Open-pit coal mine production sequencing incorporating grade blending and stockpiling options: An application from an Indian mine

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ABSTRACT

Production scheduling is a crucial aspect of the mining industry. An optimal and efficient production schedule can increase the profits manifold and reduce the amount of waste to be handled. Production scheduling for coal mines is necessary to maintain consistency in the quality and quantity parameters of coal supplied to power plants. Irregularity in the quality parameters of the coal can lead to heavy losses in coal-fired power plants. Moreover, the stockpiling of coal poses environmental and fire problems owing to low incubation periods. This article proposes a production scheduling formulation for open-pit coal mines including stockpiling and blending opportunities, which play a major role in maintaining the quality and quantity of supplied coal. The proposed formulation was applied to a large open-pit coal mine in India. This contribution provides an efficient production scheduling formulation for coal mines after utilizing the stockpile coal within the incubation periods with the maximization of discounted cash flows. At the same time, consistency is maintained in the quality and quantity of coal to power plants through blending and stockpiling options to ensure smooth functioning.

1. Introduction

In a complex mining system, production scheduling is the process of assigning the extraction sequences of mining blocks from the block model of a deposit after satisfying related constraints. The production scheduling problem is an optimization problem which can be solved either by integer programming or by mixed-integer linear programming (MILP) to maximize the net present value (NPV) (Barbaro and Ramani 1986). Works by Caccetta and Hill (2003) and Ramazan and Dimitrakopoulos (2004) illustrated the use of MILP formulation for solving open-pit production scheduling problems. NPV is an important concept in the field of production scheduling, and is defined as the value of different payments in different periods brought into the present scenario (Hustrulid and Kuchta 2006). Production scheduling consists of three different problems: sequencing the extraction of blocks, decisions regarding the destination of these blocks, and fulfilling the production requirements (Caccetta and Hill 2003; Chatterjee, Sethi, and Asad 2015).

However, for a typical production scheduling problem, the number of blocks that needs to be scheduled is very large and so is the number of scheduling periods; thus, the computational time
required to solve such problems is significantly higher. A realistic mine situation does not have such time for solving the production scheduling problem, and a different approach is required to solve the problem within a durable time domain. Different approaches, such as branch and cut (Caccetta and Hill 2003), a cutting plane technique (Bley et al. 2010) and a heuristic approach (Asad 2011) have been utilized to solve the same problem within a reasonable time-frame. A more detailed review of the different solution approaches for the mine production scheduling problem can be found in Newman et al. (2010).

Production scheduling for coal mines plays a vital role in maintaining the consistency of supplied coal from mines to power plants or other end users (Benndorf 2013). Irregularity in supplied coal quality parameters, such as the calorific value (CV), moisture content and ash content, may lead to heavy losses associated with boilers of power plants and sometimes even makes it infeasible for the captive mines to run the associated power plants (Tanaka and Wicks 2010). To avoid such losses it is necessary to ensure homogeneity in the delivery of coal quantity and quality. Stockpiling and blending are two useful methodologies which can be incorporated within the scheduling formulation to ensure a constant and consistent supply of coal from mines in a continuous mining scenario (Askari-Nasab et al. 2011; Benndorf 2013).

Optimization of different problems related to the coal mining industry goes back three decades, since Baker and Daellenbach (1984) optimized the coal mining and stockpiling strategies for a power station in two phases. Xu and Li (2011) used system dynamics for the simulation and optimization of the coal industry system in a fuzzy environment. Coal blending and stockpiling are two concepts associated with the coal mining industry and have important roles in satisfying the quality and quantity targets. Stockpiling refers to allocating ore blocks to a pile which can be used in later periods of low production to satisfy the quality and quantity targets. Blending refers to mixing of blocks to achieve the required quality of ore for coal-fired power plants. Shih and Frey (1995) developed a coal blending optimization model to minimize the cost of coal blending, deviation of coal blending cost, sulphur emissions and deviation in sulphur emissions. Benndorf (2013) demonstrated an application of conditional simulation for optimizing coal blending strategies in large continuous open-pit mining operations.

