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The use of Probabilistic Noise Modelling in the Design of Open-cut Mines

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ABSTRACT
Community, regulatory and environmental pressures have resulted in the development of an iterative approach to mine plan design. This is a staged approach that considers how noise, air and water quality and ecological impacts of different mine plan options affect the viability of the mining development. The traditional deterministic noise modelling process is used to predict the area of noise affectation of a predefined mine plan resulting in the acquisition of affected properties. The deterministic modelling process typically includes a sensitivity analysis to understand the uncertainties associated with the impact of operational changes, machine selection and changes in meteorological conditions on the area of noise affectation. The results are expressed as a range of predicted noise levels at each receiver location. Contemporary iterative mine plan design processes consider the economic operability of the mine, the environmental impacts of the operation, as well as the community acceptance of the development before determining an acceptable area of affectation. Rather than determine the area of affectation for a predefined mine plan, the iterative approach requires the planners to design a mine plan that can operate within an acceptable area of affectation. Probabilistic noise modelling is then used to investigate the operational changes required by the mine for the noise levels to remain within the acceptable area of noise affectation as temporal and spatial conditions change. As with traditional deterministic modelling methods, probabilistic noise modelling includes meteorological conditions, ground properties, terrain features, source sound power and directivity, and receiver geometry. However, in probabilistic noise modelling the results are expressed as a percentage of time that different operational changes, such as equipment relocation or shut down, may be required so that the acceptable area of affectation is realised. This paper outlines the application of probabilistic noise modelling for the iterative design of open-cut mining operations.

1 INTRODUCTION

The modelling of industrial noise sources using computer-based mathematical noise models is a well-established process. The primary objective of the noise modelling process is to provide a prediction of the sound pressure level generated by an industrial operation at a specific receiver location for comparison against relevant noise goals. If the predicted sound pressure level exceeds the relevant noise goal there is an expectation that noise control strategies will be investigated and implemented to reduce the immission level at the receiver location.

For many mining operations, the management of noise immission levels is a key consideration during the design, planning and operational phases of the mining operation. The noise assessment methodology used over the life-of-mine is presented in Figure 1.

Predictive noise models are used during the design phases to inform key decision-makers on the likely contribution of the mine to the surrounding acoustic environment. To identify areas within the surrounding environment that could be exposed to high noise levels from the mining activities the first set of predictive noise models are run without noise controls in place. The preliminary noise modelling then investigates a range of potential and sometimes impractical long, medium and short term control strategies that could be implemented to reduce the contribution of the mining activities to the surrounding acoustic environment. By comparing this information with the requirements of statutory guidelines key decision-makers can nominate target noise limits for each sensitive receiver location. This provides a benchmark against which the effectiveness of different noise control strategies can be assessed.

