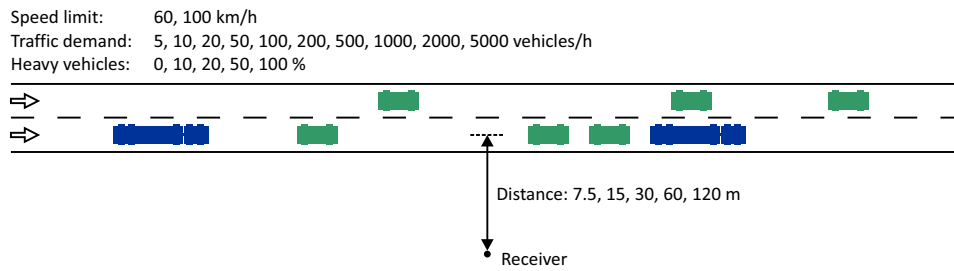


Figure 2: Schematic drawing of the simulated setting, together with variable value ranges.

185 By using a broad range for each of the variables, the idea is that the modelled scenarios include the population
 186 of noise conditions that could occur, in reality, along a single road link. An exhaustive set of scenarios is created
 187 by varying the speed limit (60 km/h or 100 km/h), the traffic demand (from 5 to 5000 vehicles/h), the percentage
 188 of heavy vehicles (from 0 % to 100 %), and the distance to the road (from 7.5 m to 120 m), as shown in Figure 2.
 189 The total number of unique scenarios thus equals $2 \times 10 \times 5 \times 5 = 500$. This simplified geometry is adequate for
 190 the purpose of this study, but more complex road network configurations could be modelled by the same system,
 191 where multiple roadway links, roadway intersections, and signalized controls on traffic could be introduced. The
 192 analysis is restricted to uninterrupted flow road traffic streams, in contrast to situations where traffic is congested or
 193 is known to be controlled by traffic signals or other devices (as in [8]). A rigorous investigation into the influence
 194 of different parameter values of the generalized algorithm for the detection of noise events from freely flowing road
 195 traffic streams is a prerequisite to any later application to interrupted traffic flow conditions. Note that the modelled
 196 settings also consider only unobstructed propagation, excluding situations with roadside barriers or shielding by urban
 197 infrastructure. We could have included the latter in our modelling, but as their effect is to reduce the emergence of
 198 peaks of passing vehicles above roadway background levels at receivers, obstructed propagation scenarios would not
 199 add unique dimensions to the population of noise scenarios that were modelled in this study.

200 The duration of each simulation was set at 1 h, with a timestep of 125 ms. The selected timestep allows for a
 201 good temporal resolution of the simulations, and equals the shortest sample interval found in the literature overview
 202 in Section 2.1. The choice of simulation duration was chosen as a compromise between simulation variability and
 203 real-life measurement pragmatics. On the one hand, variability between simulation runs can be expected due to the
 204 stochastic nature of the simulation model, and this variability is reduced by increasing the simulation duration. On
 205 the other hand, eventual field measurements based on the generalized event detection algorithm being examined, or
 206 potential future application of number of noise events as a noise limit, require that the measurement duration is kept
 207 within practical limits, and a 1 h period for these seems appropriate. The actual 1 h simulation runs included an
 208 additional warm-up period of 5 minutes. Vehicles are loaded onto the network at the entry of the road, randomly
 209 distributed in time according to a negative exponential distribution.

210 The simulation for each unique scenario was repeated 30 times, resulting in a total of 15,000 simulation runs (30
 211 $\times 500$) of 1 h time histories of road traffic noise levels near the roadway.

212 3.3. Building attenuation and background level

213 In general, standards and criteria for road, rail and air traffic noise are specified as limit levels outside of buildings
 214 (either free field, or as incident on or near the external façade). Most of these limits originated from exposure-effect
 215 studies in which exposure was measured outside of dwellings, and people’s annoyance, or some other effect, assessed
 216 whilst inside the dwelling. All predictions, mapping of exposure, assessment and (most) management of transportation
 217 noise is thus performed using outside noise levels, but with the outside noise level limits set to manage indoor human
 218 response.

219 There is a major difference in the consideration of noise events: most laboratory or field studies of sleep distur-
 220 bance have used noise stimuli specified in terms of levels at the sleeper’s ear—that is indoor levels. Thus any future
 221 limit criteria for noise events is appropriately based on indoor levels. For this study, in order to relate the simu-
 222 lated outdoor noise level time histories to noise exposure limits for sleep disturbance based on indoor levels, outdoor

223 time histories have to be modified by the attenuation provided by building façades (obviously façade attenuation is
224 frequency dependent, but for present purposes a consideration of A-weighted attenuations is sufficient). Outside-to-
225 inside attenuation of dwellings is critically dependent on the state of closure of windows in the sleeping room and, if
226 closed, window size and sound reduction of the window. Furthermore, human behavior with respect to window oper-
227 ations significantly alters the level of attenuation, and there is likely a different behavior between summer and winter,
228 tropical and temperate climates, air-conditioned or heated premises etc. There are divergent estimates of the effect
229 of the building envelope and of the state of window closure on the outdoor/indoor difference in levels of noise event
230 maxima. Marks et al. [43], assuming tilted windows, applied a 15 dB(A) attenuation to outdoor free-field measured
231 noise levels they presented to sleepers indoors. Measurements by Aasvang et al. [25] showed mean attenuation values
232 of 26 dB(A) for closed windows, and 11 to 24 dB(A) for open windows. Müller et al. [34] found median attenuation
233 values of 14, 18 and 28 dB(A) for open, tilted and closed windows respectively. The Night Noise Guidelines for
234 Europe [23] adopts an average insulation value of 21 dB(A) for outside to inside attenuation, noting that a large part
235 of the population in Europe sleeps with windows slightly open.

236 In addition to estimating the time history of road traffic noise indoors by accounting for the building envelope
237 attenuation, there is a need for additional consideration of the background levels experienced indoors, i.e. the levels
238 against which noise events from passing vehicles emerge. In urban areas, the outdoor background signal is likely to
239 originate from traffic on the road network at most hours of the day, except during the late night/very early morning
240 hours of low urban traffic flow. At those times, the background signal may be from insects or other natural sounds, as
241 would be the case in lower trafficked urban or rural areas. By contrast, the indoor background signal may additionally
242 be set by internally generated sources within the building, such as refrigerators, clocks, ventilator fans or similar. Both
243 building envelope attenuation and background level have an effect on the emergence of noise events, and consequently,
244 the outcome of any algorithm that counts noise events based on their emergence from the background.

245 In order to address the application of noise event detection algorithms to assess indoor human response to noise, the
246 parameter study performed in this work is based on the indoor sound. For the purposes of this study, this is illustrated
247 by considering just two conditions for building envelope attenuations: fully open and fully closed windows. Using
248 the mixed evidence described above, an outside to inside attenuation of 5 dB(A) is applied for the windows open
249 condition. For the closed windows, a building insulation of 25 dB(A) is used. Additionally, to simulate the indoor
250 time history, an internally generated level of 35 dB(A) is added to the simulated road traffic time history experienced
251 indoors. It can be foreshadowed that this internally generated level of 35 dB(A) only affects those scenarios which
252 generate relatively low noise exposures, i.e. those with low traffic volumes or at relatively large distance from the road,
253 and for all closed window conditions.

254 We thus base this examination of the performance of the generalized noise event detection algorithm for differ-
255 ent parameter values on building-attenuated time histories of road traffic noise signals as they would be experienced
256 indoors. We do note, however, that for longer-term practical application within the current paradigm of noise manage-
257 ment based on outside levels, the specific limits on indoor noise event levels (e.g. for sleep protection), would require
258 translation to an equivalent outdoor event limit.

259 3.4. Noise event detection algorithm parameter ranges

260 For each of the simulated scenarios, and for both building envelope conditions considered, noise event counts
261 are generated using the generalized noise event detection algorithm outlined in Section 2.2, by varying two main
262 parameters of the algorithm: the detection threshold L_α and the minimum time gap τ_g between events. For the
263 detection threshold, both the fixed and adaptive case is considered. Fixed thresholds vary from 45 to 75 dB(A) in
264 steps of 5 dB(A) (in a pilot study, also higher limits of 80, 85 and 90 dB(A) were considered, but such high thresholds
265 did not lead to results that were repeatable and/or sensitive to changes in traffic parameter or distance conditions).
266 The adaptive thresholds considered apply L_{Aeq} , L_{A50} or L_{A90} as background level L_β , and 3, 5, 10 and 15 dB(A) as
267 minimum emergences E above L_β . In this study, the adaptive thresholds L_{Aeq} , L_{A50} and L_{A90} are calculated over
268 the full 1 h simulation duration; in continuous measurement applications, one could consider to use a moving time
269 window. Four alternatives were used for the minimum time gap between events: 3, 5, 10 or 30 s. No lower limit was
270 set on the duration of events since the simulated sound level time histories only contain road traffic noise, and there
271 was no need to filter out occasional spikes of non-traffic flow related events such as door slams. This resulted in 76
272 different parameter sets (19 combinations of L_β and E , with 4 values of minimum time gap for each). Note that this
273 selection covers to some extent the redundancy in using emergence criteria in association with fixed threshold criteria;

Table 3: Naming convention for the 76 different parameter sets of the generalized noise event detection algorithm used in the modelling.