Barbaro and Ramani (1986) demonstrated a multi-period mixed-integer programming model for production scheduling, selection and location of new processing facilities, blending of processed ore and selection of markets for a coal mine. However, it had two drawbacks in that it required all the relationships to be linear and the entire coefficient to be known. Chanda and Dagdelen (1995) presented a linear goal programming model of the blending problem in short-term mine planning with an application to a coal mine. Pendharkar and Rodger (2000) presented a nonlinear programming and genetic search application for production scheduling in coal mines. Sarin and West-Hansen (2005) developed a mixed-binary programming model for generating mine production schedules for coal mines. They were able to obtain a maximized NPV with the desired quality of coal. Use of the hybrid genetic algorithm (GA)–tabu search algorithm for optimization of the open vehicle routing problem in coal mines can be found in Yu et al. (2011). Carniato and Camponogara (2011) presented an integrated MILP model for coal mining operation planning. Guo et al. (2010) used optimization methods such as GA, particle swarm optimization (PSO) and modified particle swarm optimization (MPSO) for mine scheduling, and observed that the MPSO approach yielded a better NPV than the GA and PSO approaches.

Exhaustive literature exists regarding the production scheduling and optimization of grade blending for coal mines, but literature on stockpiling and grade blending with the spontaneous combustion problem is missing. The proposed model in this work offers a formulation which includes stockpiling and blending options with the scheduling of coal blocks. The stockpiling and blending options help to maintain consistency in the quality (by blending from stockpile and from different faces) and quantity (by utilizing coal from the stockpiles in times of below-target production and storing coal in stockpiles in times of above-target production). However, the stockpiling option imposes certain constraints owing to the possible spontaneous combustion of coal within stockpiles, thus constraining
the use of stocks within the incubation period. In the proposed model it is ensured that all the coal in a stockpile is used before assigning new stocks. This contribution first gives a traditional scheduling formulation for coal mines, incorporating the blending and stockpiling options in the production scheduling formulation, and also encompassing the incubation period issue with coal. A case study of a large coal deposit is conducted to ensure the applicability of the proposed model.

2. New production scheduling formulation for coal mines

Production scheduling places emphasis on satisfying the different constraints associated with the supply of coal and at the same time maximizing the NPV over the scheduling periods. The proposed formulation of scheduling for coal mines includes a blending and stockpiling option, i.e. which blocks are to be sent to the stockpile and which ones to the beneficiation plant. Open-pit coal mine production scheduling typically consists of three parts: (1) maintaining the quality and quantity constraints of the supplied coal as per the criteria of the power plant; (2) optimizing the cost associated with production; and (3) maintaining consistency in the quality and quantity of supplied coal.

Stockpiling options within a coal mine help to facilitate coal during periods of overproduction and utilize the same coal from stockpiles in periods of low production (Figure 1a). Blending in the later stages can be done through different faces or with the stockpile (Figure 1a) to maintain the quality of the supplied coal. Figure 1(b) shows the importance of maintaining consistency in the quality of supplied coal to the power plant for the proper functioning of boilers in the power plant. Coal-fired power plants need a specific quality of coal to operate at full efficiency. Failure to meet the quality target of supplied coal to the power plant can lead to huge financial losses.

2.1. Objective function

The objective function for the proposed production scheduling formulation is the maximization of discounted cash flows, and consists of four parts. Part I in the objective function represents the NPV generated by extracting blocks in different periods $t$. The production scheduling formulation presented herein consists of stockpiling options, and thus the extracted blocks in period $t$ which are considered for stockpiling will only incur a mining cost for period $t$ and no revenue will be generated from those blocks in period $t$. The NPV and the mining cost for those blocks need to be subtracted from the objective function value (part II). Part III in the objective function represents the profit generated by utilizing the coal from the stockpile, calculated after reducing the rehandling cost (stockpiling cost) from the expected NPV, added to the objective function after discounting to period $t$, but the material is used in the next period. Also, the stockpiled material is used within the incubation period specified for the mine. In the present case study this period is 1 year, and thus all the material in the stockpile is used within 1 year, before any material is assigned to the stockpile in the next scheduling year. The proposed open-pit production scheduling model contains various constraints for maintaining the quality and quantity parameters of the supplied coal to the power plants, and thus the scheduling results may become infeasible owing to variability in the quality and quantity parameters. To overcome the aforementioned problem, a penalty term for quantity and quality parameters for coal is included in the objective function of the scheduling formulation, ensuring the feasibility of the formulation (part IV). The penalty terms included in part IV of the objective function penalize the solution if the quality and quantity targets are not satisfied, thus minimizing the deviations from the target along all periods. The value of the penalty depends on the deviation from the targets for quality and quantity and the per-unit penalty cost associated with those deviations. High penalty costs will improve the reproduction of targets while lower penalty costs will generate impractical solutions with large NPV forecasts associated with large violations of the targets for the production scheduling problem. The mathematical formulations, including the objective functions and constraints of the proposed coal mine production scheduling, are presented in the supplementary material.
2.2. Constraints