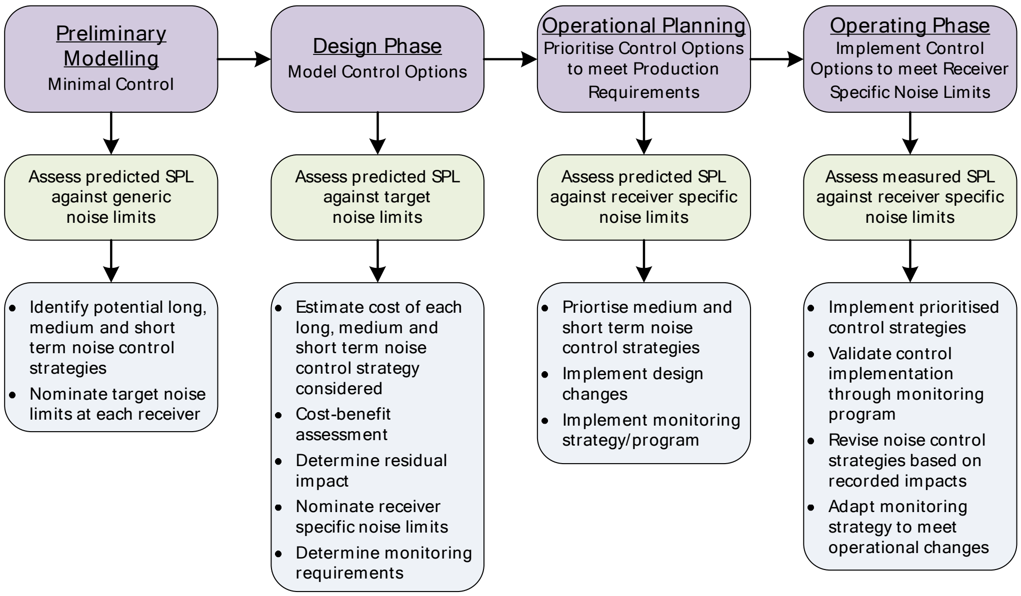

Figure 1 - Overview of Life-of-Mine Noise Assessment Methodology

During the operational phase, an open-cut mine will be subject to a range of operational constraints including self-imposed conditions to meet corporate or community expectations and conditions imposed by a range of different regulatory authorities. Noise limits imposed by regulatory authorities are typically single numeric values that only consider the spatial difference between receiver locations and the diurnal differences categorised as day, evening and night.

In the planning and operational phase, the objective is that the immission level of the mine at each receiver location remains at, or below, location-specific noise limit criterion. There is a cost associated with the implementation of different control strategies to meet these noise limits. There is also a cost associated with the failure to successfully implement appropriate noise control strategies. During the operational phase, the predictive noise modelling process is used to identify operational strategies that can be implemented to reduce the source contribution to the acoustic environment.

To assess the effect of long-term temporal variations associated with the changing topography of the mine, the noise modelling approach uses successive mine plans to represent the mine's changing layout and location within the landscape. The sensitivity of the predicted immission levels is investigated by modelling the primary items of mining equipment in multiple locations within each successive mine plan. Possible variations in equipment selection, location and utilisation are also considered in terms of the mining geology, production requirements and diurnal variations associated with continuous 24-hour operation. Traditional seasonal and diurnal descriptors are also used to investigate the effect of the temporal variations in meteorological conditions on the propagation of the noise from the mining source to a receiver location.

Historically, the mathematical models of these mining noise sources have been deterministic in nature, often using the techniques such as internal analysis described above, to investigate the uncertainty associated with the modelling output.

2 MODELLING AND UNCERTAINTY

Mathematical models developed to represent complex systems can be classified as static or dynamic, deterministic or stochastic, and continuous or discrete (Maria 1997, Law 2007). A deterministic model precisely determines an outcome from known relationships among states and events, without any room for random uncertainty. In a deterministic model, the same inputs always produce the same output. The expectation is that all the information required to solve a problem is available and that the effect of any parameter can be computed with certainty.

Where a deterministic model uses a single value to represent a parameter a stochastic model uses a range of values to simulate the variability of the parameter. The range of values are simulated statistically, and parameter values can be selected using methods such as Monte–Carlo simulation. Where sufficient information is available to generate probability density functions for each parameter, stochastic models can be used to assess aleatory uncertainty (Chutia et al., 2014).

In the real world, uncertainty arises from incomplete knowledge (epistemic uncertainty) or natural stochastic variation across space and time (aleatory uncertainty) (Tucker & Ferson 2003, Roy & Oberkampf 2011). Where epistemic uncertainty cannot be reduced by further study a number of different methods can be used to analyse the uncertainty. These methods include: logic trees where the weighting on the branch represents the judgment about the credibility of the alternative; interval analysis; the Dempster-Shafer Theory of Evidence that is based on belief and plausibility; and Possibility Theory (Abrahamsson 2002, Helton 2009, Swiler et al. 2009, Baraldi et al. 2010, Eldred et al. 2011).

Aleatory uncertainty, however, is associated with the natural randomness of a process where the outcome cannot be predicted. Aleatory uncertainty can be treated as stochastic in behaviour and is based on confidence in the probability distribution over possible outcomes (Fox & Ülkümen 2011). Li et al. (2016) refers to epistemic uncertainty in the context of evidence theory where belief and plausibility are important factors, whereas aleatory uncertainty is referred to in the context of objective or stochastic uncertainty that arises from the randomness of a physical system or environment.

In summary, epistemic uncertainty is associated with the likelihood that an outcome is true, whereas aleatory uncertainty is associated with the proportion of time the outcome is true.

