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Environmental optimisation of mine scheduling through life cycle assessment integration

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ABSTRACT

Life cycle assessments (LCA) are useful to quantify the environmental costs of mining projects, however the application of LCA is often a retrospective environmental measurement of operating mines. This paper presents a novel methodology of carrying out a LCA to generate life cycle impact assessment data that can form an environmental block model of a deposit. These spatially explicit data can then be used as a constraint within long-term mine scheduling simulations. The results indicate that significant reductions in global warming impact can be achieved at a small economic cost. For example using an environmental constraint it was possible to achieve 91.9% of the global warming impact whilst achieving 95.9% of the net present value compared to the baseline. Different constraints and economic scenarios are explored and multi-criteria decision analysis is carried out. This approach enables environmental considerations to be included in strategic mine planning. This is important because mining will continue to form an important part of our society for the foreseeable future. Integrating environmental considerations into the earliest stages of mine planning can assist in driving environmentally responsible raw material extraction.

1. Introduction

This study proposes that environmental data for mining activities can be calculated using Life Cycle Assessment (LCA) and then included in mine scheduling simulations. A methodology to incorporate this approach in mine scheduling has been developed using a case study of an iron deposit located in the Iron Quadrangle, Brazil. The aim is that this is a generally applicable methodology that can be applied for other commodities.

Mining is an essential part of society, providing raw materials for consumer goods and supporting industrial development (Carvalho, 2017) and will remain so for the foreseeable future (Elshkaki et al., 2018). However, the mining industry can cause environmental degradation, impacting landscapes, water resources and air quality. On a global scale the mining sector currently represents around 2.7% of worldwide energy use contributing to significant greenhouse gas (GHG) emissions (IPCC, 2007). As demand for raw materials rises, the quality and grades of ore deposits is decreasing, and as a result it is predicted that global warming emissions will increase (Norgate and Haque, 2010). In order to maintain current levels or reduce this for the future requires improved efficiency through the adoption of new and enhanced techniques within the mining industry. Mining companies can also reduce economic risk from improved environmental performance as governments and consumers demand increased social and environmental responsibility (Wall et al., 2017).

LCA is one of the most promising methods to quantify the environmental performance of mining operations (Durucan et al., 2006; Blengini et al., 2012). It is an objective method that measures the environmental burdens of a product or process over its lifetime, considering the additional embodied impacts of materials or energy that are consumed in the studied process (ISO, 2006). LCA follows ISO 14040 and ISO 14044 standards (ISO, 2006). A key feature of LCA is that it measures the indirect impacts of a process, such as the environmental impacts associated with the fuel production, which may energies a process. Other life cycle approaches exist alongside LCA, such as life cycle costing (LCC), which takes into account the internal and external financial costs of a product system with a similar approach to LCA (Guinée, 2002) and social life cycle assessment (SLCA) which considers social aspects associated with a product system. SLCA and LCC can be integrated with LCA to form a life cycle sustainability

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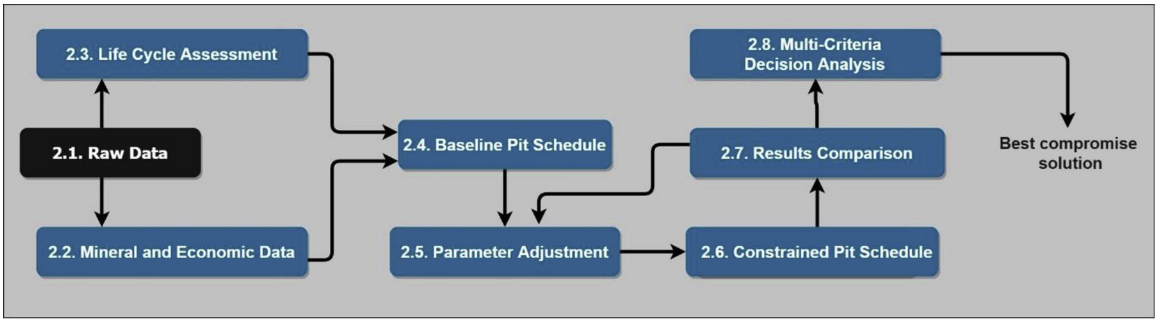

Fig. 1. Methodological framework for incorporation of life cycle impact assessment data in mine planning.

assessment (Finkbeiner et al., 2010).

The LCA approach has more commonly been used for policymakers and researchers, (Scott Matthews et al., 2014) but has recently gained traction from the mining companies themselves. Norgate and Haque (2010) carried out a mine-to-gate LCA of an iron ore mine, and found that to produce 1 kg or iron ore 11.9 kg CO_2 Eq. was emitted, with the greatest impacts associated with the loading and hauling stage. Ferreira and Leite (2015) also carried out a LCA for iron ore production from Brazil. This study examined the environmental costs of producing iron ore concentrate and highlighted that the use of grinding media as a major contributor to environmental impacts. Chaulya (2006) used a different approach, visiting three iron ore mines to measure particulate emission rates and develop formula for different surface activities. Physical properties of the ore can impact emission rates during mining activities and these, alongside other data such as spatial location form the basis of the calculations for the LCA in this paper. Energy consumption and emissions calculations are made using equations from the National Pollution Inventory (NPI, 2008) and Chaulya (2006).

LCA can be used to identify options for environmental improvements in a mining operation (Awuah-Offei and Adekpedjou, 2011). A challenge with current of LCA in the mining industry is that it has been applied in a reactive way, assessing the impacts of current operations (Vahidi et al., 2016; Arshi et al., 2018). This is helpful to develop a Life Cycle Inventory (LCI) and a baseline of impacts, however there is an opportunity to expand the use of LCA integration in mine planning and process design. The proactive approach has been used since 1993 (Keoleian, 1993) and has been applied in the chemical processing, manufacturing and building design industries (Azapagic and Clift, 1999; Steinø et al., 2013) but not as far as we know within the mining sector. There have also been advances in LCA to produce spatially and temporally explicit impact data (Maier et al., 2017) which have yet to be applied to mining.