2.2.1. Stockpile quantity constraint
Stockpiles are important and crucial aspects of coal mines, as they ensure the smooth and steady functioning of power plants by providing a consistent supply of coal from mines in low production periods. However, stockpiles are generally associated with quantity constraints as the area for stockpiling the coal is minimal and is usually inside the mine; thus, it always enforces a quantity constraint. In addition, stockpiling coal enforces the incubation period constraint owing to the problem of spontaneous heating. Therefore, the coal needs to be utilized within the stipulated incubation period before assigning any further stocks to the stockpile. The stockpile quantity constraint ensures that the amount of material assigned to a stockpile is not greater than its capacity.

2.2.2. Stockpile quality constraints
Coal-fired power plants are designed for operation within certain ranges of coal quality parameters. Violating such constraints may result in huge losses, and even failure in the functioning of power
plants in some cases. In periods of low-grade coal production, stockpile material is used for blending purposes, and thus stockpile quality constraints are added to the proposed formulation.

2.2.3. Stockpile extraction constraint
The stockpile extraction constraint ensures that a block cannot be assigned to the stockpile until it has been mined. Blocks considered for stockpiling will only incur a mining cost as defined in the objective function.

2.2.4. Production quality constraints
The mining process is a supply-chain system (Goodfellow 2014) where different activities are interlinked. Thus, maintaining homogeneity and consistency in the quality of the supplied coal to power plants plays an important role in the smooth functioning of the power plant as well as mining operations. It is crucial to maintain coal parameters, such as CV and moisture and ash content, in a production scheduling problem; hence, they are included as production quality constraints in the problem formulation for coal mines. These constraints represent the maximum and minimum CV and maximum ash plus moisture content of coal required by coal-fired power plants for the different periods of the production scheduling formulation.

2.2.5. Production quantity constraint
An effective production schedule is determined by the capacity of the formulation to achieve the target yearly requirement of coal for power plants. The quantity constraint, i.e. the minimum and maximum requirement of coal for different periods of the scheduling formulation, has a penalty term associated with each constraint. The maximum and minimum capacities of ore are calculated based on the capacity of the processing unit within the mine or the capacity of the coal handling plants.

2.2.6. Mining constraint
The mining constraint within any mining industry is determined based on the productivity of the loading and hauling equipment, selecting the minimum. The availability and utilization of the fleet impose the constraint of maximum hauling capacity of the available equipment within the mine.

2.2.7. Operational constraints
Operational constraints, such as maintaining the slope of the pit, are added to the formulation to make the proposed model more realistic. The reserve constraints, which ensure that a mining block is only extracted and stockpiled in a single period, make sure that the same blocks are not extracted and stockpiled in multiple periods during the life of the mine. The slope constraint ensures that a block cannot be extracted until the blocks placed above it have been extracted.

3. Solution approach
The optimization problem formulated above is the MILP problem, which can be reduced to the precedence-constrained knapsack problem (Kellerer, Pferschy, and Pisinger 2004) by dropping some of the constraints and solving for a single period. The knapsack problem is NP hard, and the complexity of the problem also increases when the problem is solved for the life of the mine, i.e. solving all time periods together. Both exact and heuristic solution approaches are available to solve this type of problem (Bley et al. 2010; Lamghari and Dimitrakopoulos 2012). However, because of the complexity and size of the present problem, these algorithms will be computationally complex.

