A SIMPLIFIED APPROACH TO INTERPRETATION OF THE LIKELIHOOD OF PREDICTED SHORT-TERM AIR QUALITY IMPACTS FOR NON-STEADY STATE EMISSION SOURCES

Leigh Crilley[1], Dave Claughton[1] and Jessica Radevski[1]

[1] WSP, Australia

Abstract

Air Quality Impact Assessments are pivotal for understanding and mitigating potential air pollution impacts on human health and the environment. Central to these assessments are air dispersion models, which simplify complex atmospheric processes to predict the likelihood and magnitude of potential exceedances for an emission scenario. Traditionally, to understand an impact's potential magnitude, modelling assessments conservatively assume continuous emissions at peak rates, leading to a reasonable prediction of magnitude but a potential overestimation of the likelihood and frequency of exceedances. This is most apparent for short-term predictions, (e.g., 1-hour average NO_2), where the conservative assumptions applied in modelling can introduce increased uncertainty in a predicted impact. Non-steady-state emission sources, such as backup generators in a data centre, cruise ships, and batch processing type industries pose additional challenges and are inherently variable in their emission frequency, duration, and intensity, further complicates interpreting model predictions. Additionally, the variability in meteorological conditions and existing background concentrations over the model period contribute to the cumulative complexity when predicting exceedances.

To address this, we propose a simple yet robust method to provide a more realistic understanding of the overall likelihood of an exceedance of short-term criteria based on the cumulative probability of variables that drive predicted impacts. We illustrate this approach using a non-steady state emission source case study and demonstrate its utility for calculating a more realistic likelihood of short-term air quality exceedances. Compared to previous approaches, the presented methodology seeks to simplify the interpretation and calculation of exceedance predictions from modelling exercises.

This paper aims to highlight the need to shift our perspective from treating predicted concentrations as absolute values for comparison with legislated criteria to understanding them as indicators of the potential likelihood and magnitude of an impacts.

Keywords: criteria pollutants, cumulative probability, exceedance likelihood, air quality impact assessment, dispersion modelling.

1. Introduction

Air quality impact assessments (AQIA) and dispersion modelling are essential components of understanding the potential for impacts to air from proposed activities that are not yet operational. Current AQIA methods derive an understanding of potential impacts from a non-existing activity are typically required to be predictive in nature, as the ability to observe impacts from non-existing activities continues to elude air quality professionals.

In an AQIA, predicted pollutant concentrations are derived from a combination of predicted emissions rates and variable meteorological conditions in a dispersion model. These predicted pollutant concentrations are combined with measurements from the existing environment to assess the potential impacts. Currently, to understand the potential worst-case magnitude of short-term impacts, an AQIA may assume the following three unrelated events occur simultaneously:

- peak short-term concentrations in the existing environment data
- peak emission rates from the activity being assessed; and
- unfavourable meteorological conditions for dispersion of the emitted pollutant.

This approach, in which all three unrelated events are assumed to occur simultaneously, can result in a reasonable prediction of the worst-case magnitude of short-term impacts but may lead to an overestimation of the likelihood and frequency of short-term exceedances as it uses peak values.

One method regularly used to minimise the influence of peak values in the existing environment dataset is use a percentile (e.g. 70th) of the applied background measurements (EPAV, 2007). This approach, while still considering the variable nature of the existing environment, can still overestimate the likelihood and frequency of peak pollutant contribution from an activity if steady state peak emissions rates are included in a dispersion model.

Another regularly used method is contemporaneously addition of an hourly time series of the existing environment to an hourly time series of predicted pollutant concentrations (NSW EPA, 2022). This contemporaneous approach addresses the time-varying nature of predicted pollutant concentrations and existing environments; however, for emissions sources that are in a non-steady state, a contemporaneous method can still lead to an overestimation of the likelihood and frequency of elevated pollutant contribution from an activity if steady state peak emissions rates are included in the dispersion model. It's important to note that non-steady-state emission sources, such as backup generators in a data centre, docked cruise ships, and batch processing type industries, are inherently variable in their emission frequency, duration, and intensity, which presents a significant challenge in assessing short-term impacts.