Threshold	L_α [dB(A)]	Minimum time gap between noise events			
		$\tau_g = 3$ s	5 s	10 s	30 s
Fixed	45	T45E00G03	T45E00G05	T45E00G10	T45E00G30
	50	T50E00G03	T50E00G05	T50E00G10	T50E00G30
	55	T55E00G03	T55E00G05	T55E00G10	T55E00G30
	60	T60E00G03	T60E00G05	T60E00G10	T60E00G30
	65	T65E00G03	T65E00G05	T65E00G10	T65E00G30
	70	T70E00G03	T70E00G05	T70E00G10	T70E00G30
	75	T75E00G03	T75E00G05	T75E00G10	T75E00G30
Adaptive	$L_{Aeq} + 3$	LEQE03G03	LEQE03G05	LEQE03G10	LEQE03G30
	$L_{Aeq} + 5$	LEQE05G03	LEQE05G05	LEQE05G10	LEQE05G30
	$L_{Aeq} + 10$	LEQE10G03	LEQE10G05	LEQE10G10	LEQE10G30
	$L_{Aeq} + 15$	LEQE15G03	LEQE15G05	LEQE15G10	LEQE15G30
	$L_{A50} + 3$	L50E03G03	L50E03G05	L50E03G10	L50E03G30
	$L_{A50} + 5$	L50E05G03	L50E05G05	L50E05G10	L50E05G30
	$L_{A50} + 10$	L50E10G03	L50E10G05	L50E10G10	L50E10G30
	$L_{A50} + 15$	L50E15G03	L50E15G05	L50E15G10	L50E15G30
	$L_{A90} + 3$	L90E03G03	L90E03G05	L90E03G10	L90E03G30
	$L_{A90} + 5$	L90E05G03	L90E05G05	L90E05G10	L90E05G30
	$L_{A90} + 10$	L90E10G03	L90E10G05	L90E10G10	L90E10G30
	$L_{A90} + 15$	L90E15G03	L90E15G05	L90E15G10	L90E15G30

e.g. an emergence of $E = 5$ dB(A) above $L_\beta = 45$ dB(A) is identical to an emergence of $E = 0$ dB(A) above $L_\beta = 50$ dB(A).

Table 3 shows the naming convention adopted for the parameter sets of the generalized event detection algorithm utilized; for convenience, the number of noise events obtained through application of the generalized algorithm with a particular parameter set is identified below by the same label as the parameter set itself. For example, the label LEQE10G03 denotes the outcome (i.e. the number of events) of the algorithm that detects the occurrence of noise events that emerge at least 10 dB(A) above L_{Aeq} , with a minimum time gap of 3 s between successive noise events. To clarify that the algorithm is applied to the sound level simulated indoors with fully open or closed windows, the suffix 'OP' or 'CL' is added to the variable name.

Figure 3 provides illustrations of the application of the complete sound level simulation and event detection methodology, for one of the 30 instances simulated for one of the 500 available scenarios. The generalized event detection algorithm is illustrated with two parameter sets, each applied to both the window open and closed situations (i.e. T60E00G03OP and T60E00G03CL; LEQE05G03OP and LEQE05G03CL). The outdoor sound level time history is shown in a solid green line, whereas the indoor sound level time history is shown in a solid blue 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 red bars, through two different detection algorithm settings, one with a fixed threshold at 60 dB(A) (detecting 1 or 0 noise events for open and closed window conditions respectively), the other with an adaptive threshold at $L_{Aeq} + 5$ dB(A) (detecting 4 or 1 noise events for open and closed window conditions respectively).

4. Basic performance of the generalized algorithm

4.1. Validity

Selection of appropriate parameter values for the road traffic noise event detection algorithm from the large set of alternatives considered in this work will eventually have to be assessed through human effects research—that is, by examining if and how different noise event measures 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 *validity* (is the number of events detected reasonable, and does the algorithm differentiate well between different conditions?)

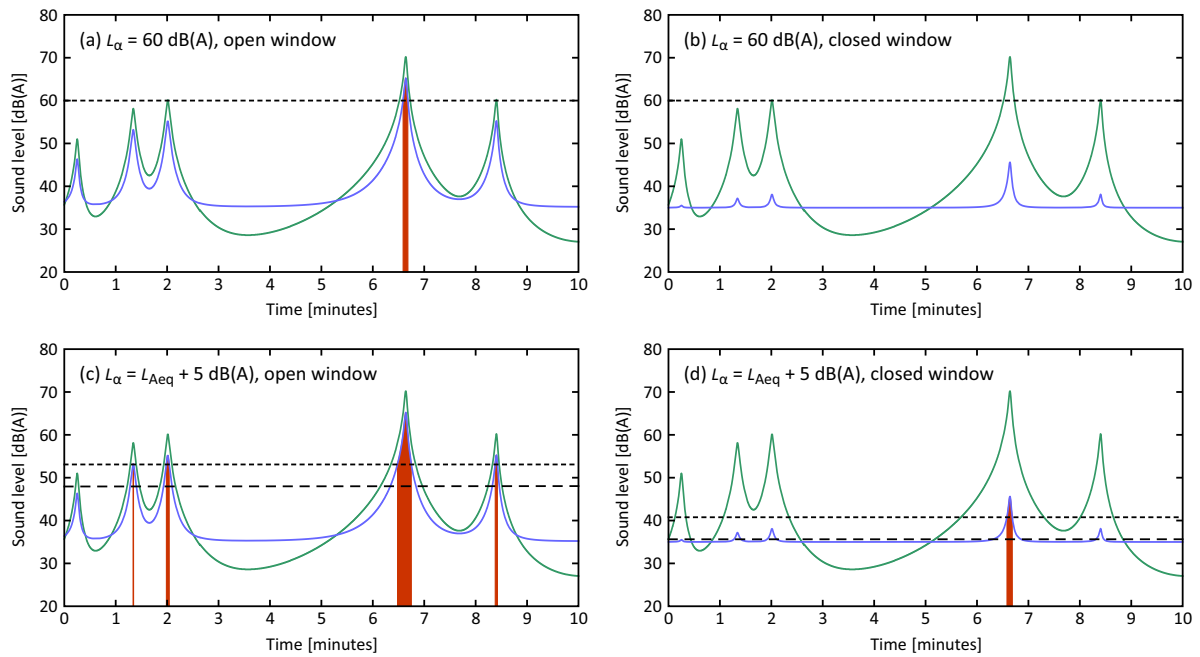


Figure 3: Simulated time history of the outdoor sound level (free-field, solid green line) at a distance of 30 m from a two-lane road with a speed limit of 60 km/h, and a traffic volume of 50 vehicles/h, of which 20 % heavy vehicles. The indoor sound level time history is shown in a solid blue line, for open windows on panels (a) and (c), for closed windows on panels (b) and (d). The detection of noise events within the indoor sound level time history is illustrated using two algorithm settings, on panels (a) and (b) with L_{α} set to 60 dB(A) (short dashed line), and on panels (c) and (d) with L_{α} set to $L_{Aeq} + 5$ dB(A) (long dashed line represents L_{Aeq}). In both algorithm settings, the minimum time gap between events is set to 3 s. Detected noise events are tagged using a vertical red bar, for the duration of the event.

Table 4: Mean of the number of noise events per hour detected by the generalized algorithm, averaged over the 500 scenarios, for each parameter set considered. The numbers in parentheses show the standard deviation of the number of noise events per hour detected in the 30 simulation replications of each scenario, again averaged across the 500 scenarios. The cells shaded in red indicate parameter sets that may not result in the detection of a sufficient number of events and therefore show low validity (see Section 4.1); the cells shaded in blue indicate parameter sets that result in low reliability (see Section 4.2).

