LANE, G.R., KRAFFT, G., CAMBITSIS, A., DAYA, K., and VAN DER WESTHUIZEN, A. A rules-based production scheduling approach allowing multiple scenarios to be generated to test the impact of advance rate variability. *The 6th International Platinum Conference, 'Platinum–Metal for the Future',* The Southern African Institute of Mining and Metallurgy, 2014.

A rules-based production scheduling approach allowing multiple scenarios to be generated to test the impact of advance rate variability

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'There is uncertainty in mine planning assumptions which is not reflected in the final output' (Krafft, 2014)

A valid mine design and corresponding production schedule of all the required mining activities to develop and mine ore is critical to effectively manage developed ore reserves and plan the resources required for mining.

Maintaining the appropriate sequence of all the different mining activities – development, construction, equipping, ledging, and stoping – is critical to sustain the mining rate into the future. The advance rates of these different development activities, and therefore the rate at which the operation is replacing its developed ore reserves, determines the sustainable mining rate of the operation. Mine faster than the rate at which development is opening up, and the mine runs out of developed ore reserves; mine slower and working capital is wasted in opening up areas that will only be mined far in the future.

Mining companies need to effectively manage their long-term stoping development ratio, otherwise they may find themselves in the situation that they cannot sustain current mining rates. Furthermore, the production plan often does not take into account the variability and confidence levels in the planning assumptions, which impacts the future sustainable mining rate. Mine planners generally have different levels of confidence in achieving certain advance rates (one may plan optimistically, another realistically, and another pessimistically) and the overall final production schedule for a shaft is an aggregation of these different confidence levels.

The variability in the development and stoping activity advance rates that are historically achieved by different teams has the single biggest impact on the achieved and sustainable mining rate, but is often ignored.

This paper presents a case study from work done at a large platinum mining company that showed how a rules-based production scheduling approach allowed for a stochastic model to be applied to the production schedule that took the variability of the all the underlying advance rates into account. This enabled hundreds of production schedules to be generated quickly using different input assumptions to test the impact of this variability on the final production schedule achieved.

The case study demonstrates how the mining sequence is impacted by the variability in the advance rate of different critical path development activities and therefore the long-term impact on timing of subsequent activities in the mining sequence.

A final production schedule could therefore be generated with a chosen confidence level that takes the variability into account and demonstrates the sustainable mining rate that can be achieved.

Introduction

Production planning is based on averages, and does not adequately factor in the variability of the orebody, mining elements, team efficiencies, and the interaction between processes, especially where variability is concerned.

Current mine planning systems and the mine planning paradigm require a 'single value' production output per metric. This necessitates that a 'single average value' is chosen for each assumption relating to grade, reef width, density, stope and excavation sizes, over and underbreaks, and – importantly – the team advance rates for development and stoping activities.

This invariably leads to the input assumptions being either too optimistic or too pessimistic, with the result that the range of uncertainty is not reflected in the output, be it production (e.g. tons) or techno-economic analysis (e.g. net present value – NPV).

For example, for ore grade, a single value is used as an

assumption for a given planning period. Often there is geological sampling data that indicates the grade could lie within a range (i.e. its variability). This uncertainty is simply not reflected in the final output; rather an average value is used for planning purposes that does not reflect the uncertainty.

The development and stoping teams do not all achieve the same average advance or efficiency. This variability in team performance impacts the activity schedule relating to development, ledging, equipping and stoping, with a result that the risk associated with achieving the schedule is not quantified. The cumulative impact of the variability of advance rates on interconnected activities, and especially the critical path, has a major impact on the mine's ability to achieving a sustainable mining rate.

This paper is a case study from a large platinum mining company, where the historical variability in performance of all the underlying variables impacting the schedule was applied to generate a probability-adjusted production schedule. This was achieved by using the Cyest Mine Scenario Planning Solution together with the Cyest Stochastic Engine (Monte Carlo simulation) to generate multiple production schedules. This allowed for the variability in the production schedule to be quantified within chosen confidence limits.

The aim of the exercise was to determine the 80% confidence level (C80) of the detailed mine plan that had been produced, in CAE Mining's Studio 5D planning software, for this particular shaft.

Stochastic modelling (Monte Carlo simulation)

Lane (2012) describes stochastic modelling or Monte Carlo simulation as the technique of creating a mathematical model of a project or process that includes uncertain parameters that can and cannot be controlled. Monte Carlo methods rely on random sampling from probability distributions where they are 'plugged into' a mathematical model and used to calculate outcomes for each random instance of each variable.

This process is repeated thousands of times. Computer software has made this technique available to most business users.

Such a model can help management quantify the impact of uncertainty of underlying variables and the consequences of different mitigation decisions.

A stochastic modelling approach to production scheduling would therefore take into account the variability and uncertainty in the underlying assumptions relating to team advance rates, and result in a probability-adjusted production schedule with confidence limits.

An important aspect of stochastic modelling in the context of this case study was the ability to generate thousands of iterations of a production schedule that took into account the mining sequencing rules and crew and resource allocations.

The Cyest Mine Scenario Planning Solution was utilized for this stochastic modelling exercise due to its automatic rules-based scheduling and resource allocation.

Figure 1 depicts examples of mine planning and scheduling assumptions that have variability and would therefore have an impact on the variability in the final production schedule. Note that the distributions in Figure 1 are for illustrative purposes and are all shown as normal distributions, whereas in reality the actual distributions may be skewed based on historical data.

It is important to note that variability in team advance rates on a schedule has a significant impact on the schedule, as delays in preceding critical path activities can prevent the subsequent activity from starting on time. Therefore the cumulative effect of this variability on the interconnected activities on the critical path, which is basically the development activities required to open up the ore reserve for mining and therefore sustain the mining rate, would have a major impact on the mine's ability to achieve its production targets.

Rules-based production scheduling

A production schedule for a specific mine design and layout is a sequence of activities or excavations that must be performed in a certain order, in order to access the ore reserve to stope or mine.

These activities can be represented as a set of scheduling rules that can be applied to a particular mining method.

Figure 2 shows a simple example of a mining sequence for the development activities from the shaft to the raise line.