3 NOISE MODELLING METHODOLOGY

The propagation of sound from a source to a receiver in the open air is a function of a number of factors, some of which are interrelated. These factors include the meteorological conditions, ground properties, terrain features both natural and man-made, the source sound power and directivity, and receiver geometry (Manning 1981, Salomons 2012, Marsh 1982 and Wilson et al., 2014). The predictive modelling of the sound signal Lp_i from source i in the open-cut coal mine of interest at a receiver location can be represented as:

$$Lp_i = \mathrm{f}(Lw_i, V_1, V_2, V_3, V_4, V_5, V_6, V_7, V_8, V_9) \qquad \text{dB(A)} \qquad (1)$$

where: Lp_i = the predicted sound level from source i in the open-cut mine of interest at the receiver location
Lw_i = the sound power level of source i
V_1 = the distance from the source to the receiver and associated geometric divergence
V_2 = wind speed, wind direction and atmospheric stability
V_3 = atmospheric absorption due to temperature and humidity
V_4 = ground conditions (including vegetation)
V_5 = source to receiver geometry (intervening topography including natural and man-made features)
V_6 = mine plan design
V_7 = equipment location within the mine plan
V_8 = equipment orientation and sound power level directivity

If source i is one of n sources within the mine of interest that contributes to the acoustic environment at the receiver location, then the contribution from the n sources to the acoustic environment can be written as:

$$Lp_{\mathrm{Mine}} = 10log_{10}\left(\sum_{\mathrm{i=1}}^{\mathrm{n}} 10^{Lp_i/10}\right) \qquad \text{dB(A)} \qquad (2)$$

Wilson et al. (2014) notes that “the value of model predictions is greatest when the accuracies are well understood”. This would include the model's representation of the real world and methodology used to apply the model to real-world situations.

To simplify the modelling process and reduce the computational effort the parameters described in equation (1) have been described historically using single numeric values (or the equivalent when applied to the terrain geometry). This results in a deterministic output. Interval analysis has then been used to understand the sensitivity of the modelled output to the input variables.

Modelling complexity is increased when the single numeric values are replaced with probability density functions. The benefit of using stochastic inputs is that the modelling process results in a stochastic output that can be used to investigate uncertainty (Wilson et al., 2014). Brasldi et al. (2010) describes an even more complex hybrid modelling method for assessing both epistemic and aleatory uncertainties where a Monte-Carlo simulation samples the epistemic variables in an outer loop, and aleatory variables are sampled in the inner loop. This method obtains a different statistical distribution for each realisation of the epistemic variables.

In terms of 'risk', these modelling methodologies are describing the 'hazard' or consequence of the modelled event, either as a deterministic or stochastic output. To understand the operational risk the hazard needs to be combined with 'likelihood' or probability of occurrence. Our *a priori* is that probabilistic modelling described the method used to account for the likelihood of occurrence of the described hazard.

Each of the parameters in equation (1) describe the hazard but also affect the probability of occurrence of the described hazard. To assess operability, the quantifiable hazard (i.e. predicted $Lp_{\mathrm{M}ine}$) needs to be described based on the known mine plan design; the proposed production rate and operation of the selected equipment within the mine; and the source to the receiver geometry and associated ground conditions. The predicted $Lp_{\mathrm{M}ine}$ at a receiver location for the proposed mining activity (i.e. for the known relationships between the states and events) is then a function of the weather conditions. The predicted $Lp_{\mathrm{M}ine}$ at a receiver location for the proposed mining activity will vary according to weather conditions, but the probability of occurrence is directly related to the likelihood of the weather conditions occurring.

Having described the hazard for the proposed mining activity as a predicted $Lp_{\mathrm{M}ine}$ and the probability of the hazard occurring, based on methods developed for risk management, risk reduction strategies can then be prioritised based on:

- Elimination of the hazard
- Substitution of the hazard with a less hazardous alternative
- Management the hazard using engineered or procedural controls
- Mitigation of the impact of the hazard

This approach to probabilistic noise modelling and risk management can now be applied to the design, planning and operational phases of the mining operation.

4 PROBABILISTIC NOISE MODELLING AND NOISE CONTROL

4.1 Stochastic versus Probabilistic

Figure 2 shows the frequency distribution of the predicted $Lp_{\mathrm{M}ine}$ attributed to a source-of-interest at a receiver location 1.5 km from the source. The predicted $Lp_{\mathrm{M}ine}$ is for a known mine plan, known machine sound power levels, location and orientation, known source to receiver geometry, and defined atmospheric absorption conditions and ground conditions. The meteorological condition (V_2) in equation (1) is the only stochastic variable used to produce Figure 2. Changing V_2 results in different predictions of $Lp_{\mathrm{M}i}$ but each V_2 event has a different probability of occurrence based on the measured occurrence of the actual meteorological event. That is, each entry in the histogram in Figure 2 is weighted according to the percentage of time each V_2 event occurs.