Threshold	L_α [dB(A)]	Open window				Closed window			
		$\tau_g = 3$ s	5 s	10 s	30 s	$\tau_g = 3$ s	5 s	10 s	30 s
Fixed	45	15.7 (2.8)	15.3 (2.7)	13.9 (2.4)	9.3 (1.8)	43.1 (4.9)	34.0 (4.1)	22.6 (3.3)	10.3 (2.2)
	50	22.5 (3.6)	21.1 (3.4)	17.8 (2.8)	10.6 (1.9)	37.1 (4.4)	28.4 (3.8)	18.4 (2.9)	8.4 (2.0)
	55	31.1 (4.4)	27.7 (4.0)	21.2 (3.3)	11.2 (2.1)	24.0 (3.5)	18.8 (3.1)	12.6 (2.5)	6.0 (1.8)
	60	39.9 (4.6)	33.1 (4.1)	23.3 (3.4)	11.1 (2.2)	10.3 (2.5)	8.7 (2.2)	6.4 (1.9)	3.5 (1.4)
	65	43.0 (4.9)	33.8 (4.1)	22.4 (3.3)	10.2 (2.2)	2.5 (1.4)	2.3 (1.3)	2.1 (1.1)	1.5 (0.9)
	70	36.9 (4.4)	28.3 (3.8)	18.3 (3.0)	8.3 (2.0)	0.5 (0.7)	0.5 (0.6)	0.5 (0.6)	0.4 (0.6)
	75	24.0 (3.5)	18.8 (3.1)	12.6 (2.5)	6.0 (1.8)	0.1 (0.3)	0.1 (0.3)	0.1 (0.3)	0.1 (0.3)
Adaptive	$L_{Aeq} + 3$	60.6 (9.4)	54.2 (7.8)	42.8 (5.8)	22.5 (3.7)	54.0 (8.5)	48.0 (6.9)	37.4 (5.0)	19.1 (3.2)
	$L_{Aeq} + 5$	42.1 (8.2)	39.2 (7.1)	33.5 (5.5)	20.6 (3.5)	35.3 (7.1)	32.7 (6.1)	27.7 (4.6)	16.5 (2.9)
	$L_{Aeq} + 10$	14.8 (4.3)	14.5 (4.2)	13.8 (3.8)	11.5 (2.9)	10.4 (3.3)	10.2 (3.2)	9.7 (2.9)	8.0 (2.2)
	$L_{Aeq} + 15$	4.8 (2.1)	4.8 (2.1)	4.7 (2.0)	4.4 (1.8)	2.7 (1.4)	2.7 (1.4)	2.6 (1.4)	2.5 (1.3)
	$L_{A50} + 3$	76.9 (6.1)	63.0 (5.2)	43.2 (4.2)	19.0 (2.6)	71.8 (5.6)	58.4 (4.8)	39.6 (3.9)	17.6 (2.5)
	$L_{A50} + 5$	65.5 (5.6)	56.1 (5.0)	41.1 (4.1)	19.7 (2.6)	56.6 (5.0)	48.0 (4.5)	34.5 (3.7)	16.2 (2.5)
	$L_{A50} + 10$	37.1 (4.1)	34.4 (3.9)	28.9 (3.4)	17.2 (2.5)	24.9 (3.4)	22.9 (3.2)	19.1 (2.9)	11.3 (2.2)
	$L_{A50} + 15$	20.1 (2.8)	19.3 (2.7)	17.4 (2.6)	12.3 (2.1)	9.1 (2.1)	8.8 (2.0)	8.0 (2.0)	6.0 (1.7)
	$L_{A90} + 3$	53.4 (7.4)	40.6 (5.9)	25.4 (4.0)	10.2 (2.0)	65.0 (6.5)	50.4 (5.3)	32.9 (3.9)	14.2 (2.4)
	$L_{A90} + 5$	65.2 (8.1)	50.5 (6.6)	32.9 (4.6)	14.2 (2.4)	66.4 (6.3)	51.4 (5.2)	33.3 (4.0)	14.7 (2.4)
	$L_{A90} + 10$	60.8 (6.9)	50.9 (6.0)	36.0 (4.7)	17.0 (2.7)	44.4 (4.8)	36.8 (4.2)	25.6 (3.5)	11.8 (2.3)
	$L_{A90} + 15$	40.8 (5.5)	36.8 (4.9)	29.4 (4.1)	15.9 (2.6)	19.5 (3.4)	17.7 (3.1)	14.4 (2.7)	8.1 (2.0)

and *reliability* (does the algorithm produce consistent counts of number of noise events when applied to identical conditions?).

Table 4 shows the mean number of noise events detected by the generalized algorithm using each of the 152 parameter sets in Table 3 (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 parameter sets result in a wide variation in terms of the number of noise events detected. With a few parameter value combinations, almost no events are detected, whereas in other cases, up to a mean of 77 noise events per hour are detected across the 500 scenarios. This leads to a key observation, viz that the count of noise events caused by road traffic can be very different depending on which detection algorithm is utilized—hence the importance of examining the generalized algorithm with different parameter settings.

To have face value as a potential indicator, an algorithm needs to detect road traffic noise events for many (not necessarily all) of the possible traffic flow and distance scenarios. The algorithm should also result in variation in the number of events detected as the traffic flow and/or the distance to the road changes. These conditions are met using most parameter sets, as most cells of Table 4 have non-zero mean number of noise events detected per hour, and a high correlation (Pearson $r = 0.88$) is found between mean and standard deviation (not shown in Table 4) across the 500 scenarios examined. Some parameter value combinations result in the detection of a mean number of noise events of 10 or less across the 500 scenarios, but many combinations result in means of 20 to 60 events per hour. Low mean values tend to be associated with low standard variation in the number of noise events detected, and means greater than about 20 events with standard deviations of 20 to 80 events. Therefore, it seems reasonable to suggest that indicators should detect a mean number of noise events, across all 500 traffic and distance scenarios, of at least 20 events per hour. Note that this criterion is applied to the mean number of noise events detected across all 500 scenarios which covered the traffic and distance values as shown in Figure 2. Algorithm parameter sets excluded based on this criterion are shaded in red in Table 4. Notably, over 60% of the closed-window algorithm parameter sets are excluded, as are all parameter combinations that employ a 30 s minimum gap between successive events (other than the 3 dB(A) and 5 dB(A) exceedances above L_{Aeq}).

4.2. Reliability

The reliability of an algorithm can be assessed by examining the variation in the number of noise events detected across the 30 replications of the one-hour simulations for each scenario. The numbers in parentheses in each cell of Table 4 show the standard deviation in the number of noise events detected in the replications, pooled across the 500 scenarios. The standard deviations range from 0.3 events to 9.4 events across all algorithm parameter sets. As an initial cut, a standard deviation of less than 5.0 is suggested as being sufficiently reliable for practical measurement of the number of noise events (for a standard deviation of 5.0, some 90 % of replicated event detections would be within ± 8 events of the true value; for a standard deviation of 3.0, some 90 % of replicated event detections would be within ± 5 events). In Table 4, those parameter sets that result in event counts regarded as unreliable are shown with blue shading. Notably, this has resulted in exclusion of near 40 % of the adaptive-threshold parameter sets. Note that, as the range of scenarios considered is the same for all algorithm parameter sets, performing the analysis on the basis of the relative variability rather than the standard deviation would have resulted in the same ordering of the algorithm parameter sets in terms of their reliability.

Validity and reliability criteria filter out 107 of the potential algorithm parameter sets. Table 4 shows, in the unshaded cells, the 45 prospective algorithm parameter sets that remain for further consideration (27 open-window, 18 closed-window).

5. Algorithm parameter set reduction

5.1. Clustering of algorithm parameter sets

Given the systematic variation of parameter values in the formulation of the generalized algorithm, it can be expected that subsets of these will still exhibit considerable redundancy in their counts of noise events. To explore this, a statistical data reduction procedure may be applied to identify a smaller, more manageable, subset of the 45 valid and reliable algorithm parameter sets carried forward.

However, the variation in the number of events detected by different algorithm formulations in Table 4 is not always intuitive, as varying the parameters of the generalized algorithm can sometimes have complex effects on event detection. An overview of this complexity is illustrated graphically in Figure 4 which shows scatterplots of the number of events detected by the generalized algorithm applied with pairs of parameter sets in a random sample of ten of the 45 parameter sets. Each dot in the scatterplots represents one of the 500 scenarios modelled. Figure 4 is not intended for detailed examination of the relationship between variables, or of the number of noise events detected by them. However, the matrix does allow the observation that the relationships between the number of events detected by the different algorithm formulations across the 500 scenarios are, for the most part, elaborate and non-linear. This is an important observation, as the absence of linearity influences the procedures appropriate to reduce redundancy.