The scheduling logic could also extend to include all the

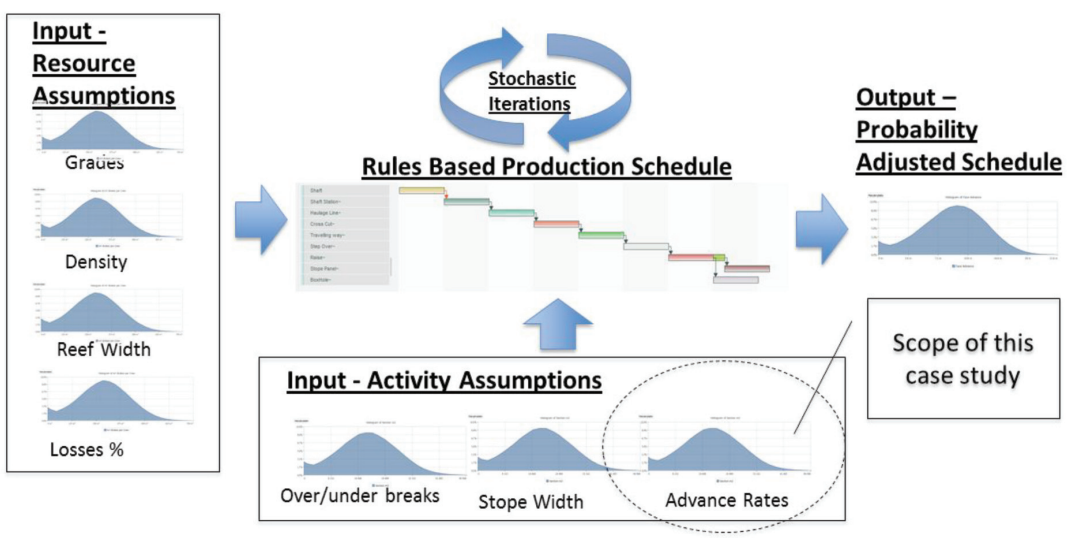


Figure 1. Assumptions that could have variability (Illustrative)

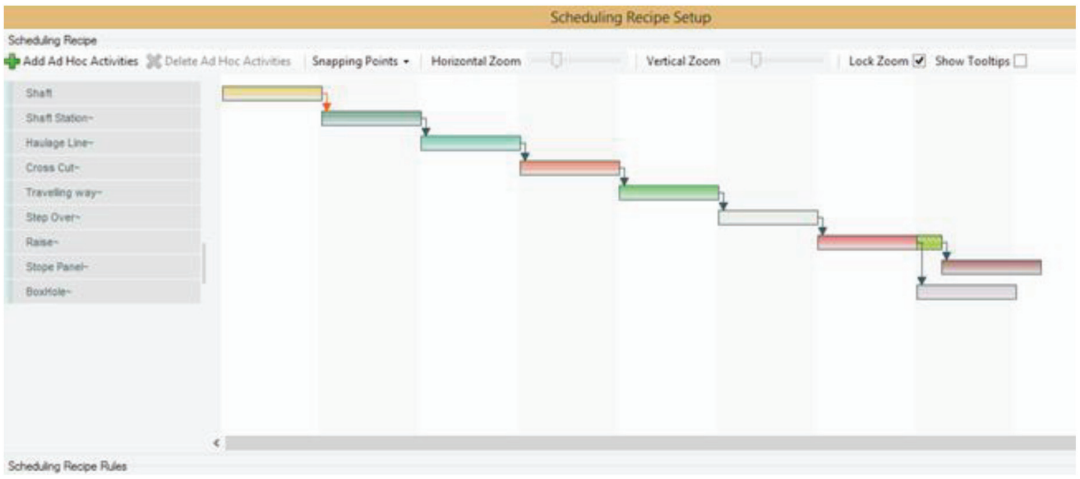


Figure 2. Example of a simple mining sequence recipe

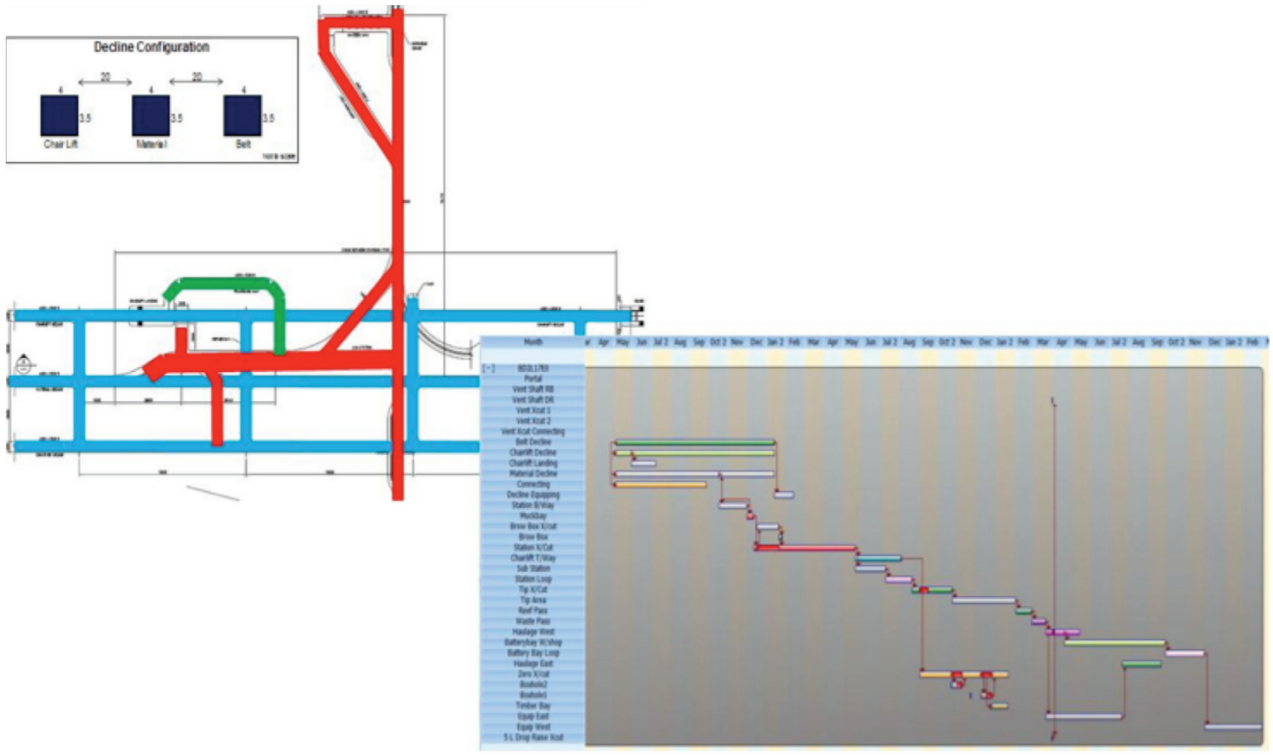


Figure 3. Template for decline station layout

other development activities such as boxholes, cubbies, travelling ways and ledging, stoping, and all construction and engineering supporting activities.