The design stage of a product or process can determine its environmental impact over its lifecycle (Baumann et al., 2002) and so is an important intervention point to achieve environmental goals (Graedel and Allenby, 1998). Designing products or a process with the environment in mind and to assume some responsibility for the product's environmental consequences as they relate to specific decisions and actions is known as eco-design. In the context of mining, mine planning can be considered an aspect of process design and offers the opportunity to apply eco-design during this phase. Mine planning refers to the process of selecting particular material for extraction and designating the order and time of extraction to minimise cost or fulfil a specific business target. This process can occur well in advance of operation and can be updated throughout the life of the mine. It usually involves generating geological data by drill holes or other sampling methods. From these data, a block model can be formulated that contains data about the location and mineral composition of each 'block' in the deposit. Ore and waste blocks have to be selected based on their economic value and sequenced to ensure that products have a consistent marketable grade. For iron ore deposits, this includes a consistent iron content but also consistent levels of contaminants such as silica, alumina and phosphorus.

Pit optimization has been an important stage of mining project development. Traditionally, the approach for this included a series of steps to plan the mine known as nested pits. This was introduced in 1965 and remains the most commonly used approach in the mining industry (Lerchs and Grossman, 1965). However, a limitation of this approach is that it may fail to optimize the economic value of the whole pit. The approach known as Direct Multi-Period Scheduling or Direct Block Scheduling (DBS) advances this and applies the correct discount factors to cash flow over production years (Almeida, 2013; Souza, 2018). The Direct Block Scheduling approach can be used to maximise the economics of a deposit but also to fulfil particular business targets. Consideration of particular targets other than directly economic is known as 'strategic mine planning'. These targets can continuously evolve and change and in the context of this paper the target examined is global warming potential. Integrating DBS and LCA allows environmental considerations to be included in mine planning in a proactive way. This paper presents how this can be achieved and examines the environmental-economic relationship of mine planning using DBS.

2. Materials and methods

Environmental LCA data can be integrated into the mine scheduling process (Fig. 1) so that it is possible to explore scenarios and change constraints after initial results generation. The method is based on the Optimum LCA Performance (OLCAP) method described by Azapagic and Clift (1999) to meet the needs of the mine scheduling approach. The best compromise solution is based on the subjective values of the user. For example, it could place preferential importance on the environmental performance or the economic performance. The case study and data used in this study is from an iron ore deposit located in Brazil. This site was selected as the deposit is large and contains a relatively simple mineral composition.

2.1. Raw data

In order to evaluate the quality and quantity of potential ore within a deposit, a variety of direct and non-direct methods can be employed, including surface sampling, sub-surface drilling and geophysical techniques (Moon et al., 2006). The minimum information requirement of deposit knowledge is an average grade of element of interest and the number of tonnes that contain this grade. The distribution of grade and tonnes across the deposit is also critical for mine planning and is commonly estimated using linear interpolation methods such as Ordinary Kriging, data from drilling and other sampling methods. In this study, data on the orebody were obtained from diamond core drilling where intact core is recovered and then sampled for grade and chemical composition. Depending on the precision and accuracy required, either a mass spectrometry or an X-ray fluorescence method is subsequently used to determine the chemical composition of a representative sample of the core. A stringent quality assurance/ quality control procedure is applied consisting of preparing and analysing blanks, standards, duplicates and possibly certified reference materials to ensure data quality (Abazalov, 2017). The authors performed Kriging Neighbourhood Analysis to produce an unbiased estimate of the various elements present across the deposit at the mining block scale (Vann et al., 2003). This produced data for Fe, Si, P, Al, Mn, and SiO_2 grades at the deposit. These data have a spatial co-ordinate with x, y and z values. The data with its spatial location together forms the block model.

2.2. Mineral and economic data

Each block is assigned an economic value and a waste value, based on the elemental grades and tonnage of the block. The waste value is calculated by multiplying the tonnage of the block, which is found by multiplying specific gravity with the dimensions of the block, with the mining cost per tonnage. The mining cost per tonne is defined at $8/t. This can be seen in Eq. 1 where WV is defined as Waste Value, T as tonnage and C_m as mining cost.

$$WV = T \bullet C_m \tag{1}$$

The economic value is calculated by considering the economic value of the iron in the block and by subtracting the mining costs, processing costs and penalties for phosphorus content. The economic value of the iron is calculated by multiplying the Fe grade with the block tonnage at an iron ore price of 108 $/t under an 85% recovery. The mining costs and processing costs are set at $8/t and $6/t respectively and the phosphor penalty is $4/t. This is shown in Eq. 2 where EV is defined as Economic Value, $\%_{Fe}$ as the iron content in the block, P_{Fe} as the price per ton of iron ore, R_{Fe} as the recovery for iron ore, C_p as processing costs, $\%_P$ the phosphor grade and P_P as the penalty per ton of phosphorus.

$$EV = T \bullet \%_{Fe} \bullet P_{Fe} \bullet R_{Fe} - T \bullet (C_m + C_p) - -T \bullet \%_P \bullet P_P \tag{2}$$

The SimSched software resolves during the calculation process if a block is waste or ore by evaluating what maximizes the NPV at that point in time: mining and processing that block or mining and sending it to the waste dump (SimSched, 2018).

2.3. Life cycle assessment

2.3.1. Goal and scope

The goal and scope of this LCA was to measure the global warming impact of mining and transporting a single block at the case study iron ore mine. The cradle-to-gate LCA had a functional unit of one block at the drop-off location at the mine and does not include crushing, grinding or other processing. The economic value was excluded from the functional unit as this will be included in the pit-scheduling in a later stage. The system boundary of the LCA includes electricity and diesel inputs and the associated dust and exhaust emissions at the mine site (Fig. 2).

2.3.2. Life cycle inventory analysis

For the mining activity, data were predicted for the production and consumption of the following inputs: diesel in mining equipment, explosives, exhaust and dust emissions from vehicles and ore and waste loading and dumping. The input variables that are central to the differences in environmental performance for the extraction of each block were; silt content, block hardness, the specific gravity and tonnage of each block and its location in deposit.

The equations used have been included in the supplementary information and follow the approach used by Chaulya (2006) for particle emissions and NPI (2008) for emissions from equipment, diesel and electricity consumption. All parameters other than the physical properties of the block remained static. This included environmental conditions and the equipment used. Diesel equipment is used unless stated otherwise and was selected based on what is consistent with regulations for the region.