The current problem formulation is solved using a year-wise formulation approach. In this approach, the scheduling problem formulation is solved for the first year only, and then the solution obtained is deducted from the input data for the problem formulation of the next year. For example, if \( X = \{x_1, x_2, \ldots, x_N\} \) is a set of all blocks within the deposit, and \( Y \subset X \) maximizes the objective function subject to all constraints for period \( T = 1 \), then all elements of set \( Y \) will be eliminated
from set $X$ to create an updated set $X - Y$, which will be the input set for the scheduling problem for the next year. Thus, the problem formulation for the next year does not contain the blocks that are already extracted in the first year. Likewise, for each year, the same procedure is followed to determine the production schedule. More details about the sequential solution approach can be found elsewhere (Chowdhury and Chatterjee 2014; De Freitas Silva, Dimitrakopolous, and Lamghari 2015). This approach solves the production scheduling problem more quickly and within a shorter timespan than the traditional approach, in which the problem formulation is solved for the whole period at once. The production scheduling formulation is a mixed-integer programming formulation and is solved using the branch-and-cut algorithm (Wolsey 1998).

4. Application of the proposed model to a large open-pit coal mine

4.1. Introduction and geology of the area

To measure the performance of the proposed model, a study was carried out on blocks in a highly mechanized open-pit captive mine in India. To estimate the quality parameters of the coal seam, a three-dimensional wireframe of the coal seam was prepared using the exploration drilling data. The coal resource estimation was made within the wireframe by discretizing it into a number of equal-sized blocks. The block size was selected based on the geotechnical parameters of the study area, and the coal resource estimation was made using ordinary block kriging (Tercan et al. 2013). Some surface waste blocks were added above the coal blocks to ensure the exact location of the coal seam from the surface topography. The block dimension of resource model is $50 \times 50 \times 10$ m$^3$ and the total number of blocks is 20,514, including the surface waste blocks within the deposit. The mine is situated in the central part of India. The mine has an internal stockpile capacity of 2 Mt with estimated productivity of 110 Mt, and the power plant has a yearly requirement of 16–20 Mt of coal. Other details about the quality and quantity requirements of the power plant are given in Table 1, and the price of coal for the current case study is given in Table 2. These data were directly obtained from the study mine and

| Sl. no. | Description                                      | Value       |
|--------|--------------------------------------------------|-------------|
| 1      | $N$                                              | 20514       |
| 2      | $T$                                              | 20 years    |
| 3      | Minimum coal production required by processing plant per year | 16 MT       |
| 4      | Maximum coal production allowed by processing plant per year | 20 MT       |
| 5      | Minimum calorific value required for processing plant | 3701 Kcal/kg |
| 6      | Maximum calorific value allowed for processing plant | 5800 Kcal/kg |
| 7      | Maximum (Ash + Moisture) for processing plant | 40%         |
| 8      | Maximum stockpile capacity | 2 MT        |
| 9      | Minimum grade of stockpile | 4900 Kcal/kg |
| 10     | Maximum grade of stockpile | 5200 Kcal/kg |
| 11     | Average grade of stockpile | 5050 Kcal/kg |
| 12     | Maximum (Ash + Moisture) for stockpile | 40%         |
| 13     | Average (Ash + Moisture) for stockpile | 20%         |
| 14     | Profit from processing one tonne of coal from stockpile | US $22.65/tonne |
| 15     | Re-handling Cost from stockpile | US $0.15/tonne |
| 16     | Maximum hauling capacity of equipment | 110 MT      |
| 17     | $PC$                                             | US $22.5/tonne |
| 18     | $r$                                              | 10 %        |
| 19     | $P_{g,u}$                                       | US $7.5/tonne |
| 20     | $P_{g,l}$                                       | US $7.5/tonne |
| 21     | $P_{o,u}$                                       | US $25.5/tonne |
| 22     | $P_{o,l}$                                       | US $25.5/tonne |
| 23     | $P_{AMU}$                                       | US $7.5/tonne |
| 24     | Incubation Period                               | 1 year      |
| 25     | Extraction cost                                 | US $0.6195/tonne |
Table 2. Price of coal based on calorific value (CV).