This paper proposes a simple yet robust method to assess potential exceedances predicted for an activity that addresses the need to account for variability in emissions from non-steady-state emission sources. Based on the cumulative probability of variables that drive predicted impacts, this method provides a more realistic understanding of the overall likelihood of an exceedance of short-term criteria.

2. Using probabilities to determine the likelihood of exceedances

When determining the likelihood of the predicted exceedances occurring, the following data variables need to be considered:

- The time-varying nature of pollutant concentrations in the existing environment data
- The time-varying nature of unfavourable meteorological conditions for dispersion of the emitted pollutant. and
- The following variables in emissions data:
  - Likely frequency of emissions occurrences over the year
  - Likely length of emission event: and
  - Variability in the emission profile/intensity from the source

Therefore, the likelihood of an exceedance occurring will depend on the above factors and can be estimated by considering the combined probability of the emission event actually occurring and any variations in emission intensities under realistic operating conditions.

The total cumulative probability of exceedance occurring can be calculated based on the principles of calculations for the probabilities for two or more events occurring. For three events that could occur simultaneously (i.e., Events A and B), the total probability of both occurring is calculated via Eqn 1:

$$P_{A,B,i} = P_A \times P_B \dots \times P_i \qquad \text{(Eqn 1)}$$

Where P_A and P_B refer to the probability of events A, B occurring, respectively, and $P_{A,B}$ is the cumulative probability of both events A and B occurring. Note Eqn 2 can be applied for three or move events.

For events that cannot occur simultaneously (i.e., either event C or D), the total probability of either event occurring is calculated via Eqn 2:

$$P_{C,D} = P_C + P_D \dots . + P_i \qquad \text{(Eqn 2)}$$

Where P_C and P_D refer to the probability of events C and D occurring, respectively and $P_{C,D}$ is the cumulative probability of either events C or D occurring.

3. Case study: Dispersion model of diesel generator emissions at a data centre

To demonstrate this probabilistic-based approach, we use an example case study of emissions from diesel back-up generators at a data centre. In this case study, diesel generator emissions would typically only occur under three scenarios; 1) during a power outage, 2) during planned partial shutdowns of the data centre for maintenance and 3) during routine maintenance checks of the generators. An example model output dataset from a dispersion model (e.g. CALPUFF) for an air quality impact assessment (AQIA) was utilised for the purposes of this paper and, therefore, is not representative of 'real' emissions from a data centre. For the modelling of emissions, the conservative assumption that emergency conditions during a power outage occurred as a steady state for every hour of the modelled year was employed in the model. Although this is unrealistic, this approach allows for emissions to be combined with varying meteorology conditions over a year to understand the potential worst-case predicted impact and is the approach typically taken for an AQIA.

The model output NOx data was converted to NO_2 using the Ozone limiting method (OLM) described in NSW Approved methods. For this case study, background data for NO_2 and O_3 was obtained from the QLD Government Air Quality Monitoring Station (AQMS) at Rocklea for the year 2021. This year was chosen as representative of typical concentrations as there were no extreme regional events (e.g. dust storms and large bushfires).

3.1. Predicted number of exceedances by a worst-case model scenario

In the 2021 data at Rocklea, there were no recorded exceedances of 1-hr average NO_2 National Environment Protection (Ambient Air Quality) Measure standard, as shown in Fig 1. For this example, we consider the impact of diesel generator emissions at a nearby receptor to the data centre. The modelled concentrations of NO_2 at this receptor were combined with the measured background concentrations to assess the potential number of exceedances, an approach analogous to a Level 2 contemporaneous assessment from NSW Approved Methods, typically employed in AQIA. With the addition of the modelled emissions, the number of 1-hour NO_2 exceedances increases to 103 at this receptor.

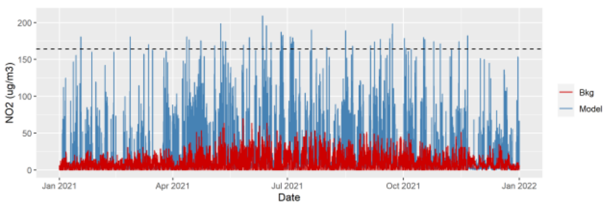

Figure 1 Time series of 1-hr NO_2 background measurements and modelled NO_2, calculated using OLM.