Figure 3 shows an example of a scheduling rule template for a decline station layout that could be applied to a mine design for each instance of this type of station layout. The schedule lengths in months would adjust based on the actual excavation lengths and team advance rates assumed.

Figure 4 shows how these scheduling rules are applied to a complete block within a half level, taking into account all stoping activities. This takes into account the actual excavation lengths and efficiencies for the development and stoping teams.

These scheduling rules applied to a complete mine design result in an overall mining sequence or production schedule that adheres to the mining rules to access and mine the ore reserve.

This production schedule must also take into account the actual resourcing levels (i.e. number of allocated stoping and development teams) that will be deployed on each level and in the shaft. Activities are thus delayed and moved out based on the crew/team allocations.

This results in a final production schedule for each level and overall shaft that pays respect to the mining sequence on each half level based on the scheduling rules and also the crew and team allocations applied.

Cyest Mine Scenario Planning Solution

This stochastic scheduling exercise was done using the Cyest Mine Scenario Planning Solution, which was originally called APMOT or Carbon14 (Smit, 2010).

The Cyest Mine Scenario Planning Solution is a non-graphical rules-based mine scheduling solution that allows

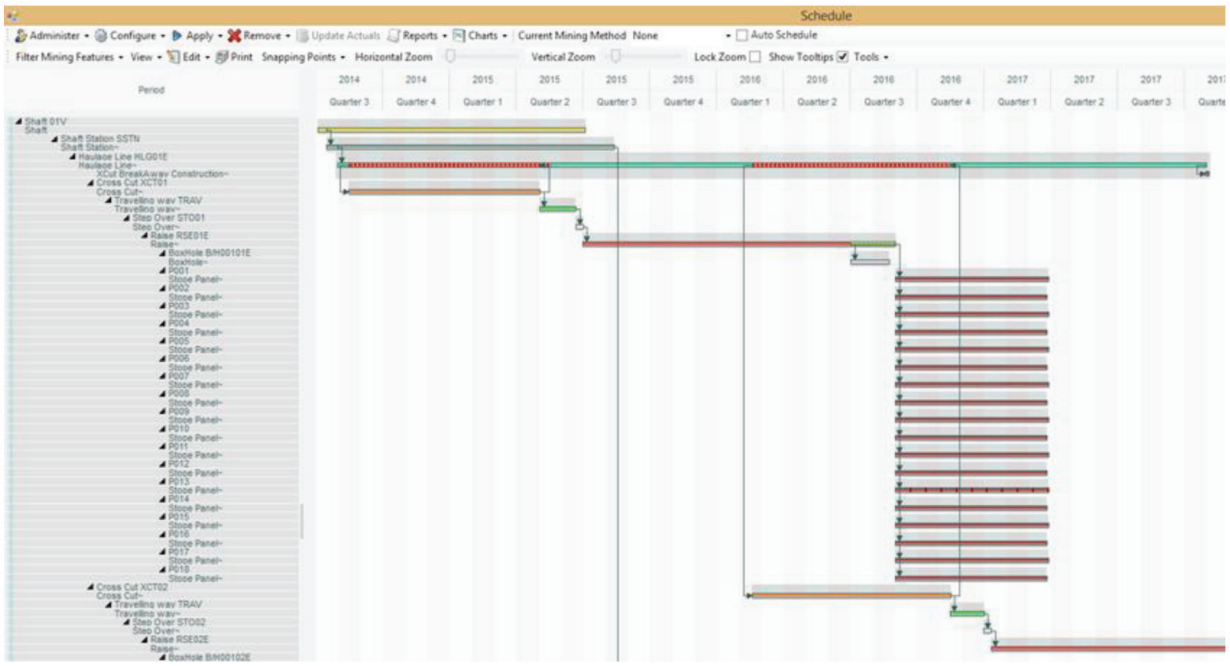


Figure 4. Scheduling rules applied to the complete raise line block

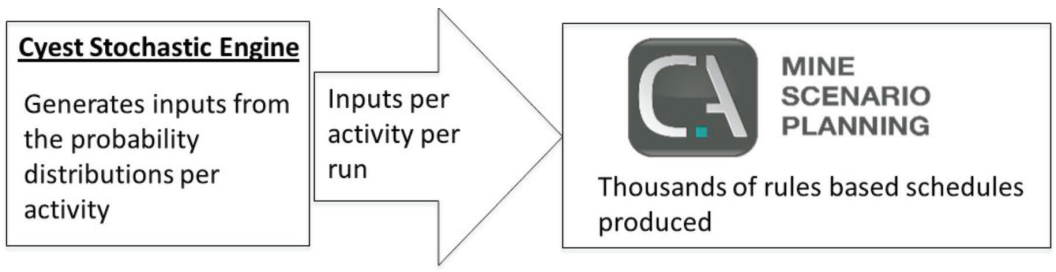


Figure 5. Cyest Stochastic Engine configured with the Cyest Mine Scenario Planning Solution

for the rapid generation of a production schedule taking the important drivers associated with geology, mine design and mining method into account.

The stochastic inputs for the schedule were generated in a stochastic engine from the defined probability distributions per variable, and each individual value per variable generated a specific production schedule scenario.

In this way thousands of rules-based production schedules could be produced for each iteration of input value from the Cyest Stochastic Engine as depicted in Figure 5.

Case study – underground platinum mine

The case study is based on the application of stochastic modelling to production scheduling, taking into account the impact of variability on team efficiencies for development, ledging and stoping on the final production schedule for the life of mine for a large platinum mine. The objective was to determine the 80% confidence level (C80) of the detailed mine plan that had been produced, in CAE Mining's Studio 5D solution, for this particular mine.

The impact of the variability of the grades, reef widths, and excavations sizes are important but were not included in this stage of the analysis as the client project team requirement was to understand the confidence level of the actual production tons.

Input variables

As mentioned, for this exercise, only the variability in the development, ledging and stoping team efficiencies were taken into account to understand the impact on the production schedule.