As many of the algorithm parameter sets result in non-linear inter-relationships between the number of noise events detected, examining redundancy using bivariate correlations was not possible. Principal component analysis also requires linearity between variables. Instead, the Categorical Principal Component Analysis (CATPCA) procedure implemented in SPSS 25 was utilized, as it allows data reduction between variables with non-linear relationships. The data set analyzed consisted of the number of noise events returned from the generalized algorithm applied, with all 45 selected parameter sets, to each of the 500 traffic/distance scenarios. A two-dimension solution of the CATPCA analysis explained 81.7 % of the total variance in the variables, and the component loadings of the 45 parameter sets (Varimax rotated) on these dimensions are shown in Figure 5(a). Seven clusters of parameter sets that have similar loadings on both dimensions are identified by broken circles in Figure 5(a). The parameter sets that constitute the seven clusters are listed in Table 5.

5.2. Relationships between parameter sets within clusters

The nature of the CATPCA analysis is that each cluster will encompass much of the redundancy between parameter sets. Bivariate scatterplots can then be used to examine selected relationships between parameter sets within clusters, particularly between similar parameter sets differentiated by just one dimension in their formulation, e.g. open vs closed windows, different minimum gap between successive events, and different exceedance thresholds. Several of these relationships are discussed below, and provide useful insight into the effects of varying parameters in the generalized noise event detection algorithm.

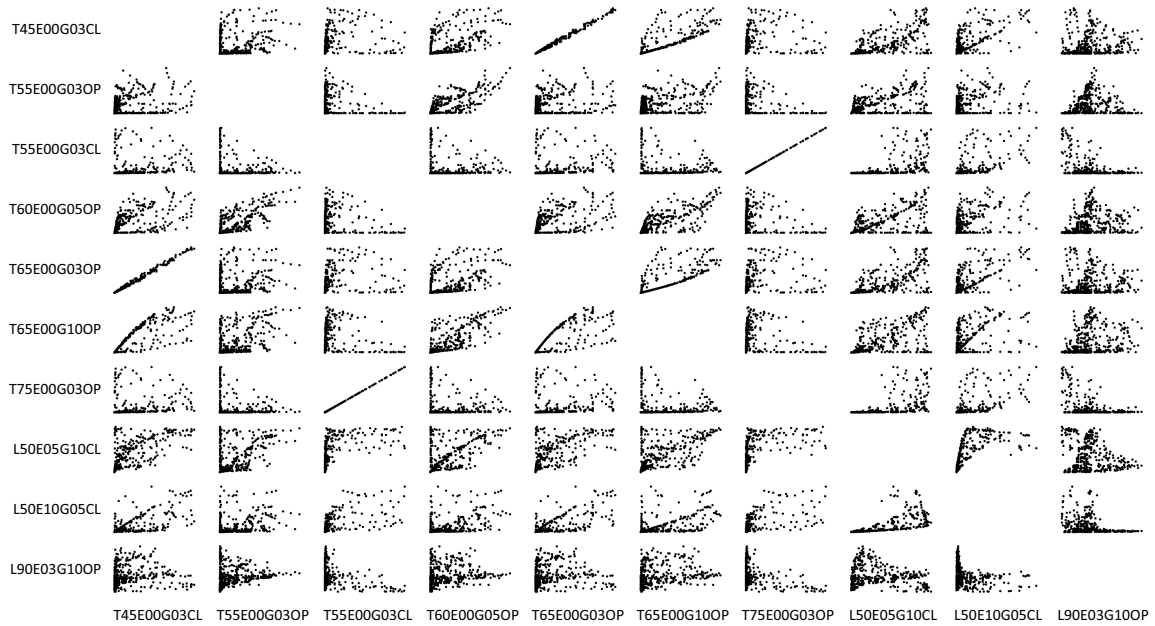


Figure 4: Scatterplot matrix of the number of noise events detected by the generalized noise event detection algorithm, for 10 parameter sets, selected randomly out of the 45 parameter sets shown unshaded in Table 4. Each of the 500 dots in each panel represents a single scenario. Both x and y axes in each plot denote the number of noise events detected by the generalized algorithm with the respective parameter set, but the scale varies for each (from 0–80 to 0–350 noise events).

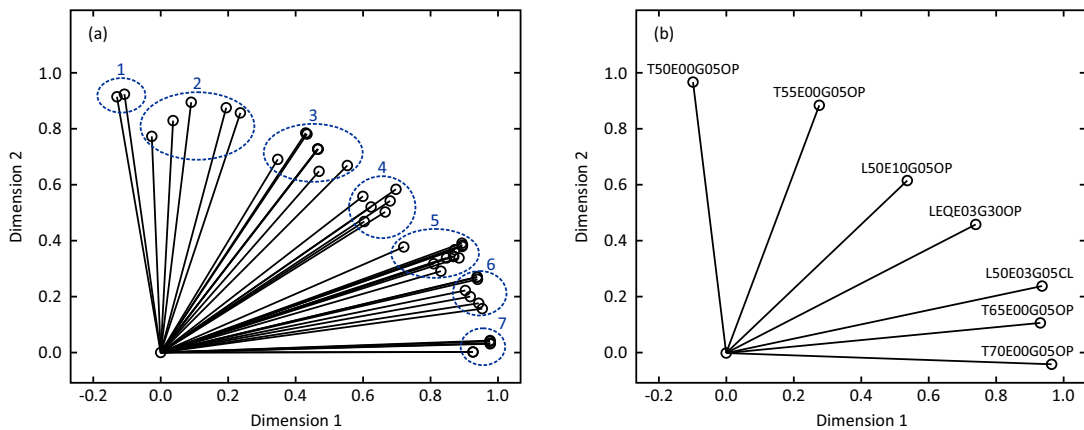


Figure 5: Varimax rotated component loadings on two dimensions from the CATPCA analysis, on the basis of (a) the 45 selected parameter sets as presented in Table 4 (non-shaded), and (b) the seven parameter sets chosen as representative of those in the clusters, as show in panel (a) with a blue circle.

Table 5: The parameter sets that constitute the seven clusters as shown in Figure 5. The prototype parameter sets selected to represent the others within a cluster are shown in bold.

Cluster	Parameter sets
1	T50E00G05OP , T50E00G03OP
2	T55E00G05OP , L90E05G10OP, L90E03G10OP, T55E00G10OP, T55E00G03OP
3	L50E10G05OP , L50E15G03OP, L90E15G10OP, L90E15G05OP, L50E10G10OP, L50E10G03OP, T60E00G10OP, L90E10G10OP
4	LEQE03G30OP , T60E00G05OP, L90E03G10CL, T60E00G03OP, L50E05G10OP, LEQE05G30OP
5	L50E03G05CL , L50E05G05CL, L50E05G10CL, LEQE05G10CL, L50E03G10OP, L50E03G10CL, L50E10G03CL, L50E10G05CL, L90E05G10CL, T45E00G10CL, T65E00G10OP
6	T65E00G05OP , L90E10G03CL, L90E10G05CL, L90E10G10CL, T45E00G05CL, T45E00G03CL, T65E00G03OP
7	T70E00G05OP , T50E00G05CL, T50E00G03CL, T70E00G03OP, T55E00G03CL, T75E00G03OP

5.2.1. Open-window vs closed-window

Clusters 5 to 7 in Table 5 include parameter sets that employ a fixed threshold, for both open and closed window conditions. Given the 20 dB(A) difference between open and closed windows used in the modelling, it is unsurprising that the 45, 50 and 55 dB(A) closed-window fixed-threshold cases are found to have strong linear relationships with the 65, 70 and 75 dB(A) open-window fixed-threshold cases respectively, and thus do not provide information dissociated from that generated by open-window cases. Given that none of the other (60 to 75 dB(A) fixed-threshold) closed-window parameter sets result in an algorithm that produces sufficient counts to be used as noise event indicator (Table 4), the consequence is that fixed-threshold parameter sets under closed-window conditions do not need to be considered further for potential road traffic noise event indicators. However, adaptive-threshold parameter sets, based on L_{A50} and L_{A90} under closed window conditions, remain as candidates.

5.2.2. Effect of time gaps between successive events

Each cluster in Table 5 includes parameter sets that differ in formulation only in terms of the minimum time gap between successive events. Figure 6, panels (a) and (b), shows scatterplots of the number of events detected using the open-window 55 dB(A) fixed-threshold parameter sets with three different minimum time gaps. As could be expected, increasing the minimum gap between successive events results in fewer events being detected, with T55E00G03OP detecting more events than T55E00G05OP, and both in turn detecting more than T55E00G10OP. Figure 6 shows that, while pairs of these parameter sets 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 number of noise events. Fixed-threshold parameter sets at other levels produced similar results, as did adaptive-threshold parameter sets based on L_{A50} and L_{A90} , though with the drop-out occurring at high numbers of events, as shown in Figure 6, panels (c) and (d). This means that, for otherwise similarly formulated parameter sets, different time gaps will tend to produce different, but correlated, numbers of noise events. Redundancy in the parameter sets considered can thus be reduced, where there are similar parameter sets differentiated by time gap, by utilizing just one of the time gaps.