The frequency distribution of the predicted $Lp_{\mathrm{M}ine}$ is also presented as 'greater-than' cumulative distribution plot in Figure 2. If the source-of-interest had an immission limit at the receiver location of 38 dB(A), the cumulative distribution plot in Figure 2 indicates the immission limit would be exceeded 19% of the time.

In the cumulative distribution plot in Figure 2, the x-axis represents the hazard and the y-axis the probability of occurrence of the event. Probability density functions can be used to represent the aleatory uncertainties associated with the machine sound power levels, and/or the atmospheric absorption conditions and/or ground conditions. Interval analysis can be used to represent the epistemic uncertainties associated with the machine location and/or machine orientation and/or mine plan design. Using Monte-Carlo simulation results in a stochastic prediction of the hazard. This is shown diagrammatically in Figure 3 for a single V_2 event. In the example in Figure 3, the probability of the event occurring remains unchanged as it is believed the hazard is plausible and could occur for the period corresponding to the V_2 event.

The cumulative probability curve and stochastic prediction of $Lp_{\mathrm{M}ine}$ presented in Figure 3 is an adaption of the Brasldi et al. (2010) hybrid modelling method described above. In Figure 3 the probability of each V_2 event occurs in the outer loop and the aleatory and epistemic uncertainties of the machine sound power levels, location etc modelled using a Monte Carlo simulation occur in the inner loop. This method can be used to obtain a statistical distribution for each V_2 event but is computationally intensive.

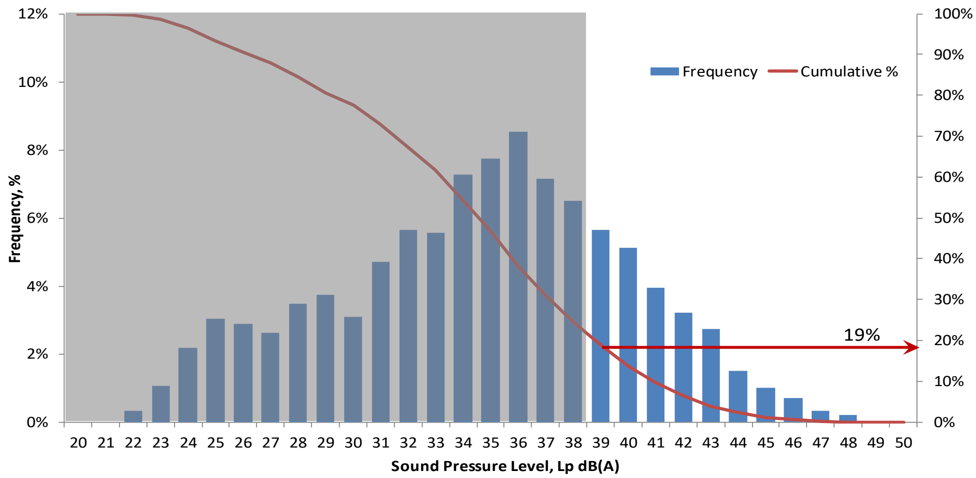

Figure 2 - Distribution Histograms and 'greater-than' Cumulative Distribution Curve of Predicted LAeq,15minute $\boldsymbol{Lp_{Mine}}$ Immission Level at the Receiver Location