2.3.3. Life cycle impact assessment

The results in this study examine the global warming potential (GWP) midpoint indicator using the TRACI 2.1. life cycle impact assessment methodology. The data for diesel, explosives, and energy use and emissions was obtained from the GaBi database. The electricity was assumed to be the average grid mix from Brazil. The LCA was carried out using GaBi 6.0 software. The inputs and outputs included in the LCA have been listed in Table 1. The data included represents the major contributors to the global warming potential impact, which is supported by previous LCA studies for mining operations (Awuah-Offei and Adekpedjou, 2011).

We have additionally included results for acidification and human health in the supplementary information. Global warming was included as the single impact as this is the approach due to the simplicity in comparison and the nature of this study was primarily to investigate the methodology.

2.4. Baseline pit schedule

Simsched Direct Block Scheduler software developed by MiningMath uses an operations research based algorithm to consider long term scheduling of the orebody (Souza, 2018). The blocks within the block model are directly scheduled on an annual basis, whilst satisfying constraints that are operational (e.g. annual throughput or stockpiling constraints) and desired constraints, such as product grade or maximum annual environmental impact. The overall goal of the simulation is to maximize the overall NPV of the project.

Essential parameters are three dimensional indices of the blocks, at

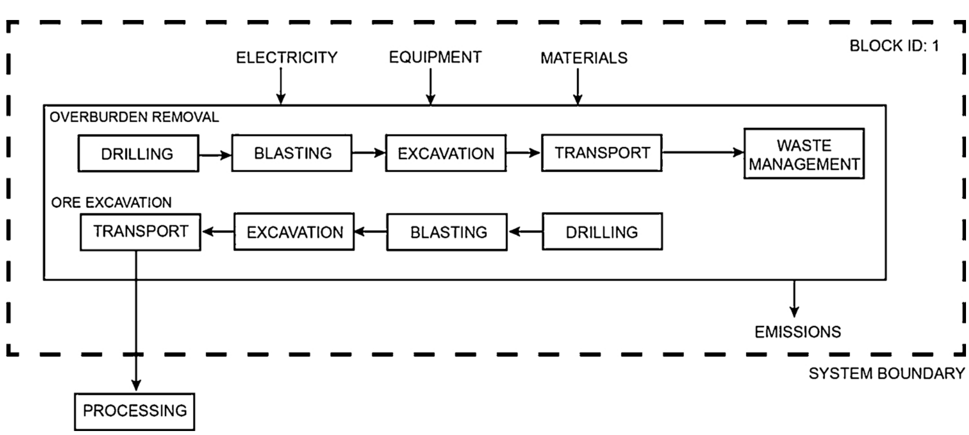

Fig. 2. System boundary of LCA for each block of iron ore mining.

Table 1
Calculations included for the life cycle inventory block data (Chaulya, 2006; NPI, 2008).

Process	Item	Description	Unit
Drilling	Electricity	Input	MJ
Blasting	Explosives	Input	kg
Excavation	Diesel	Input	MJ
Loading	Diesel	Input	MJ
Hauling	Diesel	Input	MJ
Ore Dump	Diesel	Input	MJ
All	Dust	Output	kg
All	Carbon dioxide	Output	kg
All	PM2.5	Output	kg
All	PM10	Output	kg

least one elemental grade, specific gravity, slope angle and a discount factor. The software allows for additional data per block in the model, such as global warming potential (GWP). The software also allows the annual GWP to be constrained, either over the whole life of mine or during a pre-defined period.

A schematic overview of the software execution method is shown in (Fig. 3). Direct Block Scheduling linearizes the optimization problem, after which Linear Programming (LP) is used to execute the model. Following that, Mixed Integer Programming combined with proprietary heuristics converts the continuous LP model into an integer and non-linear solution. Following that, the software verifies the feasibility and, if feasible, it verifies whether that solution has actually maximized the NPV. If the initial solution defined by Direct Block Scheduling is not feasible, certain constraints will be relaxed by the model in order for the program to find a solution. Constraints such as the slope angle are not relaxed by the software, as this may lead to an unsafe scheduled solution (SimSched, 2014). Limitations are that the program only gives a long term planned optimization and additional software packages or programming is required to define a short term plan. The calculation only includes capex and only limited operating expense is included in the NPV of the schedule. It is not a deterministic software, meaning that the changing the parameters will influence the final result in a direct way.

In this study, the calculated GWP per block and elemental content depending economic values were assigned to all the blocks within the block model. After the software has ran the optimization, a mining schedule, the economic performance of the operation, tonnages of metal produced and the annual environmental impact are provided. By constraining the annual environmental impact in the settings of the optimization it is possible to optimize the mining schedule whilst limiting the annual output of CO_2.

2.5. Parameter adjustment

The first pit scheduling simulation was carried out without environmental constraints, forming the baseline for the study for comparison of further simulations. In the software set up additional constraints were added that put a maximum on the annual output of kg CO_2. As constraint the second and third quartile of the annual output of the baseline simulation were chosen. This would allow to see what level of constraint generates a significant reduction in environmental output and at what economic cost. The constraints are seen in Table 2, with 629 Mt being the second quartile and 735 Mt the first quartile.

The Fe economic value was also adjusted for scenarios 4–9, where the basic Fe price of $108/t was increased by 1%, 3% and 4% respectively. The rationale behind providing additional value for Fe in scenarios with global warming thresholds is as described in the introduction. Mining companies may see an economic value to reduced CO_2 emissions. For example, premium prices have been attached to reduced carbon emissions and in some regions carbon has been taxed (International Council of Mining and Metals, 2013). By introducing increased economic value of Fe it is also possible to see the appropriate additional value a company could theoretically charge for a reduced carbon emission product.

2.6. Constrained pit schedule

The process described in the baseline ore sequencing was followed but with the inclusion of the environmental constraints listed in Table 2 with scenario 2 and 3. Added economic value of the block was also simulated under Q2 and Q3 constraints with scenario 4–9. This was completed to understand the increased block value that would be required to match the baseline under constrained environmental conditions.