5.2.3. Effect of emergence requirements in adaptive threshold parameter sets

An example of the effect of increasing the emergence required above an adaptive threshold is illustrated in Figure 7, which shows the number of noise events detected by the generalized algorithm using three different closed-window parameter sets, differentiated only by different emergences of 3, 5 or 10 dB(A) above L_{A50} . As could be anticipated, the greater the required emergence, the fewer noise events are detected—but, again, the counts of events using the different parameter sets are related. The spread of the number of noise events detected also increases as the emergence increases, becoming quite large for higher numbers of events. Redundancy in the parameter sets considered can thus

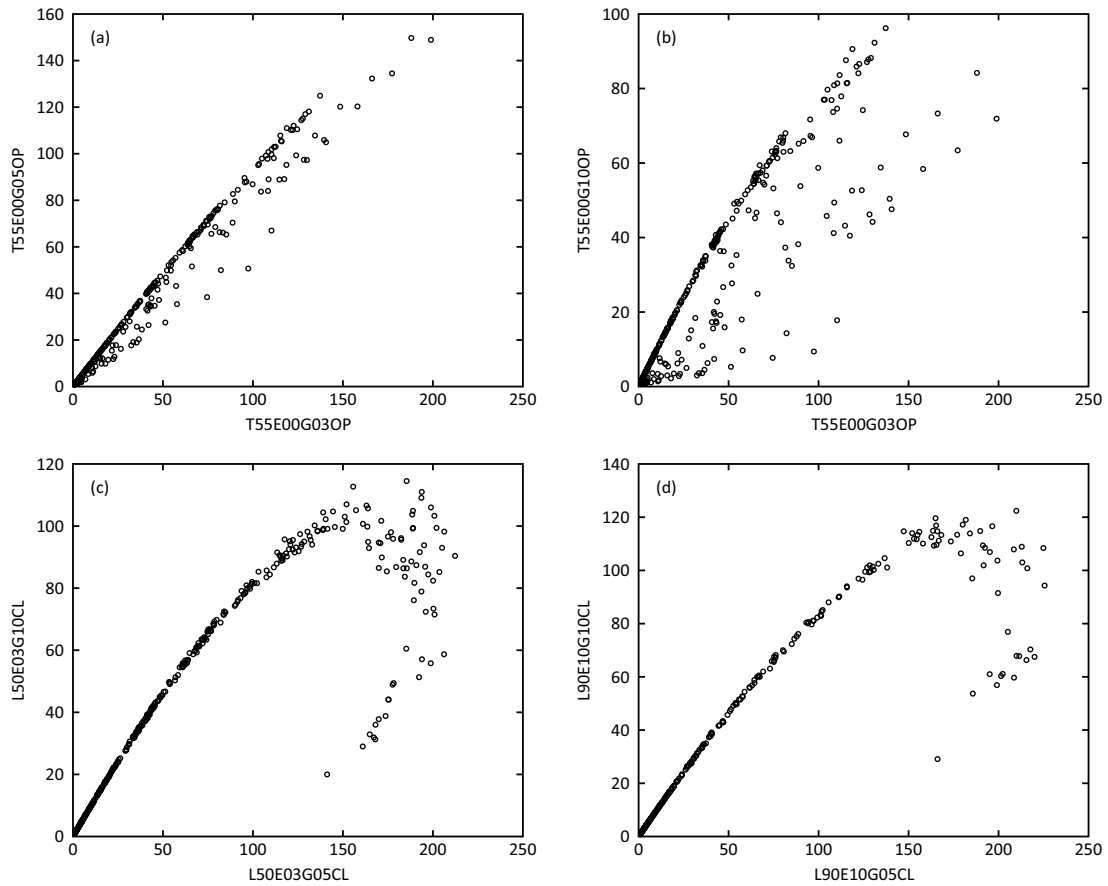


Figure 6: Scatterplots illustrating the largely linear relationships between the number of noise events detected using the generalized algorithm with (a) the open-window 55 dB(A) fixed-threshold parameter sets with minimum time gaps of 3 and 5 s between events, (b) the open-window 55 dB(A) fixed-threshold parameter sets with minimum time gaps of 3 and 10 s between events, (c) the closed-window 3 dB(A) emergence above L_{A50} parameter sets with minimum time gaps of 5 and 10 s between events, and (d) the closed-window 10 dB(A) emergence above L_{A90} parameter sets with minimum time gaps of 5 and 10 s between events.

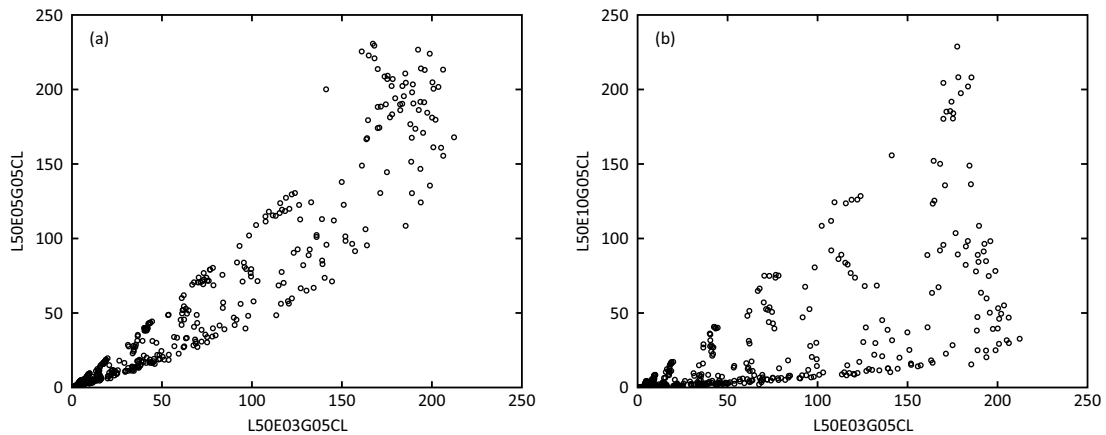


Figure 7: Scatterplots illustrating the relationships between the number of noise events detected using the generalized algorithm with the closed-window adaptive-threshold parameter sets with minimum time gap of 5 s between events, and with (a) exceedance of 3 and 5 dB(A) above L_{A50} , and (b) exceedance of 3 and 10 dB(A) above L_{A50} .

403 be reduced, where there are similar parameter sets differentiated by emergence, by utilizing just one of the emergence
 404 levels.

405 5.2.4. Relationships between other parameter sets within clusters

406 Figure 8 shows the relationships between the number of noise events detected by the generalized algorithm using
 407 various other pairs of parameter sets from within the same clusters. This includes between fixed-threshold and
 408 adaptive-threshold parameter sets, and between adaptive-threshold parameter sets that use different noise indicators as
 409 thresholds. From the 500 data points on each of the plots in Figure 8 (each representing one traffic/distance scenario)
 410 it can be seen that the number of noise events detected can be very different for different parameter sets, and that the
 411 patterns tend to be different with each pair—some with considerable scatter and with many outliers. The patterns in
 412 each of the six plots in Figure 8 confirm that there is a discernible relationship between most of the pairs of parameter
 413 sets shown, and of sufficient strength of association to explain why the CATPCA analysis allocated each of the pairs
 414 to the same cluster of variables.

415 5.3. Selection of representative parameter sets

416 Based on the examination in Section 5.2 of the relationships between parameter sets within the seven clusters, a
 417 single parameter set has been selected as representative of those in each cluster. These parameter sets are shown in
 418 bold type in Table 5. The choice of representative parameter sets was based on the following: open-window fixed-
 419 threshold parameter sets were chosen over closed-window fixed-threshold parameter sets; parameter sets using a 5 s
 420 minimum time gap between successive events were retained in favor of those using longer or shorter time gaps within
 421 the same cluster; adaptive-threshold parameter sets with the smallest emergence were chosen above those with larger
 422 emergence threshold; and finally, where choice still remained, the type of parameter set most commonly represented
 423 within the cluster was selected—or in the case of Cluster 4, the type of parameter set (emergence above an adaptive
 424 threshold based on L_{Aeq}) not included in any other cluster. We emphasize that any of the other parameter sets within
 425 each cluster in Figure 5 and Table 5 (some of which have been used by others in previous studies) could, equally, have
 426 been nominated as the cluster representative.