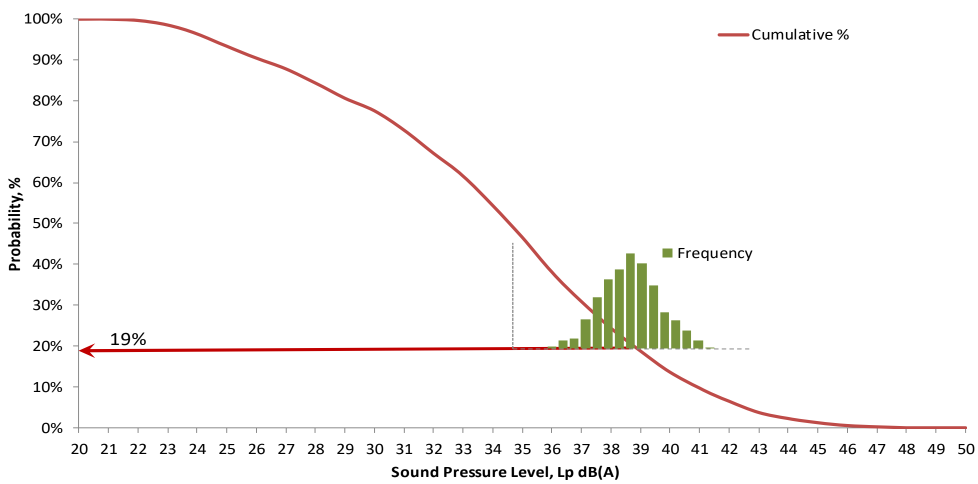

Figure 3 - Cumulative Distribution Curve showing Stochastic of Predicted LAeq,15minute $\boldsymbol{Lp_{Mine}}$ for a Single each $\boldsymbol{V_2}$ event

4.2 Modelling and Control

The probabilistic noise modelling approach can be used to systematically assess the reduction in the immission levels at the receiver locations that could be achieved through the implementation of a range of different noise control strategies. The objective is to identify a set of control strategies (long, medium and short term) that would enable the mining operation to stay within the target (or licensed) noise limits at each of the receivers located in the region surrounding the mine. The results of the probabilistic noise modelling in Figure 4 show the impact of the temporal variations of the meteorological conditions on predicted noise levels for six (6) control strategies that could be applied to the day time operations of an operating mine. To reduce the complexity, the predicate modelling results presented in Figure 4 are for a deterministic model, that does not consider the aleatory and epistemic uncertainties of the machine sound power levels, location etc in the analysis. The horizontal shift in the cumulative distribution curve to the left is due to the implementation of discrete noise control strategies (Scenarios 1 to 3b). The probability of occurrence remains unchanged.

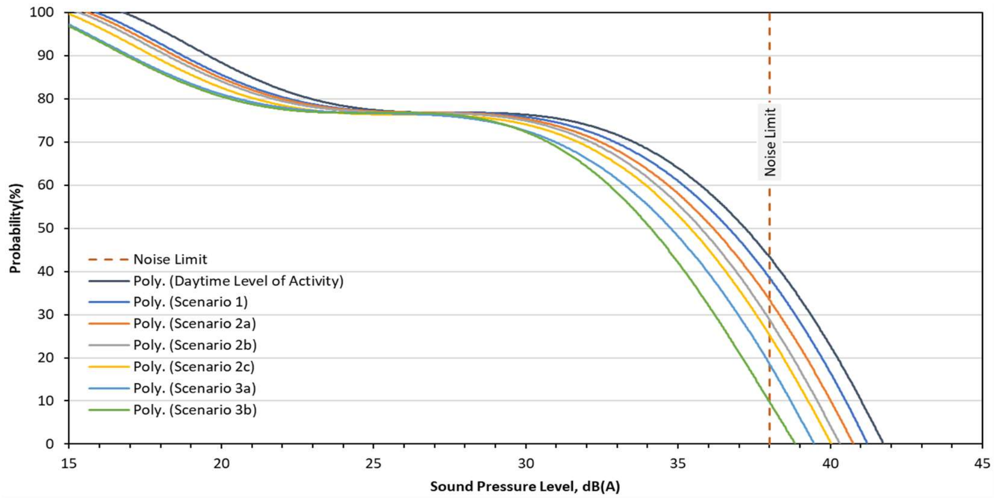

Figure 4 - Cumulative Distribution Curve showing the Predicted $L_{Aeq,15minute}$ $\boldsymbol{Lp_{Mine}}$ for six different Control Strategies applied to the Day Time Mining Operations

In the example in Figure 4, the target noise limit is 38 dB(A). The noise control strategies shown would be implemented iteratively to maintain the noise immission levels at the nominated receiver location at, or below, the target noise limit (refer to Figure 5). Analysis of the cumulative distribution curve of the probabilistic noise model results provides valuable information on the percentage of the time noise control strategies, such as machine relocation or shut down, need to be implemented.