Historical data, as defined below, was used to determine a best-fit probability distribution for the following team and activity types.

- Flat end team efficiency – m/month
- Boxhole team efficiency – m/month
- Mechanized team efficiency – m/month
- Raise team efficiency – m/month
- Ledging team efficiency – m/month
- Stoping team efficiency – m^2/month

Historical monthly data points were used for the 12-month period before the August 2012 platinum industry strike, and further historical analysis was done after this strike to test if there was an impact on the variability of team performance. The data was normalized for the number of shifts in the month and took the reduced productivity levels for December and January into account.

Figure 6 shows examples of the historical-based best-fit probability distribution curves for the team efficiencies before the strike, and Figure 7 after the strike.

Table I shows a comparison of the mean efficiencies before and after the strike according to activity.

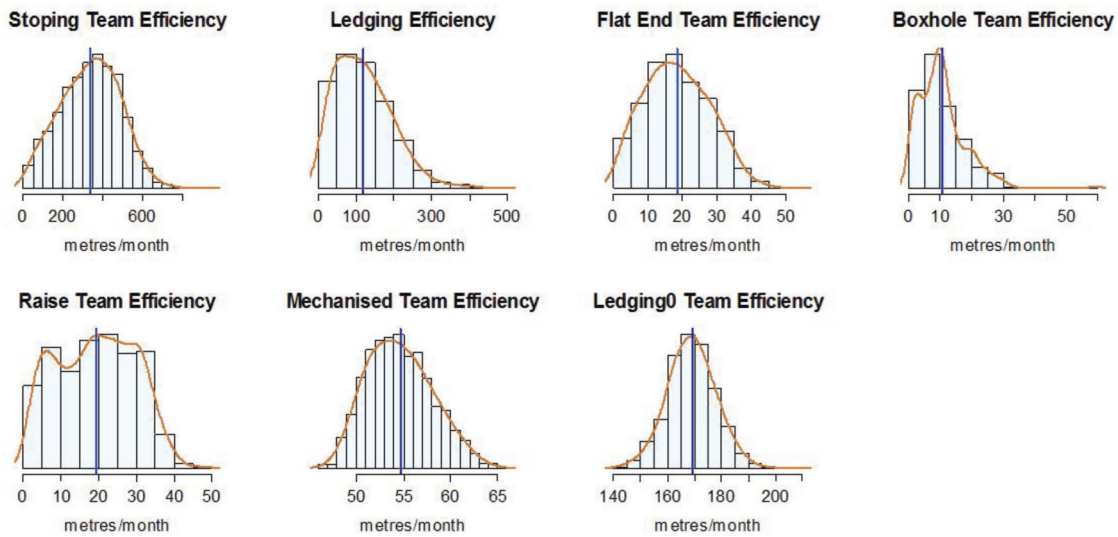


Figure 6. Historically based efficiency probability distributions before the August 2012 strike

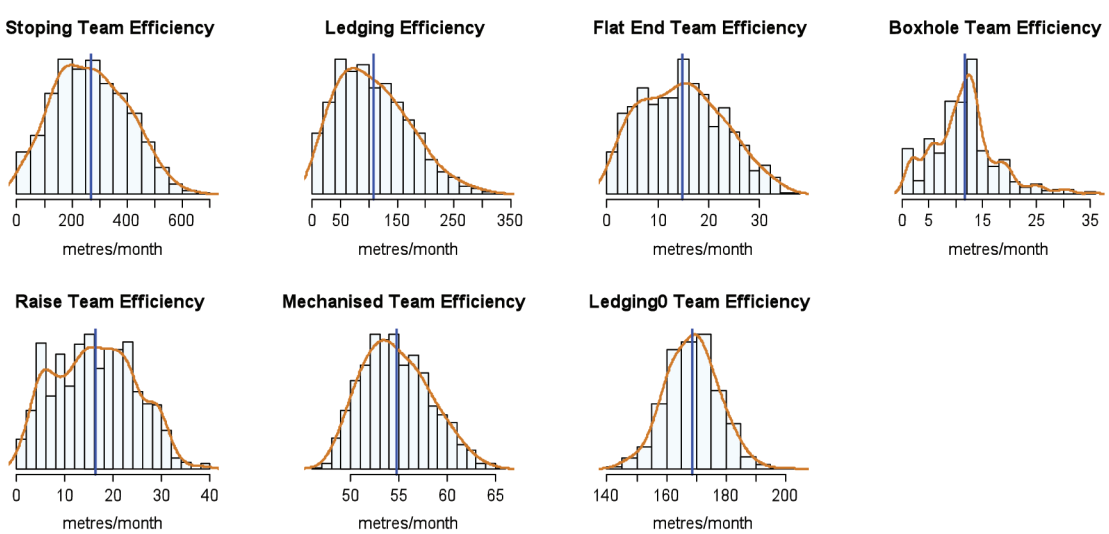


Figure 7. Historically based efficiency probability distributions after the August 2012 strike

As can be seen from this data, the stoping team mean efficiency dropped from 336 m^2/month to 268 m^2/month after the August 2012 strike. This analysis was undertaken to understand and explain the production levels after the strike compared to what was achieved during normal uninterrupted production periods before the strike.

In addition to the above analysis, the underlying value drivers of stoping team efficiency were also considered so that the drivers of this variability could be understood.

The value driver tree in Figure 8 depicts the value drivers, for which data is available, of the stoping team efficiency as being the number of crews, face length mined, number of blasts, and advance per blast.

The variability of each of these underlying value drivers was also determined using historical data as depicted in Figures 9 and 10.