2.7. Results comparison

Data generated from the constrained pit schedule can be compared in terms of environmental impact and the associated NPV impact. These

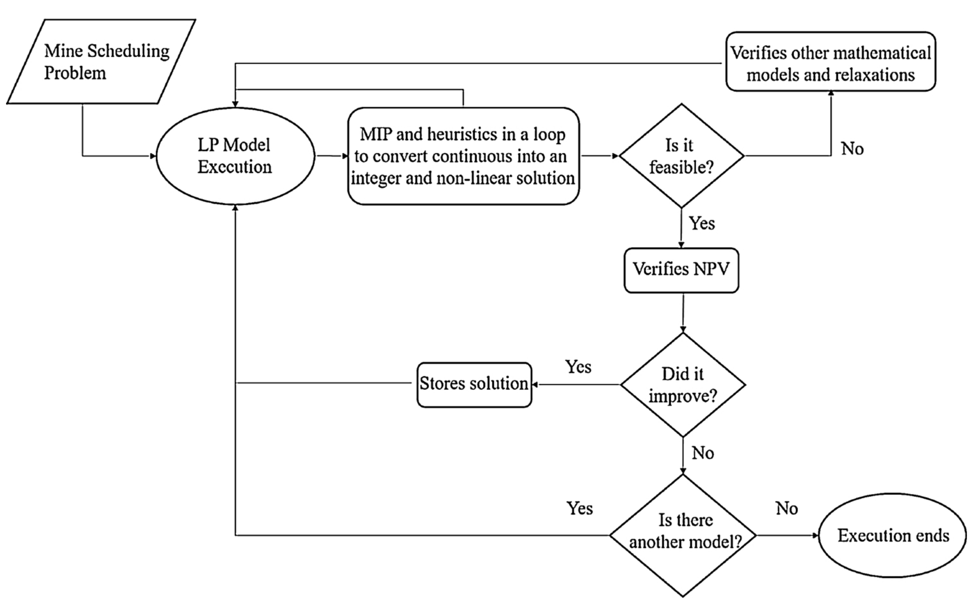

Fig. 3. Schematic overview of the simulation as performed by the software (SimSched, 2018).

Table 2
Parameter scenarios used in this study.

Scenario	Name	Net Present Value	Fe Value ($/t)	Global Warming (kg CO2 per annum)
1	B	Maximum	Standard -$108	None
2	Q3	Maximum	Standard -$108	735 Mt
3	Q2	Maximum	Standard - $108	629 Mt
4	Q3-1	Maximum	Standard * 1% - $109	735 Mt
5	Q2-1	Maximum	Standard * 1% - $109	629 Mt
6	Q3-3	Maximum	Standard * 3% -$111	735 Mt
7	Q2-3	Maximum	Standard * 3% - $111	629 Mt
8	Q3-4	Maximum	Standard * 4% - $112	735 Mt
9	Q2-4	Maximum	Standard * 4% - $112	629 Mt

data were used in the multi-criteria decision analysis. From this stage of results comparison, it is also possible to visualise relationships and make constraint adjustments for further simulations.

2.8. Multi-criteria decision analysis

The comparison of scenarios was done using the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method (Olson, 2004). This approach arranges the scenarios among the alternatives providing the distance to the ideal, and the worst possible solution. It is also possible to include the relative weights of criterion importance. The intermediate results and calculations for this process is included in the supplementary information.

3. Results

3.1. Environmental and economic block models

Fig. 4 provides a 3D model of both the economic value in the deposit and Fig. 5 a 3D model of the global warming impact of the deposit. These data were used as described in the methodology to schedule the pit, selecting which blocks to be extracted and in which order. The economic block model highlights that there are high value zones which have been calculated by Eq. 1 in the methodology. The global warming block values indicate a zone of high global warming blocks near the base of the deposit. This is partly because these blocks will require further transportation to be removed from the pit.

The major contribution to global warming is during the waste rock removal and transportation (Fig. 4). Other major contributing impacts are the excavation of the overburden, the excavation of the ore, the disposal of the overburden and the ore transportation. The ore transportation has a clearly defined spiking trend throughout the blocks which represents the relative distance of that block to the ore drop-off point which is assumed at the surface and on the west edge of the pit. Other more subtle trends can be seen, which indicate both changes in distance of required transport or areas where there is increased/decreased ore or waste product.

3.2. Baseline results

The mine scheduling simulation with no environmental constraints produced annual CO_2 Eq. emissions that ranged between 600,000 and 800,000 tonnes. There is an increase in CO_2 Eq. emissions from year 21, reaching a peak at year 35 followed by a steady, fluctuating decline until year 88. The emissions reflect the simulated mining extraction during these periods to create the highest NPV. The cumulative NPV value in Fig. 5 shows the optimization of the target cut-off grade. The NPV value reached for the baseline was $64,989 million at year 91 (Fig. 6).

3.3. Introducing constraints

By introducing annual CO_2 Eq. constraints to the mine schedule simulation both the annual and cumulative global warming potential emissions and NPV are effected. The annual and cumulative emissions for the Q3 constraint, which limits the global warming impact to three quarters of the average global warming value, can be seen with Fig. 7. The annual CO_2 Eq. emissions are similar to the baseline, fluctuating by

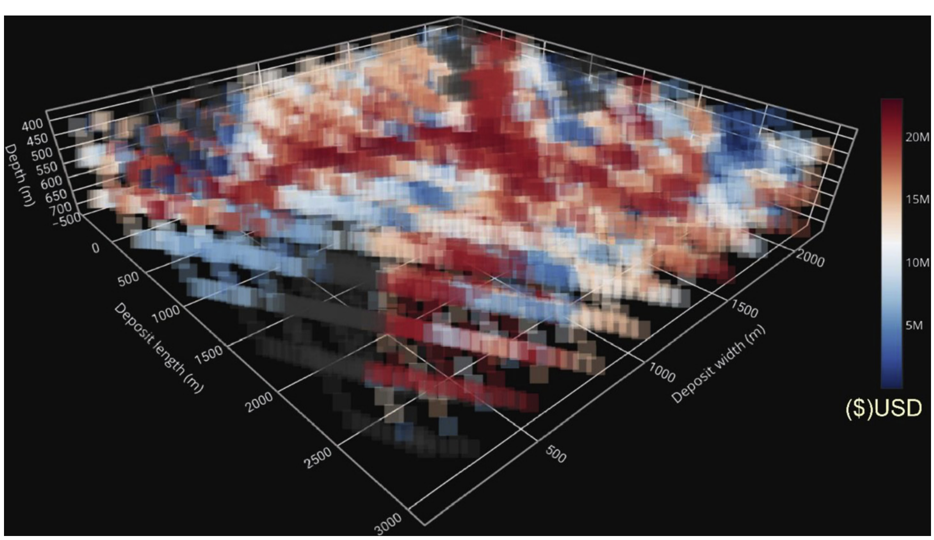

Fig. 4. Economic block model (available 3D model at https://plot.ly/~rp416/165/environmental-optimisation-of-mine-scheduling-through-life-cycle-assessment-inte/).