427 This data reduction to seven prototype parameter sets does not imply that the other parameter sets in Table 5
 428 are not appropriate to use in future practice: they still meet the requirements of valid and reliable measures of noise
 429 events. Note again that determination of the best algorithm to utilize for event counting will eventually have to be
 430 based on studies on human perception of events. For example, while the choice for a 5 s minimum time gap may
 431 seem arbitrary, the number of noise events, as detected with an algorithm employing a particular minimum time gap,
 432 could subsequently be increased/decreased if this is suggested from human-response studies, by the use of a detection

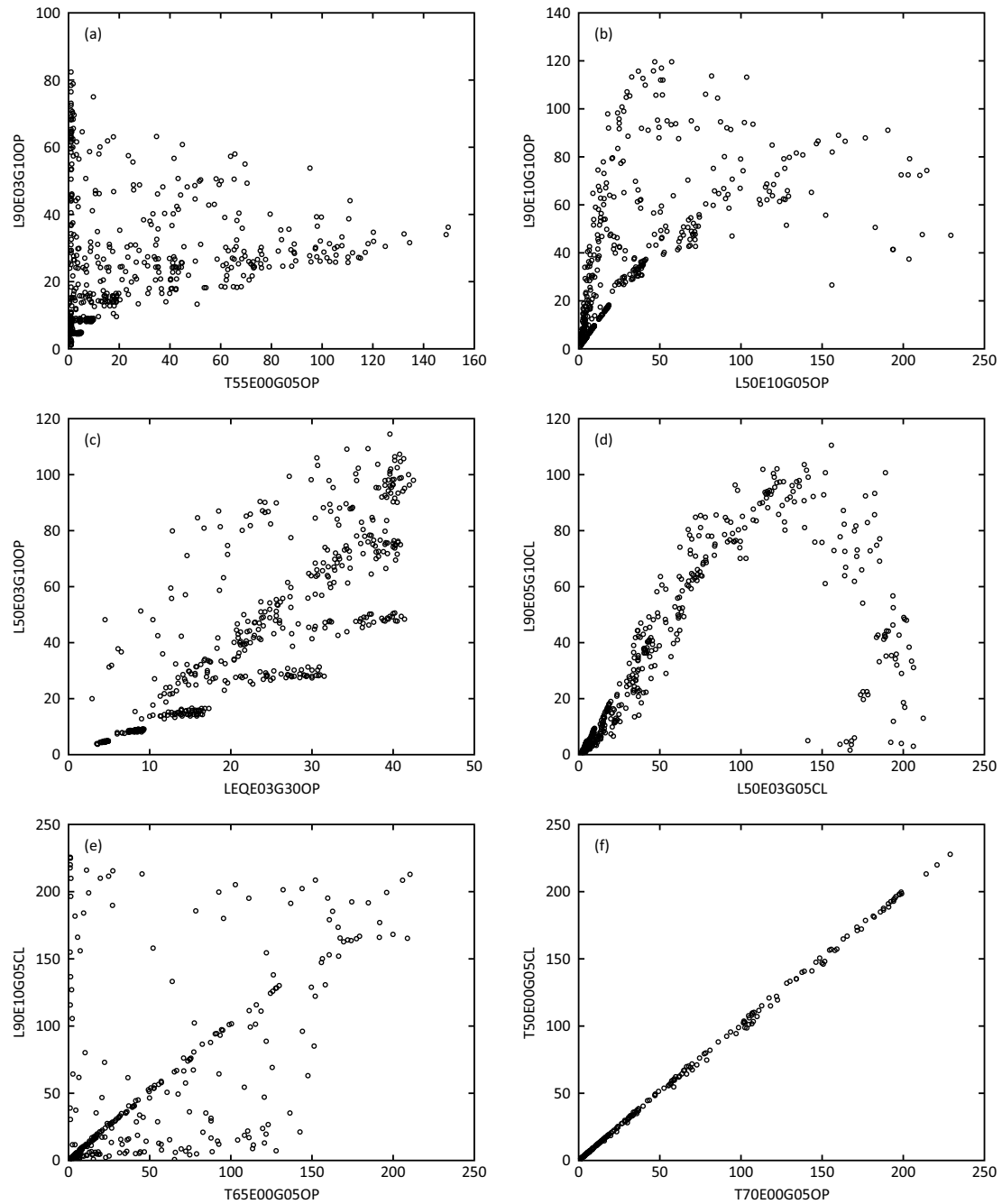


Figure 8: Scatterplots illustrating the relationships between the number of noise events detected by the generalized algorithm using pairs of parameter sets within the clusters in Table 5: (a) Cluster 2, (b) Cluster 3, (c) Cluster 4, (d) Cluster 5, (e) Cluster 6, (f) Cluster 7.

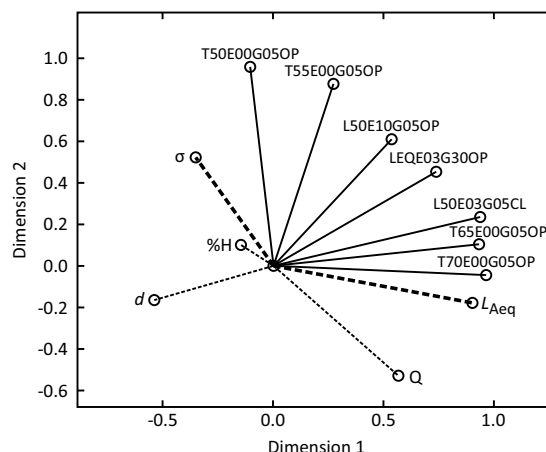


Figure 9: Varimax rotated component loadings on two dimensions from the CATPCA analysis for the seven representative parameter sets, the same as in Figure 5, but with three supplementary scenario variables (total traffic flow Q , percentage of heavy vehicles $\%H$, and distance d to the road) and two supplementary acoustic variables (energy-equivalent level L_{Aeq} and standard deviation σ of the sound level outside the dwelling), also loaded on the two-dimension solution.

433 algorithm with longer/shorter time gap. This data reduction to a smaller set has only been done to generate a more
 434 manageable number of parameter sets for the generalized noise event detection algorithm, which could be used for
 435 later analysis of acoustic conditions under which noise event measures may be useful.

436 It is possible to examine this set of representative parameter sets further, by running the CATPCA procedure again,
 437 using only the seven representative parameter sets. The outcome is the two dimension solution, Varimax rotated,
 438 shown in Figure 5(b). The two dimensions account for 84.9 % of the total variance in the seven variables, which are
 439 widely separated on the two dimensions of Figure 5. By including supplementary variables, some interpretation of the
 440 two dimensions of the CATPCA solution can be provided. Figure 9 shows the CATPCA solution in which three traffic
 441 and sound propagation variables (total traffic flow Q , percentage of heavy vehicles $\%H$, and distance d to the road)
 442 and two acoustic variables (energy-equivalent level L_{Aeq} and standard deviation σ of the sound level outside the dwelling)
 443 were included as supplementary variables (these do not enter the analysis itself but only facilitate interpretation). From
 444 Figure 9, Dimension 1 can be interpreted as the overall level of the road traffic noise, because L_{Aeq} (the outside energy
 445 equivalent sound level) loads highly on that dimension. Dimension 2 is orthogonal to Dimension 1 and thus largely
 446 unrelated to the overall sound level. However, the standard deviation σ of the sound level outside the dwelling, loads
 447 reasonably high on it. This second dimension can therefore be partially interpreted as the variability of the sound level
 448 outside the dwelling caused by traffic. Interpretation of the two dimensions in terms of road traffic parameters and
 449 distance conditions is not so straightforward, with each of the variables Q , $\%H$ and d loading on both dimensions,
 450 though d does load predominantly, and as would be expected, negatively, on Dimension 1—the overall level of road
 451 traffic noise.

452 The interpretation of the two dimensions in Figure 9 facilitates interpretation of the various clusters of event-
 453 detection parameter sets. Clusters 1 and 2 (represented by the 50 and 55 dB(A) fixed-threshold parameter sets, open
 454 window) are associated with higher variability of the road traffic noise signal than they are with the overall level of
 455 traffic noise. Clusters 5, 6 and 7 (represented by the $L_{A50} + 3$ dB(A) adaptive-threshold, closed window, and the 65
 456 and 70 dB(A) fixed-threshold parameter sets, open windows) are associated with high overall levels rather than the
 457 variability of the signal. Clusters 3 and 4 (both represented by adaptive-threshold parameter sets) are interim between
 458 these, being associated with both level and variability of the road traffic noise signal. Broadly, this suggests that the
 459 number of noise events detected by using different parameter sets is differentially associated with overall level of the
 460 traffic noise and with the variability of the road traffic signal. Figure 10, which shows the number of noise events
 461 per hour detected using each of the seven representative parameter sets, as a function of traffic demand and distance
 462 to the roadway, reflects this finding: the traffic demand range in which the detected number of noise events varies
 463 more or less linearly with the traffic demand gradually shifts to higher values, from cluster 1 to cluster 7. At any

464 particular distance from a roadway, the level of the road traffic noise will increase monotonically as the traffic flow
465 increases. However, the variability of a traffic noise signal will initially increase as traffic flow increases from zero, but
466 then decrease at the higher flow rates—the troughs between successive peaks in the traffic noise signal fill in, hence
467 resulting in lower variability. By contrast, both level and variability of a traffic noise signal decrease with increasing
468 distance from the roadway. These complex interactions between level and variability of the road traffic noise signal
469 suggest that a detailed analysis of the behaviour of different noise event detection models across the population of
470 acoustic conditions near roadways will be necessary.