The mean, minimum, and maximum values of the distributions were adjusted by the project team based on the

Table I
Mean values for advance per activity for before and after the August 2012 strike

Activity	Unit	Mean value (before strike)	Mean value (after strike)
Flat end dev.	m/month	18.5	14.9
Boxhole dev.	m/month	10.5	11.7
Mechanized dev.	m/month	54.7	54.7
Raise dev.	m/month	19.3	16.2
Ledging (wide)	m^2/month	169	169
Ledging (normal)	m^2/month	120	108.5
Stoping	m^2/month	336.7	267.8

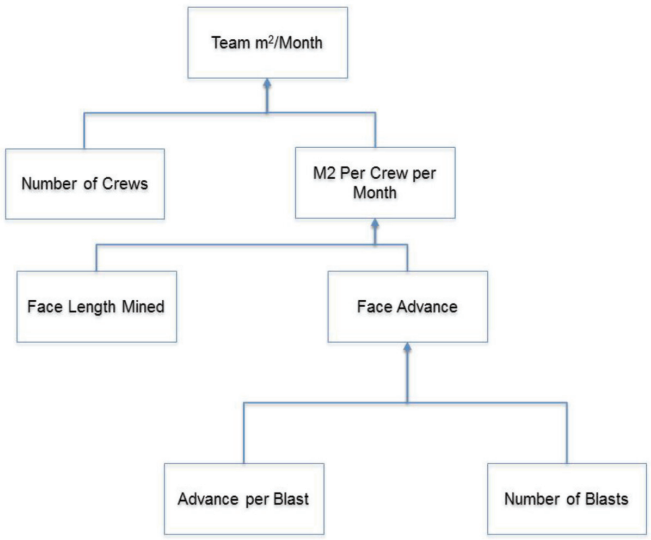
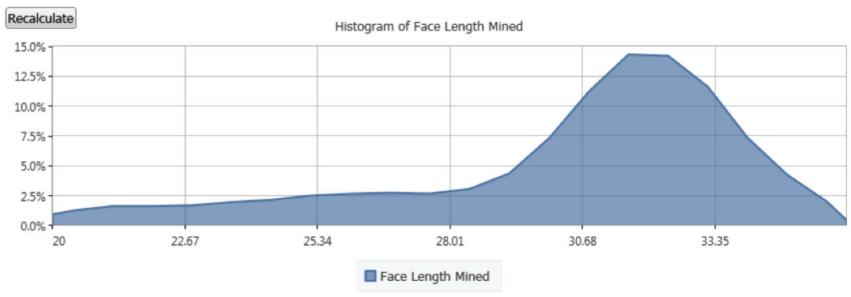


Figure 8. Example value driver tree for stoping efficiency

specific project design parameters. For example, the project team made design changes to improve ore flow from a half level by increasing boxhole sizing, designed multi-entry stations, and dual tramming to reduce ore flow congestion and thereby try to reduce lost blasts associated with this. The panel length distributions were also adjusted to take into account the final layout and what the project team believed could be achieved. The flat end development rate mean was also adjusted based on changing from the mine doing this work to a contractor using mechanized equipment. This approach is an acceptable means of adjusting the mean and variability based on justifiable design considerations, mining method, and other interventions that will be put in place to improve the operations.

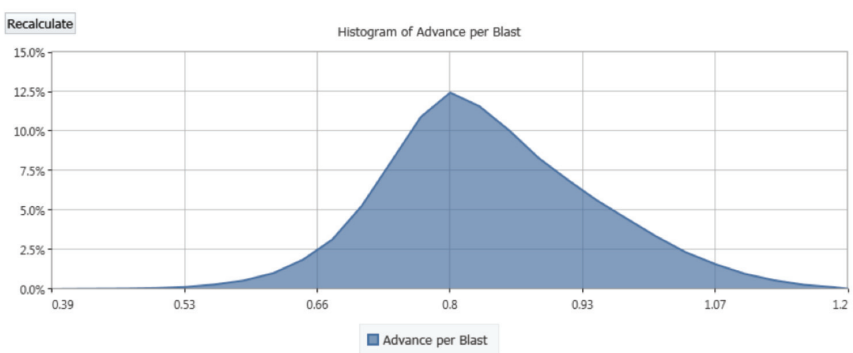
This resulted in significant improvement in the distributions, which would also be used in some of the runs to assess the impact and confidence levels of what the project team believed was achievable based on the mine design and operating assumptions.



	Face Length Mined
Mean:	30.41
Median:	31.47
Mode:	31.6
Standard Deviation:	3.38
Sampled Range:	[20.01, 35.72]
Skewness:	-1.24
Excess kurtosis:	0.75
Upper Confidence:	95
Lower Confidence:	5

Confidence	Face Length Mined Greater Than	Face Length Mined Less Than
10	33.59	24.86
20	32.96	27.8
30	32.43	30.08
40	31.94	30.92
50	31.47	31.47
60	30.92	31.94
70	30.08	32.43
80	27.8	32.96
90	24.86	33.59

Figure 9. Probability distribution for face length per panel



	Advance per Blast
Mean:	0.84
Median:	0.82
Mode:	0.8
Standard Deviation:	0.1
Sampled Range:	[0.42, 1.18]
Skewness:	0.29
Excess kurtosis:	0.21
Upper Confidence:	95
Lower Confidence:	5

Confidence	Advance per Blast Greater Than	Advance per Blast Less Than
80	0.75	0.92

Figure 10. Probability distribution for advance per blast

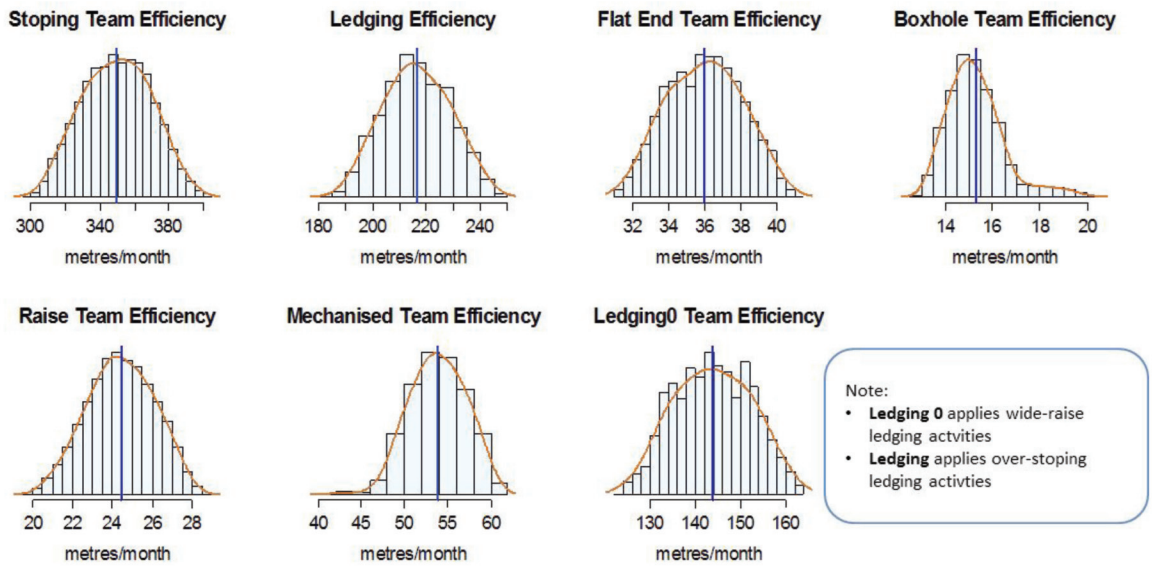


Figure 11. Probability distributions after project team adjustments

Table II
Mean values after project team adjustments due to design changes

Activity	Unit	Mean value (before strike)	Project team adjusted
Flat end dev.	m/month	18.5	36
Boxhole dev.	m/month	10.5	15.3
Mechanized dev.	m/month	54.7	58.9
Raise dev.	m/month	19.3	24.4
Ledging (wide)	m^2/month	169	149
Ledging (normal)	m^2/month	120	216
Stoping	m^2/month	336.7	349.8