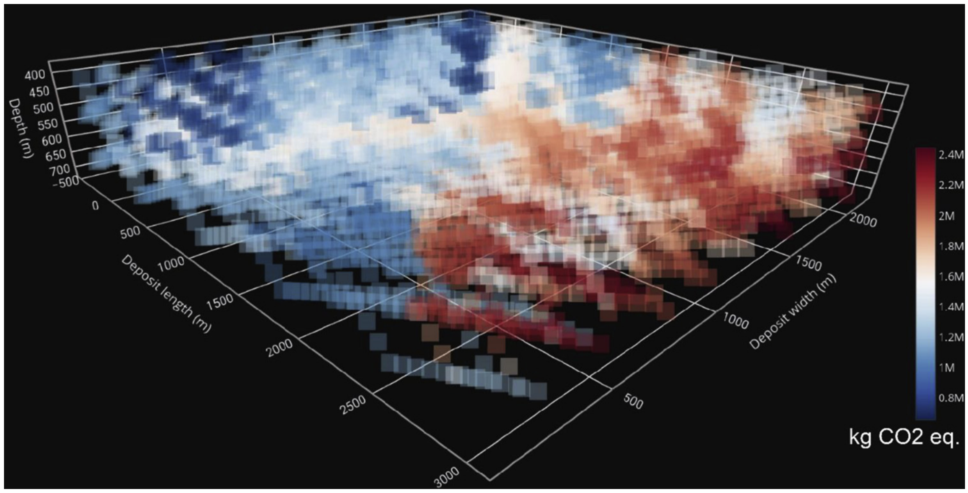

Fig. 5. Carbon footprint block model with global warming impact value for block (right).

around 100,000 tonnes above or below the baseline. The cumulative emissions indicate that CO_2 Eq. emissions are higher under this constraint until year 41. From years 41 to 53 the cumulative emissions reduce relative to the baseline and from years 54 to 81 the emissions increase to the point of reaching baseline levels. There is a final drop at the end of life to that finalises the cumulative global warming reduction of the Q3 scenario by 176,116 tonnes compared to the baseline. This reduction in CO_2 Eq. emissions came at a reduction in NPV of $355.9 million.

By contrast the Q2 constraint has a much more significant reduction in CO_2 Eq. emissions on an annual and cumulative basis. The Q2 constrained simulation reduced cumulative emissions of CO_2 Eq. by 4.9 million tonnes compared to the baseline scenario. This reduction in global warming emissions came at an NPV cost of $2.6 billion. This is due to the higher constraint limiting the extraction of higher impact blocks. The NPV and GWP impact rate is not linear as shown in these constraint scenarios. For example the Q3 scenario produced NPV at 99.45% of the baseline whilst having a GWP impact of 99.7% of the baseline. The Q2 scenario produced NPV at 95.9% of the baseline whilst having a GWP impact of 91.9%. This indicates that an optimal solution may be possible by exploring constraints and different economic values (Fig. 8).

3.4. Coupled CO_2 thresholds and economic criteria

As described in the introduction some mining companies adopt voluntary environmental standards and carbon dioxide emission limits as well as selling raw material product at a premium price because of a reduced global warming footprint (Tole and Koop, 2013). Some regions, such as in Canada have also introduced carbon taxes. Either way this leads to an economic incentive to reduce CO_2 emissions. Placing the Q3 and Q2 thresholds with economic value increase for Fe by 1%, 3%, and 4% allows us to evaluate at what value increase is required to maintain baseline NPV whilst reducing GWP impact. Fig. 9 highlights CO_2 Eq. emissions for the six scenarios with increased Fe value.

From the baseline of 64.99 million tonnes of CO_2 Eq emissions, the reduced cumulative CO_2 Eq. emissions from the Q3 scenarios are 0.23 million tonnes for Q3-1, 0.21 million tonnes for Q3-2, and 0.31 for Q3-4. The Q2 scenarios reduce the CO_2 Eq. emissions substantially more with Q2-1 saving 4.98 million tonnes, 4.98 million tonnes for Q2-3, and 1.63 million tonnes for Q2-4. This last scenario adjustment of 4% increased Fe value

Fig. 9 reflects a similar structure to Fig. 7 for annual production with high fluctuation from years 1 to 11 and towards the end of the project life and the lowest annual emissions seen during years 31 to 61. This indicates that the underlying simulation is only making small changes to selecting and ordering block extraction. These small changes can significantly impact the cumulative CO_2 emissions. There are three strands of performance for cumulative CO_2 emissions. All Q3 scenarios perform in a similar way with regards to CO_2 emissions. Q2-1 and Q2-3 also perform in a similar way. This suggests that these CO_2 constraints don't impact the DBS simulation by much. The 4% economic value