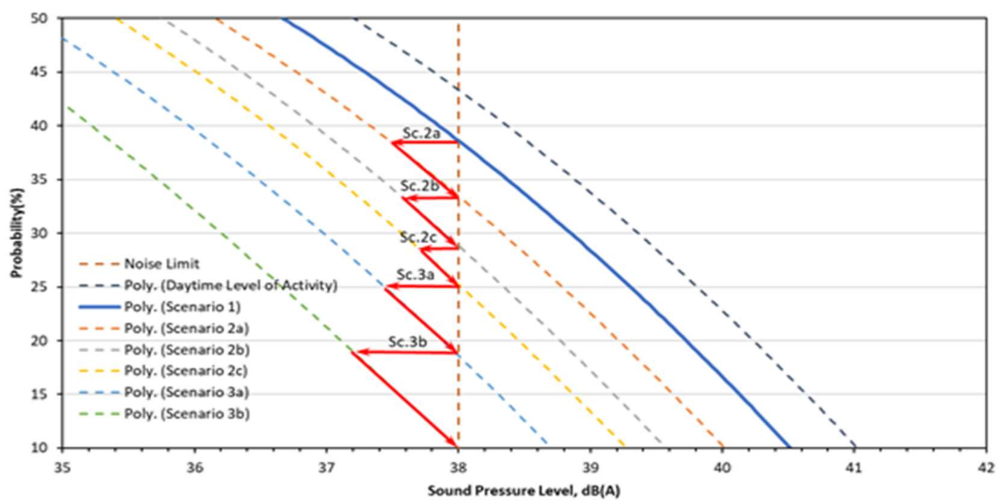

Figure 5 - Iterative Implementation of Control Strategies

4.3 Modelling Requirements

Probabilistic noise models require a detailed set of meteorological conditions that are representative of the meteorological conditions that would be expected during the life of the mine. The modelling approach involves analysing the local meteorological conditions to determine the percentage of occurrence of inversions and wind effects in the region for each respective season and time period. The predictive noise model is then run for each set of meteorological conditions described by the wind speed interval, wind direction interval and temperature gradients representing A to G class stability conditions for each source to receiver transmission path. When combined with multiple mine plan options, topographical changes, sound power model options, source location options and multiple receivers, a large probabilistic noise model can result in up to 400 million source model to receiver calculations. The proportion of time each of these combinations applies is then combined with the resulting predicted sound pressure level to determine the occurrence of the immission level at the receiver location.

4.4 Modelling Results

Table 1 provides an example of the stepwise iteration of potential noise control options that could be applied to night time mining operations of a typical open-cut mining operation in order to achieve target noise limits at two receiver locations.

Table 1 - Interpretation of Modelling Results – Night Time Operations

Description	Predicted Operational Outcome	
	Receiver A	**Receiver B**
Sc.1a Full Operations with exposed haul roads and with day-only activities off	Can only operate 58% of Nights	Can operate 56% of Nights
Sc.1b Full Operations with revised haul road and with day-only activities off (alternate to Sc.1a)	Can operate 80% of Nights	Can operate 72% of Nights
Sc.2 Slow dump dozers, slow trucks on dumps and slow or stop most of the ancillary equipment (based on Sc.1b)	The constraints apply 20% of Nights	The constraints apply 28% of Nights
Sc.3 Shut down waste excavator and associated fleet (based Sc.2)	The constraints apply 14% of Nights	The constraints apply 16% of Nights
Sc.4 Shut down second waste excavator and associated fleet (based on Sc.3)	No additional constraints required	The constraints apply 12% ofNights

The analysis of the percentage of the time noise control strategies need to be implemented, as presented in Table 1, is a key piece of data in the cost-benefit analysis of the mining operation over the long term. The economic assessment of a mining project places a quantitative value on the cost of each of the noise control strategies considered technically feasible. Probabilistic noise modelling can also be used to investigate different mining methods, mine plan designs and production rates. The results of the probabilistic noise modelling can then be used in the assessment of the reasonableness of technically feasible noise control strategies. A reasonable noise control strategy is one that strikes a balance between the cost to the industry, to the community and to the environment and the social and economic benefits derived from the industry.

The same modelling process is used to provide strategic information on the viability of different noise control strategies to mine plan designers over the medium term and to the mining supervisors over the short term. The difference is that the noise modelling is based on the actual mine plan and mining sequence of the operation, the actual equipment used in the mining operations and the operational requirements of the mine. The objective of the modelling is to assess the effectiveness and technical feasibility of each strategy prior to the prioritisation of strategies that match the operational requirements of the mine. The prioritisation of control strategies needs to also account for the spatial difference between receiver locations. The desired outcome would be that the mining operation achieves the relevant target noise limits at each receiver location under all temporal variations.