Figure 11 shows the distributions after the project team made adjustments relating to the panel lengths, lost blasts, advance per blast, contractor flat end development, and other parameters.

As can be seen from Figure 11 and Table II, there was significant improvement in the mean values. For example:

- The stoping mean improved from 336 m^2/month to 350 m^2/month
- The flat end development mean improved from 18.5 m/month to 36 m/month.

The largest single contributor to the sustainable mining rate is flat end development and other primary development, as these activities determine the developed ore reserve available for mining. This is how fast the ore reserve is being opened up and therefore determines the sustainable mining rate.

Tables I and II show the following the significant changes in the mean rates of flat end and raise line development:

- Before strike: flat end development 18.5 m/month and raise line development 19.3 m/month
- After the strike: flat end development 14.9 m/month and raise line development 16.2 m/month
- With project team intervention: flat end development 36 m/month and raise line development 24 m/month.

The impact of the change on the flat end development rate will be demonstrated in the case study results.

The rules-based production schedule

The mine design criteria used were based on the original mine design and production scheduling assumptions used by the mine in CAE Mining Studio 5D.

The mining sequence scheduling rules were generated for a typical mining half level and consisted of all the development and stoping activities required to be executed as depicted in Figure 12.

Crews and resourcing were applied to this schedule so as to mimic the actual resourcing the mine would deploy. The schedule produced was compared to the original production schedule produced by the mine in CAE Mining's Studio 5D to confirm that it matched the detailed mine planning as depicted in Figure 13.

This base case comparison used the identical mine design criteria and all advance rate assumptions for all activities, and was used to prove that the rules-based production schedule done in the Cyest Mine Scenario Planning Solution was a realistic match to the detailed scheduling done in CAE Mining's Studio 5D Solution.

This rules-based production schedule was therefore a realistic representation of the mine's schedule and would be used for the probability-adjusted scheduling.

Application of variability to the production schedule

The variances for each variable as defined for the different cases were applied to the following production scheduling assumptions:

- Flat end team efficiency – m/month
- Boxhole team efficiency – m/month
- Mechanized team efficiency – m/month