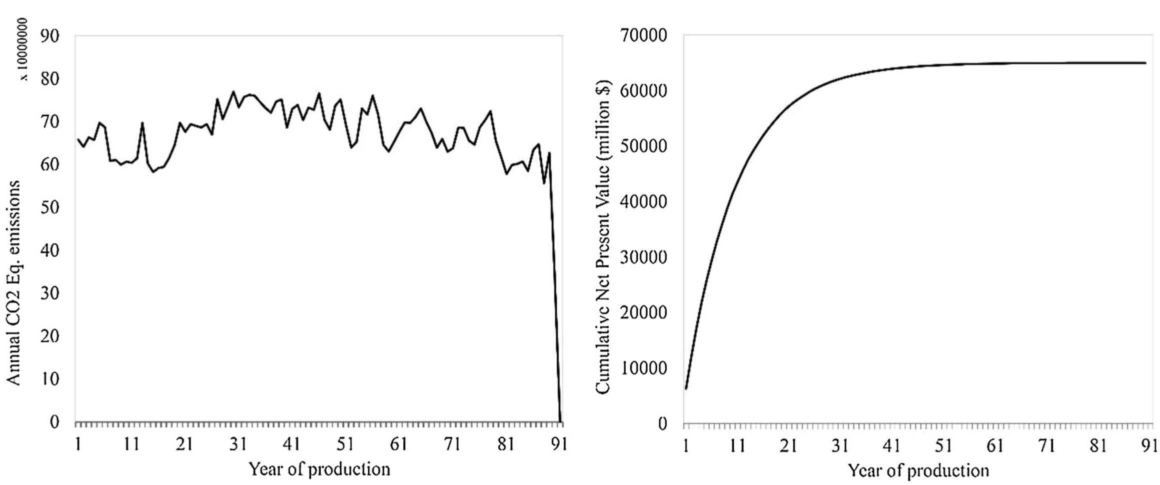

Fig. 6. Baseline annual CO_2 Eq. emissions (left) and cumulative NPV (right) from SimSched software.

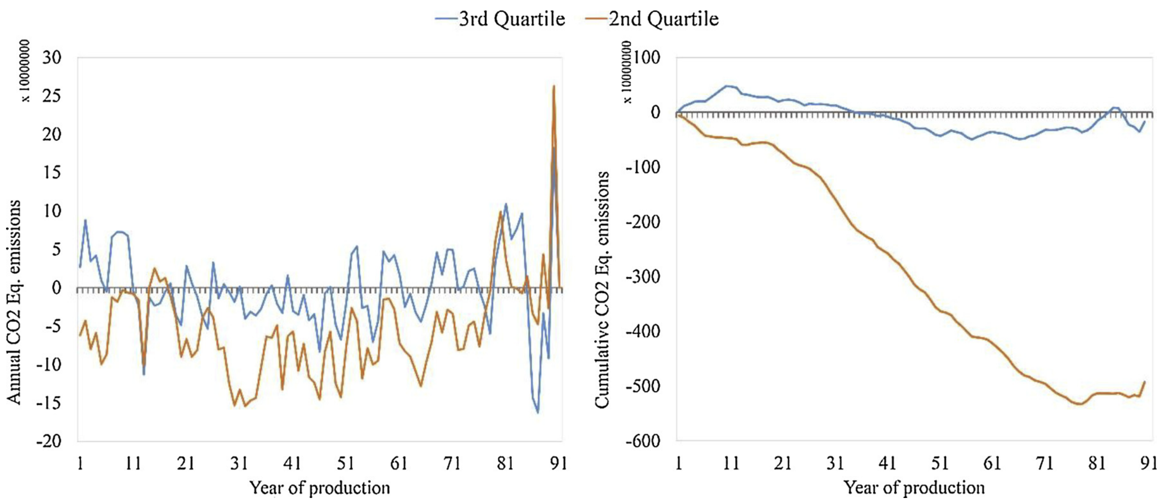

Fig. 7. CO_2 Eq. emissions relative to the baseline for two threshold scenarios on an annual basis (left) and cumulatively over the life-of-mine (right).

increase for Q2 substantially increases the cumulative CO_2 emissions compared to Q2-1 and Q2-3. This is due to the increased economic value of Fe making new areas of the deposit economically feasible to extract even within the CO_2 emission thresholds.

The NPV performance of these scenarios are compared to the baseline in Fig. 10. The best performance is by Q3-4. This would be expected as the economic value of the blocks is increased and there is a limited constraint on the simulation. This is followed by Q3-3 and Q2-4. This indicates that the additional constraint of Q2-4 is roughly equal to a 1% increase from Q3-3 whilst significantly reducing CO_2 emissions. The worst performing scenario was Q2-1 followed by Q2-3. These scenarios had higher emission constraints and only 1% and 3% increase in the economic value of each block.

The Life Cycle Impact Assessment (LCIA) scores for the different scenarios indicate that the CO_2 Eq. emissions range from 8.22 to 8.38 per tonne of iron ore extracted at the mine. These values are within the range of Norgate and Haque (2010) who calculated a CO_2 Eq. of 11.9 per tonne of Fe concentrate and Ferreira and Leite (2015) who calculated 13.32 kg CO_2 Eq. per tonne of Fe concentrate. However, both studies included the iron ore treatment, specifically the grinding, which accounted for 31.53% of the impact. The mining stages accounted for around 2.78 kg CO_2 Eq. per tonne.

Table 3 also presents the economic cost per kg of CO_2 Eq. saved from the baseline scenario. The negative values means that the scenario would make money. This is because the additional value given to the block in these scenarios means that it outperforms the baseline in terms of economic performance.

3.5. Multi-criteria decision making analysis

The range of scenarios were compared for performance in both the GWP impact and the NPV category. The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) was used for decision making analysis and results are shown in Fig. 11. Three different scenarios rating the relative importance of NPV and GWP are compared. Scenario 8 which represented 3rd quartile for constrained GWP and the maximum added value of 4% performed best when a weighting of 75% was given for NPV and 25% for GWP. This was followed by scenario 9 and then 6. The worst being scenario 3. This highlights that the best performing scenarios with high economic weighting have a low environmental constraint and a higher Fe value.

When NPV and GWP weighting were equal scenario 7 performed the best. This scenario had the higher GWP constraint (Q2) and had a Fe increased value of 3%. This was followed by scenario 9, and then 8. The worst performing scenario being scenario 2. Placing equal weighting on NPV and GWP leads to closer TOPSIS scores. The Q2 GWP constrained scenarios slightly outperforming the Q3 scenarios for the same Fe values.