5 CONCLUSION

For a large dynamic industrial operation such as an open-cut mine, temporal variations of the noise immission level of the operation at a receiver location can be attributed to the changing topography of the mine over the long term; changes in the location of the primary items of mining equipment, and seasonal and diurnal variations over the medium term; and diurnal variations including changes in meteorological conditions and the constant movement of mining equipment around the mine over the short term. As a result, the management of the noise immission levels at each receiver location is a key concern in the design, planning and operational phases of the mine. Without due consideration, the implementation of noise control measures can become costly due to the capital expenditure of retrofitted equipment, the loss of productivity due to equipment shutdown and the cost of fines and/or loss of reputation due to non-compliance with relevant statutory requirements. It is possible to use time-based operational data to retrospectively attribute a cost to the implementation of different control strategies and implement remedial actions.

Probabilistic predictive noise modelling is a tool that can be used to both evaluate the effectiveness and prioritise the use of different noise control strategies. The probabilistic noise modelling approach can be used iteratively to identify and assess the effectiveness of technically feasible noise control strategies that could be implemented. Once identified as technically feasible the cost of a noise control strategy can be quantified and prioritised for implementation over the long, medium or short term.

6 ACKNOWLEDGMENT

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7 REFERENCES

Abrahamsson, M. (2002). *Uncertainty in quantitative risk analysis: characterisation and methods of treatment*, Fire Safety Engineering and Systems Safety, Lund University

Baraldi, P., et al. (2010). *Methods of uncertainty analysis in prognostics*. International Journal of Performance Engineering, Vol. 6, No. 4, July 2010, pp. 303-330.

Chutia, R., et al. (2014). *Uncertainty modelling of atmospheric dispersion by stochastic response surface method under aleatory and epistemic uncertainties*. Sadhana Vol. 39, Part 2, April 2014, pp. 467–485. Indian Academy of Sciences.

Eldred, M. S., et al. (2011). *Mixed aleatory-epistemic uncertainty quantification with stochastic expansions and optimization-based interval estimation*. Reliability Engineering and System Safety 96 (2011) 1092–1113.

Fox, C. R. and G. Ülkümen (2011). *Distinguishing two dimensions of uncertainty*. Chapter 1 in Brun, W., Keren, G., Kirkebøen, G., & Montgomery, H. (2011). *Perspectives on Thinking, Judging, and Decision Making*. Oslo: Universitetsforlaget.

Helton, J. C. (2009). *Conceptual and computational basis for the quantification of margins and uncertainty*. Sandia National Laboratories (United States)

Law, A. M. (2007). *Simulation modeling and analysis*. 3rdEdt McGraw-Hill New York.

Li, G., et al. (2016). *Aleatory and epistemic uncertainties analysis based on non-probabilistic reliability and its kriging solution*. Applied Mathematical Modelling Vol. 40 2016, pp. 5703–5716.

Manning, C. J. (1981). *The propagation of noise from petroleum and petrochemical complexes to neighbouring communities*. Concawe.

Maria, A. (1997). *Introduction to modeling and simulation*. Proceedings of the 1997 Winter Simulation Conference, pp. 7-13.

Marsh, K. J. (1982). *The CONCAWE model for calculating the propagation of noise from open-air industrial plants*. Applied Acoustics Vol. 15(6) 1982, pp. 411-428.

Roy, C. J. and W. L. Oberkampf (2011). *A comprehensive framework for verification, validation, and uncertainty quantification in scientific computing*. Comput. Methods Appl. Mech. Engrg. Vol. 200(25-28) 2011, pp. 2131–2144.

Salomons, E. M. (2012). *Computational atmospheric acoustics*. Springer Science & Business Media.

Swiler, L. P., et al. (2009). *Epistemic uncertainty quantification tutorial*. Proceedings of the IMAC-XXVII, 2009 Orlando, Florida USA

Tucker, W. and S. Ferson (2003). *Probability bounds analysis in environmental risk ass*essment. Applied Biomathematics

Wilson, D. K., et al. (2014). Description and quantification of uncertainty in outdoor sound propagation calculations." The Journal of the Acoustical Society of America Vol. 136(3), pp. 1013-1028.