471 **6. Conclusions**

472 This paper has explored a generalized algorithm to detect noise events in the time history of the sound level
473 caused by road traffic streams. This generalized algorithm was rigorously developed from the literature, and is based
474 on fixed thresholds or on emergence above adaptive thresholds of L_{Aeq} , L_{A50} and L_{A90} . Threshold level, emergence,
475 and minimum time gap between successive events were varied. This resulted in 76 different noise event detection
476 protocols, applicable to both window-open and window-closed conditions. These parameter value combinations were
477 systematically applied to detect events in simulated time histories of road traffic noise across a population of acoustic
478 conditions found near roadways; 500 different scenarios were considered with varying traffic flow, vehicle mix, speed
479 limit and distance to the roadway.

480 An appropriate parameter set for the noise event detection algorithm will eventually have to be selected through
481 human effects research by examining if, and which, noise event measures of a road traffic noise signal correlate best
482 with human response to that signal. However, any method used to detect and count the events in road traffic noise must
483 first produce stable estimates of the number of events, and should vary sensibly as the traffic and distance conditions
484 change. It was shown that the number of noise events detected in the time history of the sound level caused by road
485 traffic is highly dependent on the parameters utilized—justifying a study of this nature into alternative formulations
486 of detection algorithms as a step towards identification of appropriate algorithm(s) which use could eventually be
487 standardized.

488 About 20 % of the detection parameter sets resulted in an unreliable algorithm, resulting in different numbers of
489 events counted for traffic noise signals that are generated by identical traffic and propagation conditions. Such unstable
490 measures would not be suitable for use as limit criteria. It was also found that approximately 50 % of the parameter
491 sets did not give rise to an algorithm that results in a reasonable range of numbers of noise events when applied
492 across all acoustic conditions. Excluding these, 45 reliable and functional variations on the generalized exceedance
493 algorithm remained. Subsequent application of dimension-reduction procedures to reduce redundancy between these
494 identified seven that were representative of the original set. The numbers of noise events detected with the generalized
495 algorithm through the application of several of these parameter sets were found to be associated with the overall
496 road traffic noise level, whereas other parameter sets were associated more with the variability of the road traffic
497 noise. This small number of noise event detection parameter sets parsimoniously represents the large number of
498 possible exceedance indicators developed from those described in literature, but has been compiled without the loss
499 of information that could occur through arbitrary discard of any particular detection formulation. The identification
500 of this small subset of parameter value combinations of a generalized noise event detection algorithm is an important
501 step towards further work to evaluate the acoustic conditions under which event counting in road traffic noise signals
502 may be appropriate.

503 **Acknowledgments**

504 The authors gratefully acknowledge the assistance provided through the inaugural grant from the Australian
505 Acoustical Society Research Grants Program for the conduct of this work.

506 **References**

- 507 [1] Fidell S, Pearsons K, Tabachnick BG, Howe R. Effects on sleep disturbance of changes in aircraft noise near three airports. *J Acoust Soc Am*
508 2000;107(5):2535–47.

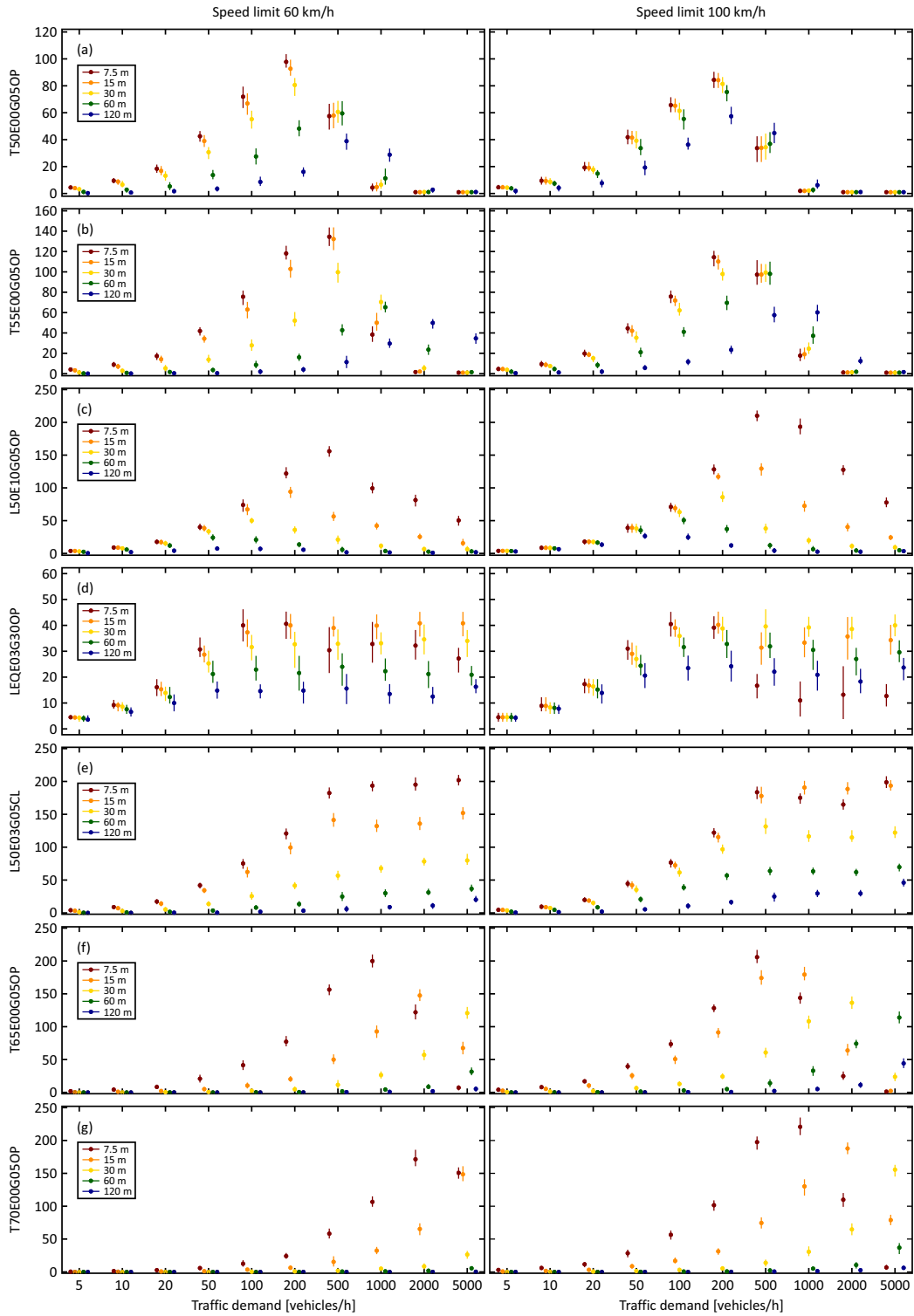


Figure 10: Number of noise events per hour detected by the generalized algorithm using each of the seven representative parameter sets (panels ordered according to cluster number), as a function of the traffic demand and the distance to the roadway, for speed limits of 60 km/h (left panels) and 100 km/h (right panels), and for 10 % heavy vehicles. The dots represent the mean value over the 30 replications for each scenario; the vertical lines represent the range that contains 90 % of the outcomes of the 30 replications for each scenario (i.e. from the 5-percentile to the 95-percentile of the number of events).