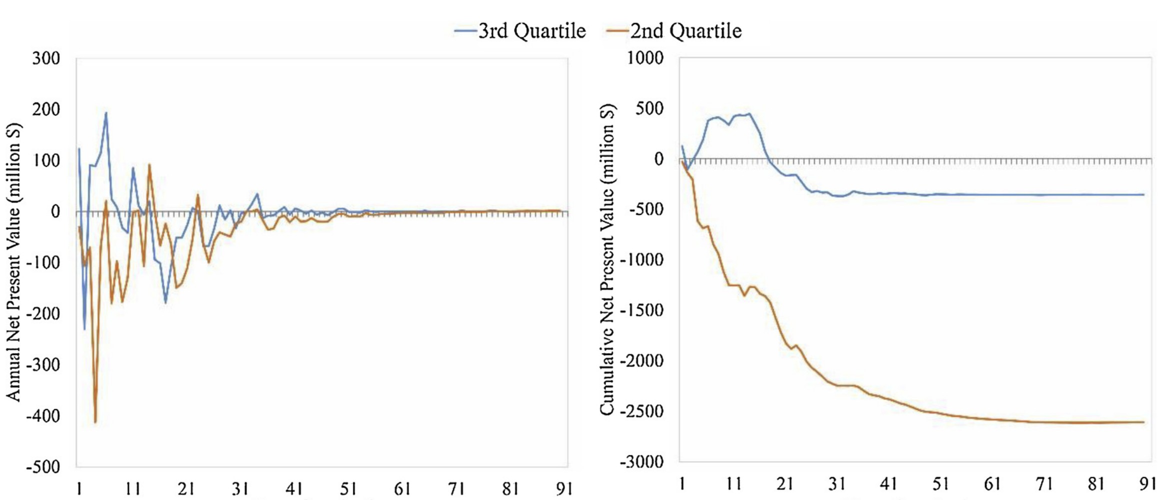

Fig. 8. Net present value relative to the baseline for two threshold scenarios on an annual basis (left) and cumulatively over the life-of-mine (right).

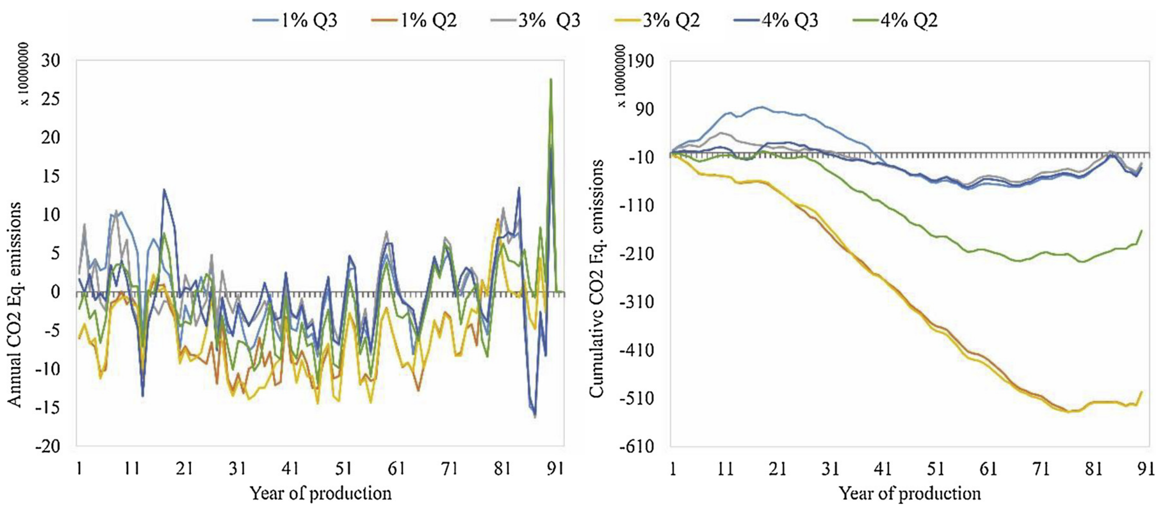

Fig. 9. CO_2 emissions relative to baseline.

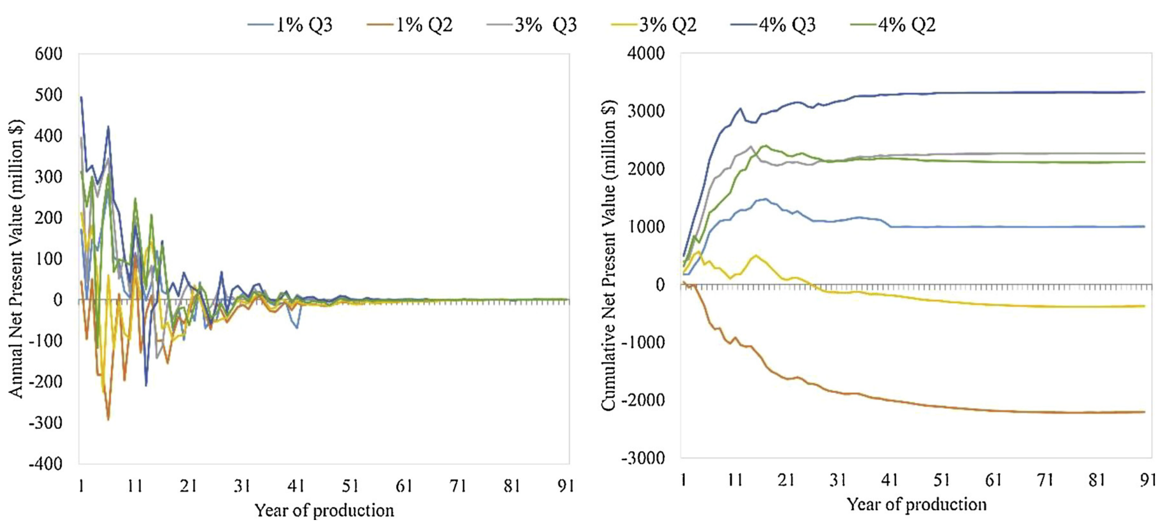

Fig. 10. Net Present value relative to baseline.

Table 3
Environmental performance and cost of improvement for the different scenarios.