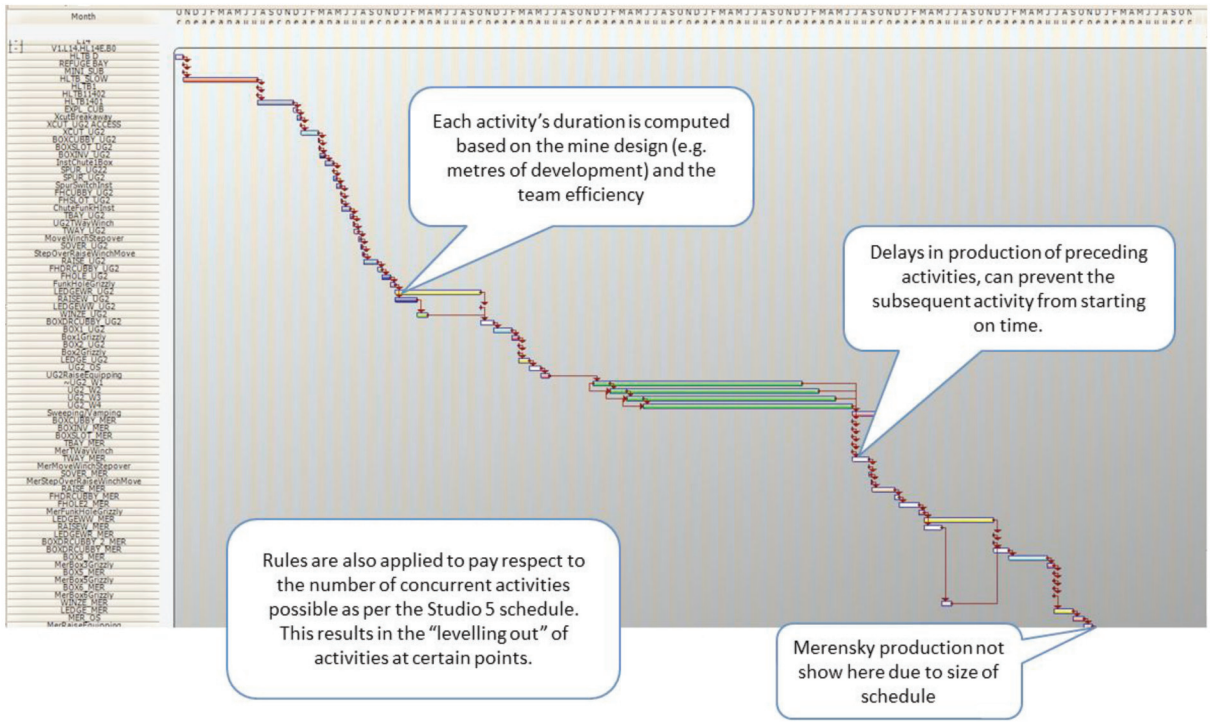


Figure 12. The mining sequence rules for a half level

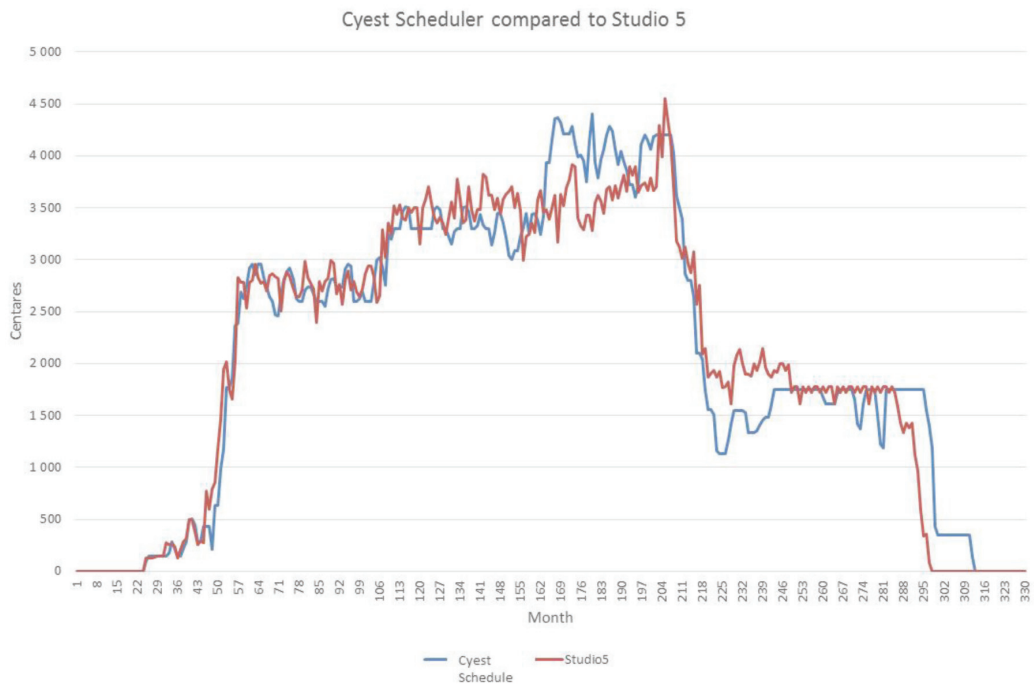


Figure 13. Comparison of the Cyest Mine Scenario Planning Solution output and CAE Mining's Studio 5D

- Raise team efficiency –m/month
- Ledging team efficiency –m²/month
- Stoping team efficiency –m²/month.

Eight hundred stochastic runs were generated for one half level to understand the impact that the different distributions and assumptions had on the final probability-adjusted production outputs.

Below is an example of six stochastic runs that were performed, with the results shown in Figure 15 (the parentheses contain the series name on the chart):

- Project deterministic base case to compare to the original CAE Mining's Studio 5D schedule produced by the project team (Base Case)
- Run 4 based on project team adjusted distributions as defined in Figure 11 (Run4)
- Run 4 with Period 1 (before strike) historical stoping variability (Run4 w per 1 Stp)
- Run 4 with Period 1 (before strike) historical stoping and boxhole variances (Run4 w per 1 Stp+BH)
- Period 1 (before strike) historical distributions for all

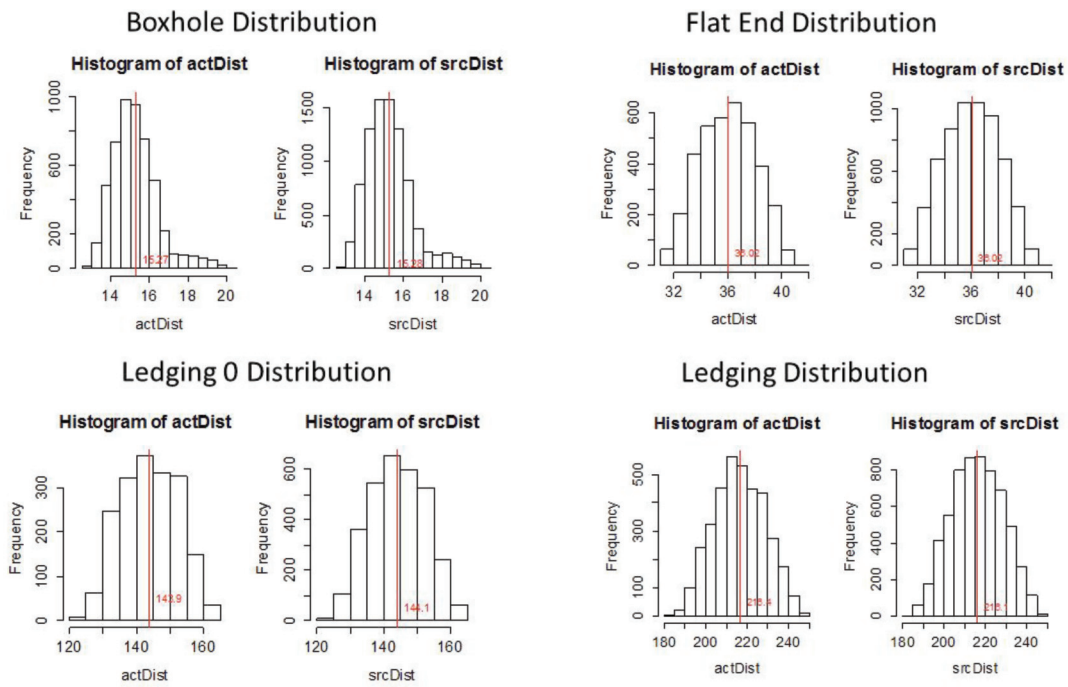


Figure 14. Comparison of Monte Carlo generated distributions and source data distributions

teams and no adjustments as per Figure 6 (Period 1)

- Period 2 (after strike) historical distributions for all teams and no adjustments as per Figure 7 (Period 2).

Different runs were performed based on these different input assumption distributions to understand the sensitivity of the different team efficiency distributions and the impact that some of the project teams' adjustments would have on the confidence level of the final production schedule.

Testing the distributions against the source data

As part of the stochastic runs, a test was done on each output distribution for the activities as calculated by the Monte Carlo simulation to confirm that they matched the source data distributions.

Figure 14 confirmed that the Monte Carlo simulation was generating distributions that matched the source data distributions.

The final output – probability-adjusted production schedule

The aim of the exercise was to determine the 80% confidence level (C80) of the detailed mine plan that had been produced, in CAE Mining's Studio 5D, for this particular shaft.

An important consideration is that the confidence level for the schedule cannot be determined independently for each month's production schedule, as the previous month's schedule impacts the next month. This is due to the cumulative effect on the critical path (primary development) that impacts future stoping ability. Therefore a confidence level can be applied only to the cumulative production, as this pays respect to the interdependency between the months due to the scheduling affect.