- 509 [2] Passchier-Vermeer W, Vos H, Steenbekkers JHM, van der Ploeg FD, Groothuis-Oudshoorn K. Sleep disturbance and aircraft noise exposure—
510 exposure-effect relationships. TNO Report 2002.027; TNO Prevention and Health; Leiden, The Netherlands; 2002.
- 511 [3] Couvreur L, Laniray M. Automatic noise recognition in urban environments based on artificial neural networks and hidden Markov models.
512 In: Proc. Inter-noise. Prague, Czech Republic; 2004, p. 555–62.
- 513 [4] Griefahn B, Bröde P, Marks A, Basner M. Autonomic arousals related to traffic noise during sleep. *Sleep* 2008;31(4):569–77.
- 514 [5] Basner M, Müller U, Griefahn B. Practical guidance for risk assessment of traffic noise effects on sleep. *Appl Acoust* 2010;71(6):518–22.
- 515 [6] Treagus R, Beazley CJ. Noise monitoring program for assessing the impact of maximum traffic noise levels. In: Proc. Acoustics'05.
516 Busselton, Australia; 2005, p. 271–6.
- 517 [7] Beaumont J, Semidor C. Interacting quantities of the soundscape due to transport modes. In: Proc. Inter-noise. Rio de Janeiro, Brazil; 2005,
518 p. 3408–14.
- 519 [8] Can A, Leclercq L, Lelong J, DeFrance J. Capturing urban traffic noise dynamics through relevant descriptors. *Appl Acoust*
520 2008;69(12):1270–80.
- 521 [9] Öhrström E, Björkman M, Rylander R. Laboratory annoyance and different traffic noise sources. *J Sound Vib* 1980;70(3):333–41.
- 522 [10] Fields JM. The effect of numbers of noise events on people's reactions to noise: an analysis of existing survey data. *J Acoust Soc Am*
523 1984;75(2):447–67.
- 524 [11] Öhrström E, Rylander R, Björkman M. Effects of night time road traffic noise—an overview of laboratory and field studies on noise dose and
525 subjective noise sensitivity. *J Sound Vib* 1988;127(3):441–8.
- 526 [12] Suzuki S, Kawada T, Kiryu Y, Sasazawa Y, Tamura Y. Transient effect of the noise of passing trucks on sleep EEG. *J Sound Vib*
527 1997;205(4):411–5.
- 528 [13] Samuels SE, Parnell J. Peak noise events occurring in road traffic noise. In: Proc. Acoustics'04. Gold Coast, Australia; 2004, p. 307–12.
- 529 [14] Heimann D, Schady A. Derivation of sound-level characteristics to assess traffic development scenarios. *Appl Acoust* 2016;103:1–9.
- 530 [15] Campbell JA, Parnell J. A vehicle maximum noise level study. In: Proc. Acoustics'04. Gold Coast, Australia; 2004, p. 501–6.
- 531 [16] Mitchell P. Speed and road traffic noise—The role that lower speeds could play in cutting noise from traffic. Technical report; UK Noise
532 Association; Kent, UK; 2009.
- 533 [17] De Muer T, Botteldooren D, De Coensel B, Berglund B, Nilsson ME, Lercher P. A model for noise annoyance based on notice-events. In:
534 Proc. Inter-noise. Rio de Janeiro, Brazil; 2005, p. 3323–32.
- 535 [18] De Coensel B, Botteldooren D, De Muer T, Berglund B, Nilsson ME, Lercher P. A model for the perception of environmental sound based
536 on notice-events. *J Acoust Soc Am* 2009;126(2):656–65.
- 537 [19] Roberts MJ, Western AW, Webber MJ. A theory of patterns of passby noise. *J Sound Vib* 2003;262(5):1047–56.
- 538 [20] Brink M, Basner M, Schierz C, Spreng M, Scheuch K, Bauer G, et al. Determining physiological reaction probabilities to noise events during
539 sleep. *Somnologie* 2009;13:236–43.
- 540 [21] Brown AL. An overview of concepts and past findings on noise events and human response to surface transport noise. In: Proc. Inter-noise.
541 Melbourne, Australia; 2014, p. 1925–32.
- 542 [22] European Commission. Directive 2002/49/EC of the European Parliament and of the Council relating to the assessment and management of
543 environmental noise. 2002.
- 544 [23] Night noise guidelines for Europe. Tech. Rep.; World Health Organization Regional Office for Europe; Copenhagen, Denmark; 2009.
- 545 [24] Jones K, Cadoux R. Metrics for aircraft noise. ERCD Report 0904; Environmental Research and Consultancy Department, Civil Aviation
546 Authority; London, UK; 2009.
- 547 [25] Aasvang GM, Øverland B, Ursin R, Moum T. A field study of effects of road traffic and railway noise on polysomnographic sleep parameters.
548 *J Acoust Soc Am* 2011;129(6):3716–26.
- 549 [26] Griefahn B, Marks A, Robens S. Experimental shift work and noise exposure during sleep. In: Proc. ICBEN. London, UK; 2011, p. 595–602.
- 550 [27] Brown AL. Issues in the measurement of sleep-related noise events in road traffic streams. In: Proc. Acoustics'13. Victor Harbor, Australia;
551 2013, p. 1–6.
- 552 [28] Makarewicz R, Gołębiewski R. The uncertainty of noise composed of separate sound events. *Arch Acoust* 2016;41(1):133–8.
- 553 [29] Murray BJ. Assessment of road traffic maximum noise events at night time. In: Proc. Acoustics'01. Canberra, Australia; 2001, p. 1–5.
- 554 [30] Taylor SM, Hall FL, Birnie SE. Transportation noise annoyance: testing of a probabilistic model. *J Sound Vib* 1987;117(1):95–113.
- 555 [31] Hall FL, Taylor SM, Birnie SE. Activity interference and noise annoyance. *J Sound Vib* 1985;103(2):237–52.
- 556 [32] Lambert J, Champelovier P, Vernet I. Annoyance from high speed train noise: a social survey. *J Sound Vib* 1996;193(1):21–8.
- 557 [33] Fidell S, Pearsons K, Tabachnick B, Howe R, Silvati L, Barber DS. Field study of noise-induced sleep disturbance. *J Acoust Soc Am*
558 1995;98(2):1025–33.
- 559 [34] Müller U, Basner M, Plath G, Samel A. Aircraft noise effects on sleep: acoustical setup and results of DLR laboratory and field studies. In:
560 Proc. Inter-noise. Prague, Czech Republic; 2004, p. 2670–7.
- 561 [35] Mietlicki F, Ribeiro C, Sineau M. Noise generated by the Paris ring-road: state of knowledge and issues. In: Proc. Inter-noise. Innsbruck,
562 Austria; 2013, p. 2815–24.
- 563 [36] Wunderli JM, Pieren R, Habermacher M, Vienneau D, Cajochen C, Probst-Hensch N, et al. Intermittency ratio: a metric reflecting short-term
564 temporal variations of transportation noise exposure. *J Expo Sci Environ Epidemiol* 2015;:1–11.
- 565 [37] Campbell JA, Isles S. RTA Environmental Noise Management Manual. Haymarket, NSW, Australia: Roads and Traffic Authority of New
566 South Wales; 2001.
- 567 [38] De Coensel B, Botteldooren D. The quiet rural soundscape and how to characterize it. *Acta Acust Acust* 2006;92(6):887–97.
- 568 [39] Tulen JHM, Kumar A, Jurriëns AA. Psychophysiological acoustics of indoor sound due to traffic noise during sleep. *J Sound Vib*
569 1986;110(1):129–41.
- 570 [40] Liguori C, Paoillo A, Ruggiero A, Russo D. Outlier detection for the evaluation of the measurement uncertainty of environmental acoustic
571 noise. *IEEE Trans Instrum Meas* 2016;65(2):234–42.
- 572 [41] Ribeiro C, Anselme C, Mietlicki F, Vincent B, Da Silva R. At the heart of Harmonica project: the Common Noise Index (CNI). In: Proc.
573 Inter-noise. Innsbruck, Austria; 2013, p. 4088–97.

- 574 [42] Sato T, Yano T, Björkman M, Rylander R. Road traffic noise annoyance in relation to average noise level, number of events and maximum
575 noise level. *J Sound Vib* 1999;223(5):775–84.
- 576 [43] Marks A, Griefahn B, Basner M. Event-related awakenings caused by nocturnal transportation noise. *Noise Control Eng J* 2008;56(1):52–62.
- 577 [44] Bite P, Augusztinovicz F, Flindell IH. Unexpectancy in environmental noise assessment. In: *Proc. Forum Acusticum*. Budapest, Hungary;
578 2005, p. 1831–5.
- 579 [45] Gjestland T, Oftedal G. Assessment of noise annoyance: The introduction of a threshold level in L_{eq} calculations. *J Sound Vib*
580 1980;69(4):603–10.
- 581 [46] De Coensel B, Brown AL, Tomerini D. A road traffic noise pattern simulation model that includes distributions of vehicle sound power levels.
582 *Appl Acoust* 2016;111:170–8.
- 583 [47] Peeters B, van Blokland G. The noise emission model for European road traffic. Technical Report — Deliverable 11 of the Imagine project
584 IMA55TR-060821-MP10; M+P Consulting Engineers; Vught, The Netherlands; 2007.
- 585 [48] Brown AL, Tomerini D. Distribution of the noise level maxima from the pass-by of vehicles in urban road traffic streams. *Road Transp Res*
586 2011;20(3):50–63.
- 587 [49] ISO 9613–Part 2. Acoustics — Attenuation of sound during propagation outdoors — Part 2: General method of calculation. International
588 Standard ISO 9613-2; International Organization for Standardization; Geneva, Switzerland; 1996.