Scenario	B	Q3	Q2	Q3-1	Q2-1	Q3-3	Q2-3	Q3-4	Q2-4
$ Per kg CO_2Eq saved	0	2.02	0.53	−4.22	0.44	−10.54	0.08	−10.67	−1.30
kg CO_2Eq. per tonne Fe	8.38	8.37	8.22	8.36	8.23	8.36	8.24	8.36	8.31

4. Discussion

The calculations used to predict CO_2 Eq. emissions are taken from literature and not specific to the study site. It would be possible to improve the quality of the data gathering samples at the site and include site-specific environmental conditions such as wind speed, rainfall, and silt content. The process developed in this study is a first attempt at including environmental considerations in mine planning. The approach does not need to be static. As a project is developed and understanding of the geology increases, environmental calculations or measurements can be updated to include more accurate results to inform future decisions in both long-term and short-term mine planning. The same approach could be used in short-term mining planning with greater detail to evaluate the impacts of equipment selection and mining and hauling schedules. Gathering further data about equipment performance and changing environmental conditions during different stages of production could enhance the accuracy of the results from the calculations used to generate the LCI data. The approach could also be adjusted and applied for governments and institutions if applied to economic scarcity models when deciphering the real price of resource dependence and resource extraction costs. Using an approach which considers the normally externalised environmental costs within the model could develop the Hotelling Model, the Real Price Model or the Extraction Costs model (Hotelling, 1931; Norgaard, 1990).

In this study, GWP has been placed as a static cost to a mining operation. However it is possible to treat carbon in the same way as NPV, with greater reductions in GWP today being more important than the same in 50 years. This was explored in Bauer et al. (2013) and the approach could be used in the simulation. Another variable that could be explored is changing technology during the life of the mine. For example, mining equipment transitioning to electric vehicles and reducing exhaust emissions. The energy source may also change over the life of mine, which would in turn effect environmental impact. During the life of a mining operation, environmental conditions could

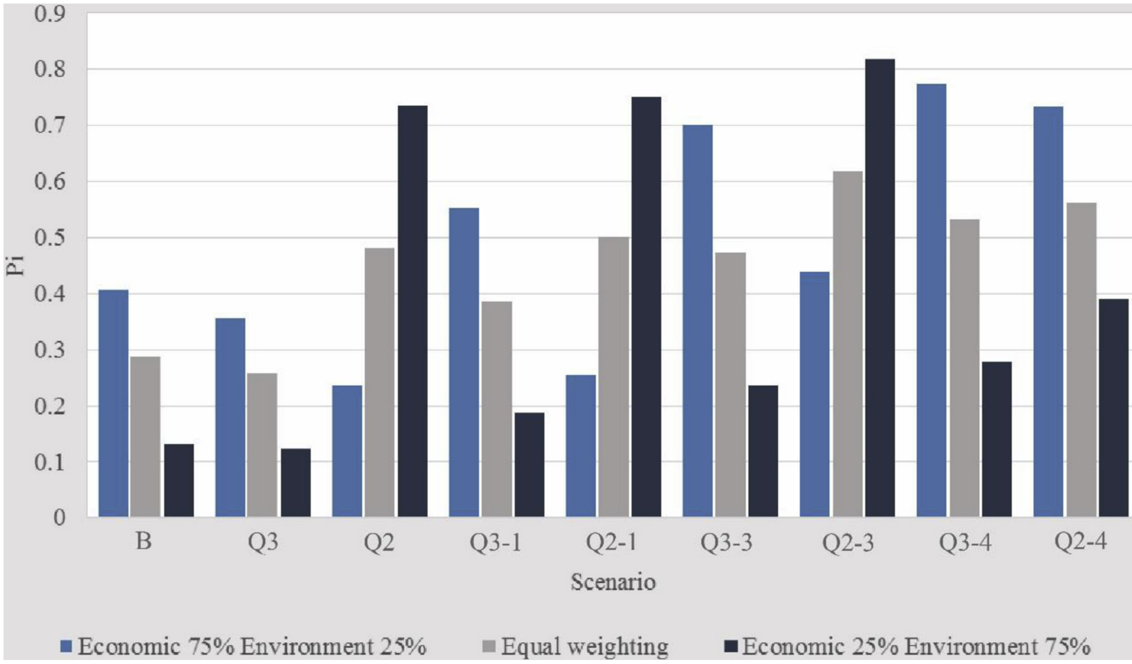

Fig. 11. Results of the TOPSIS multi-criteria decision analysis with different weight for economic and environmental criteria.

significantly change. These temporal variables were deemed as beyond the scope of this work but could be a useful area for future research.

Although this has been applied to GWP, the approach could be replicated for other impacts categories. This could include particulate matter formation which is particularly important as this can cause health problems for both mine workers and local populations and water impacts using approaches developed by Northey (2018). The measured impacts also only include those which are caused by the mining operation. The processing stages in iron ore production have been measured to have a high impact (Ferreira and Leite, 2015; Gan and Griffin, 2018). A LCA of the crushing and grinding, processing, and transportation of the materials and included alongside the mine planning optimisation to optimize the process in a holistic way as is done with geometallurgy. Incorporating these different stages of production would fit the parametric LCA approach which has been used in the architecture and design sector (Skalna, 2018).

5. Conclusion

This study presents a method to include environmental considerations in long-term mine scheduling simulations. The results show that it is possible to reduce GWP impacts by introducing GWP constraints but this will cause a non-optimal economic performance. By exploring GWP constraints and adjusting the economic value of the ore it is possible to determine the economic cost required to reduce CO_2 emissions under different scenarios. For example the results showed that with no adjustment to the economic value of the ore, the cost of reducing CO_2 emissions for the Q3 scenario was US$2.02 and US$0.53 for Q2.

In a LCA context, the approach was able to reduce CO_2 emissions. The baseline produced 8.38 kg CO_2 Eq. per kg ore extracted and Q2-1 was able to reduce this to 8.23 kg CO_2 Eq. per kg ore extracted. With the results it was possible to carry out multi-criteria decision analysis using TOPSIS to incorporate economic and environmental performance. The challenge of subjectivity remains with this method, but under equal weighting was Q3-3 performed best. Q3-3 also performed best in the higher environmental weighted scenario, whilst Q3-4 performed best in the higher economic weighted scenario.

The approach presented in this study has the potential to assist in decision making for mine planning, including environmental data during the planning stage and has the potential to be applied throughout the mine life to short term mine planning and include the processing stages of the operation.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.resconrec.2018.11.022.

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