Figure 15 is the cumulative production (stoping square metres) profile for the 350-month production life of one half level based on an 80% confidence level (C80).

As can be seen in Figure 15, there is a large impact on the final production achieved due to the variability in the underlying scheduling assumptions between the different runs.

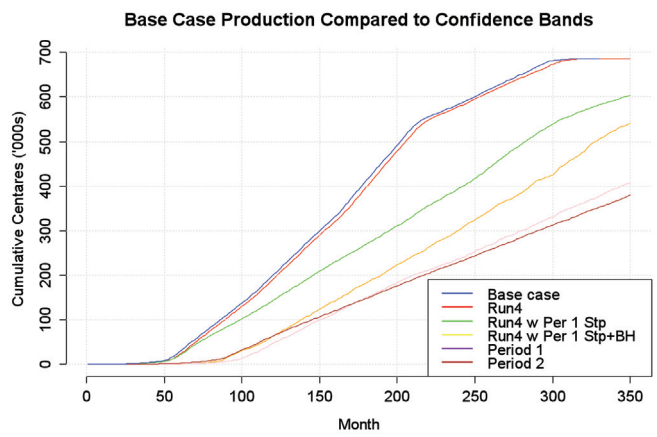


Figure 15. Cumulative production profile in centares for 80% confidence level

- The original base case (top line) achieved a cumulative 680 000 centares (m^2), and as expected the first stochastic schedule 'Run4' (second line from top), using the project team adjusted distributions, achieved the same cumulative output, which may represent some optimism bias by the project team. The team made tangible design changes such as larger boxholes, multi-entry stations, and two-way tramming to improve material flow out of the half level, which would reduce lost blasts due to congestion and cleaning. Together with the addition of longer panel lengths in the design, this would contribute to improved stoping efficiencies. The flat end development rates were also improved significantly by looking at the effect of changing to contractor mining by a company with an established track record

  Optimism bias is a cognitive predisposition found in most people to judge future events more positively than their experience warrants. In the case study by Lane

(2012), the project team took overly optimistic views on all assumptions that they could control, which was confirmed by the stochastic modelling

- 'Run4 w per 1 stp' (third line from top) was then adjusted and the original historically based stoping team efficiencies used. This resulted in a reduction to 600 000 centares (m^2), which is a 12% reduction in achieved production over the 350-month schedule.

  Importantly, this shows that the variability in the actual stoping team efficiency does cause monthly variance in production, but there is very little cumulative effect as there is no other activity dependency after stoping. In fact, the variability in the stoping team rate can be mitigated by adding more stoping teams as long as there is sufficient ground available to mine i.e. panels available
- 'Run4 per 1 Stp+BH' (fourth line from top) with the historical boxhole distributions shows a small cumulative reduction. Interestingly, the actual impact, due to the boxhole variability occurs at the start of the schedule, where it delayed the start of stoping. Once ground has been opened up, the variability in the boxhole rates has very little impact. As can be seen, the line is almost parallel to the 'Run4 w per 1 stp' run
- Runs 'Period 1' and 'Period 2' (lines 5 and 6 from top) use the unadjusted historical variability distributions for all the activity or team rates, Period 1 being before the August 2012 industry strike and period 2 after. This run results in a significant reduction in the cumulative production to less than 400 000 centares (m2) by the end of period 350. This is a 40% reduction in the achieved cumulative production over this period from this half level.

  This supports the statement made earlier that the largest single contributor to this reduction is the flat end development efficiency (and to a lesser extent the raise line), as this determines the rate at which the immediately mineable ore reserve is opened up or replaced. This determines the final sustainable stoping rate and therefore results in a continual lag in achieving the required mining rate. The cumulative effect of the flat end development rate and the associated variability has a significant long-term impact, as this determines the 'ore replacement rate' and therefore the sustainable stoping rate.

Conclusions

This stochastic scheduling case study has demonstrated the following:

- Most importantly, the exercise demonstrated to the mine that, based on the historical achievements and variability in the underlying team and activity advance rates. the half level production could, cumulatively over its 350-month life, be 40% lower than originally planned
- Variability and underachievement in the advance rate of critical path activities has the single largest impact on the mining rate in the future. The case study demonstrated that underachievement on the primary development that is responsible for opening up the orebody, which in this case is the flat end development and raise line development rate, and the variability of this advance rate, has a cumulative effect on the production schedule. This is not easily mitigated in the short term due to the length of time it takes for this development to be done
- This exercise also demonstrated that the variability in activities such as stoping have only a short-term impact on the schedule, and therefore impacts the monthly production and confidence level. This is due to the fact that there are no other activities dependent on stoping that would have an impact on future stoping (not on the critical path). This variability and resulting reduction in stoping confidence levels can be easily mitigated by mobilizing additional stoping teams. This ability to add stoping teams depends on ground being available to mine i.e. panels available
- This stochastic modelling exercise has demonstrated the significant impact that variability has on the confidence in., and most probable production from, the operation. This is due to the variability in a preceding activity resulting in a delay in the start of the next dependent activity.

Acknowledgements

The authors would like to thank the client, the Cyest Technology team that set up the stochastic environment, and George Krafft and Andreas Cambitsis, who did the scheduling and stochastic runs.

The insights gained were very valuable in assisting the mining industry in generating more realistic and risk-adjusted production schedules.

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Gary Lane

Managing Director, Cyest Technology

Gary Lane graduated with a Bsc Civil Engineering degree in 1990 from WITS University on an Anglo American Scholarship. Gary then spent 10 years working in various project engineering and project management positions within the group companies for New Mining Business, Anglo Technical Department, Debswana Diamond Mining Company and De Beers.

Gary completed an MBA in 2000 through Bond University in Australia and left Anglo American to found Cyest Corporation in 2001 with two colleagues from Monitor Consulting. Gary has built up the mining consulting business that became known as Cyest Analytics which has been involved in strategic mine planning and mechanised mining optimisation for mining client. In January 2014 Gary became the MD of Cyest Technology which focuses on the development and implementation of mine planning and optimisation solutions for the mining Industry globally.

Gary played an important role in the vision and overall leadership of the Syndicated Driven Development Program (SDDP) with Bentley Systems for the New Mining Planning Solution that is jointly being development by Cyest and Bentley and which brings a new paradigm to effective mine planning.

Gary's personal vision is to drive a quantum change in the mining industry by getting them to embrace technology to enhance decision making in mine planning and execution by understand their key value drivers that impacts performance.