While the initial number of exceedances calculated is concerning, the dispersion modelling has assumed continuous steady-state emissions from the diesel generators. For some applications, this assumption is valid and representative, such as stack emissions from industrial processes. However, for applications where emissions are in a non-steady state, the model predicted concentrations, while conservative, actually represent a very worst-case scenario. As such, when model predicted concentrations are combined with background measurements, this approach can calculate an unrealistic number of exceedances for sources whose emissions will actually be intermittent. Consequently, this approach typically predicts exceedances to occur during unfavourable meteorology for atmospheric dispersion, such as when there is a shallow boundary layer and/or low wind speeds.

For non-steady state emission sources like backup generators at a data centre, the likelihood of unfavourable meteorology conditions leading to an exceedance can be estimated by both the probability of unfavourable conditions occurring and the probability of an emission event and its intensity. The probability of unfavourable meteorology conditions occurring was estimated to be the predicted number of exceedances over a year by the sum of the model and background at a receptor. As such, an exceedance was only predicted for a given receptor when meteorological conditions were unfavourable, in terms of wind direction and speed as well as atmospheric stability. This is referred to as unfavourable meteorological conditions. Consequently, the predicted number of 1-hr NO_2 exceedances by the model can be considered as a conservative number of exceedances.

3.2. Example cumulative probability calculations for the case study

In this example, emissions from the diesel generators would be in a non-steady state; that is, they would not occur continuously as modelled (See Figure 1). The likelihood of unfavourable meteorology conditions leading to a 1-hr NO_2 exceedance occurring is estimated to be both the probability of unfavourable meteorology conditions occurring and the probability of the operation of the diesel generators. The probability of unfavourable meteorology conditions (P_{UMC}) occurring was estimated to be the predicted number of 1-hr NO_2 exceedances over a year (N_{ex}), as shown by Eqn 3:

$$P_{UMC} = \frac{N_{ex}}{8760} \quad \text{(Eqn 3)}$$

P_{UMC} represents the probability of an exceedance considering the two variables already considered, i.e. background concentrations and meteorology. Therefore, by applying the probability of unfavourable meteorology conditions coinciding with an emission event(s), a more realistic likelihood of exceedances can be calculated.

In this case study, diesel generators would realistically only be used under three scenarios;

- during an unplanned power outage
- during planned partial shutdowns of the data centre for maintenance
- during routine maintenance checks of the generators.

Furthermore, the actual emissions will also depend on the number of diesel generators being used for each scenario. In this case study, there are a total number of 36 backup generators, each with a nominal power of 2,500 kW. For the dispersion model, all 36 generators were assumed to be operating. For events where only a subset of generators were employed, then the emission intensity can be approximated by the ratio of the number of generators operating (N_G) to the total number of generators (in this case 36).

In this case study, the frequency and emission intensity of the three scenarios for diesel generator operations were as follows. For major power interruptions, all back-up generators would be required simultaneously but would only occur very infrequently and for a limited time period as described in Eqn 4:

$$P_{ES} = \left(\frac{L_{ES}}{8760}\right) \qquad \text{(Eqn 4)}$$

Where L_{ES} represents the total length of emergency shutdowns (in hours) over a year (8760 hours). For this case study, it was assumed that there was only one emergency shutdown per year, lasting 2 hours.

The second scenario in the case study considered planned partial shutdowns for maintenance, scheduled to occur every 6 months and last for 6 hours. As this were only a partial shutdown, only a subset of generators are required, and therefore, the emission intensity would vary proportionally to the actual number of generators used relative to the total number of generators, as used in the model. Eqn 5 described the probability of emissions from partial shutdown (P_{PS}):

$$P_{PS} = \left(\frac{L_{PS}}{8760} \times \frac{N_G}{36}\right) \qquad \text{(Eqn 5)}$$

Where L_{PS} is the total length of partial shutdowns over a year (i.e., total of 12 hours) and N_G the actual number of generators used, which in this case study was 18.

The final scenario to consider was the routine operation of the generators for maintenance checks. In this case study, the maintenance schedule was 30 min test of 6 generators twice a week during business hours. Therefore, the probability of emissions from routine maintenance is described by Eqn 6:

$$P_M = \left(\frac{L_M}{8760} \times \frac{N_G}{36}\right) \qquad \text{(Eqn 6)}$$

Where L_M is the total length of the partial shutdowns (i.e., a total of 52 hours) over a year and NG is the actual number of generators used, which in this scenario was 6.

3.3. Estimated realistic number of exceedances for the case study

Therefore, by applying the probability of unfavourable meteorology conditions (P_{UMC}) coinciding with realistic diesel generator operation and the number of generators being used for the three scenarios to the number of 1-hr NO_2 exceedances under unrealistic operational conditions, a more realistic number of exceedances can be calculated, as shown by Eqn 7:

$$N_{ROC} = P_{UMC} \times (P_{ES} + P_{PS} + P_M) \times 8760 \qquad \text{(Eqn 7)}$$

Where N_{ROC} is number of exceedances under realistic operating conditions. As the three scenarios for diesel generator operation cannot occur simultaneously, as if there was a full unplanned power outage any planned maintenance would be postponed the probability of the three scenarios occurring over a year can be calculated by Eqn 2. For the conditions for this case study, the N_{ROC} would be calculated using Eqn 7 as follows:

$$N_{ROC} = \left(\frac{103}{8760}\right) \times \left(\frac{2}{8760} + \left(\frac{12}{8760} \times {}^{18}\!/_{36}\right) + \left(\frac{52}{8760} \times {}^{6}\!/_{36}\right)\right) \times 8760$$

$$N_{ROC} = 0.2$$

That is, under the more realistic operating conditions considered, the likelihood of 1-hr NO_2 exceedances is close to zero. This can be considered reasonable, as the likelihood of an emission event from the backup diesel generators over a year is low, and therefore, the likelihood of an event leading to an exceedance is also low as background levels were considerably lower than criteria.

4. Discussion and Conclusions

The above case study demonstrates that after considering the probability of an emission event due to actual realistic operating conditions, the likelihood of a 1-hr NO_2 exceedance reduced notably compared to the very worst-case scenario employed in the model. This cumulative probability-based approach works best for emissions source(s) that have events that have a known and specific pattern temporally and in intensity. However, as demonstrated in this case study, provided reasonable conservative assumptions can also be made for certain emission events whose actual frequency is unknown (e.g., backup generators due to power interruptions), then this approach is likely to be applicable. For source(s) that have highly variable emissions, either in terms of emission intensity and/or temporal patterns, then this approach may lead to under- or overestimation of the 'realistic' number of exceedances and, therefore, should be avoided.

In addition to the scenario from the case study, this approach is likely to be applicable to other applications, such as transport layovers (e.g., trucks or trains idling in layover areas). For similar modelling scenario this approach would be applicable, the following generalised equation could be utilised to determine the more realistic number of exceedances:

$N_{ROC} = P_{UMC} \times P_{EE,i} \times 8760$

$$N_{ROC} = \left(\frac{N_{ex}}{8760}\right) \times \left(\sum_i^n \left(\frac{N_{EE}}{8760}\right) \times R_{EI}\right) \times 8760 \quad \text{(Eqn 8)}$$

where N_{EE} refers to the likely number of hours of emissions per year for emission event i and R_{EI} is the emission intensity ratio relative to that modelled. Eqn 8 assumes that each emission event cannot occur simultaneously, which is likely the case for many applications, and that the modelling occurred for 1 year (i.e., 8760 hours). For emission events that could occur simultaneously, Eqn 8 would need to be modified with consideration to Eqn 1.

The current work has focused on applying cumulative probabilities to model source emission, yet to calculate the number of exceedances, background concentrations must also be considered. The typical approach is to obtain 1 year of data from a nearby monitoring station from a representative year (generally the same year modelled) and assume this is representative of background concentrations when calculating potential number of exceedances overall (i.e., sum of model and background). However, background measurements can be affected by regional-scale air quality events, such as bushfires or dust storms, that can lead to exceedances. Certain regional-scale events, such as prescribed burning, occur at regular times of the year, and exploring utilising a similar approach to the account for such events in background data will be the focus of future work.

5. Acknowledgments

The authors acknowledge the support of their employer WSP Australia in preparing this paper.

6. References

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