| Grade | CV band (kcal/kg) | ROM coal price (US$/t) |
|-------|------------------|------------------------|
| G1    | 7000 < CV        | 4                      |
| G2    | 6700 < CV ≤ 7000 | 73.05                  |
| G3    | 6400 < CV ≤ 6700 | 58.35                  |
| G4    | 6100 < CV ≤ 6400 | 52.35                  |
| G5    | 5800 < CV ≤ 6100 | 42                     |
| G6    | 5500 < CV ≤ 5800 | 28.8                   |
| G7    | 5200 < CV ≤ 5500 | 25.2                   |
| G8    | 4900 < CV ≤ 5200 | 22.65                  |
| G9    | 4600 < CV ≤ 4900 | 17.55                  |
| G10   | 4300 < CV ≤ 4600 | 15.45                  |
| G11   | 4000 < CV ≤ 4300 | 12.6                   |
| G12   | 3700 < CV ≤ 4000 | 12                     |
| G13   | 3400 < CV ≤ 3700 | 10.95                  |
| G14   | 3100 < CV ≤ 3400 | 10.05                  |
| G15   | 2800 < CV ≤ 3100 | 9.15                   |
| G16   | 2500 < CV ≤ 2800 | 8.25                   |
| G17   | 2000 < CV ≤ 2500 | 7.2                    |

Note: *For CVs exceeding 7000 kcal/kg, the price will be increased by US $2.18/t over and above the price applicable for the CV band exceeding 6700 but not exceeding 7000 kcal/kg, for every 100 kcal/kg increase in CV or part thereof (G2).*

ROM = run of mine.

can vary from one mine to another depending on mine location, coal type, coal hardness and many other parameters. Figure 2 represents the borehole section of the deposit. There are some bands of carbonaceous sandy shale of varying thickness of about 1.2–1.8 m between the coal seams. However, since the band of sandy shale is very thin, selective mining is not possible. Stockpile management is a crucial aspect of a mining operation. However, unlike other minerals, stockpiling of coal is associated with the constraint of spontaneous heating, and can result in serious economic and safety problems (Fierro et al. 1999).

This article, however, does not emphasize models for coal stockpile management, and the quality of material from the stockpile is assumed to have an average grade, as mentioned in Table 1. Coal stockpile management can be integrated quite easily with the current production scheduling model. However, the study mine does not have the option of stockpile management, and therefore it was not incorporated in the present case study.

4.2. Production scheduling results

Production scheduling for the current case study is done sequentially applying the branch-and-cut algorithm. Therefore, no prior knowledge of the ultimate pit and life of the mine are required for this model. The case study application demonstrated that the mine can last for 20 years. The resultant production schedule for the life of the mine is shown in Figure 3(a) and (b), showing the cross-sectional view of the ultimate pit. It can be observed from Table 1 that the maximum hauling capacity of available equipment in the mine in the present case study is 110 Mt, and thus the maximum allowable stripping ratio is 5.875. Figure 4 represents the resultant stripping ratio over the scheduling period, which is under the maximum allowable mining capacity. The graph in the Figure 4 shows an increasing trend, since the production scheduling problem is a maximization of NPV function, and thus it defers the overburden block allocation during the solution. The peaks observed in the graph represent the period of high overburden removal. Scheduling years 4, 9, 12 and 18 show high stripping ratios. As seen in Figure 3(a), these periods are associated with a large expansion of the pit, thus increasing the amount of overburden. Expansion of the pit is associated with high overburden volume owing to the slope constraint, which needs to be maintained to ensure the stability of the pit. However,
Figure 2. Borehole section of the deposit.

Figure 3. Two different sections along (a) East-West, and (b) North-South direction, of the production schedules of the study mine.
Figure 4. Stripping ratio over the production scheduling period of the study mine.

Table 3. Results of the relaxed problem formulation compared with normal production scheduling formulation.

| Case | Period (years) | Formulation type           | No. of blocks | Solution time (s) | Objective function value (US$) | % Gap       |
|------|----------------|----------------------------|---------------|-------------------|--------------------------------|------------|
| I    | 3              | Proposed solution approach | 20,514        | 6,251.92          | $1.28 \times 10^9$            | 2.327%     |
|      |                | Linear relaxation problem  |               | 2,053             | $1.31 \times 10^9$            |            |
| II   | 5              | Proposed solution approach | 20,514        | 23,595.49         | $1.89 \times 10^9$            | 2.822%     |
|      |                | Linear relaxation problem  |               | 43,628.20         | $1.94 \times 10^9$            |            |
| IIIa | 20             | Proposed solution approach | 20,514        | 35,640.97         | $4.09 \times 10^9$            | –          |
|      |                | Linear relaxation problem  |               | 346,541.2         | $4.36 \times 10^9$            |            |

Note: *The gap for Case III cannot be calculated because no solution was obtained for the linear relaxation problem.

The stripping ratio over the whole period of production scheduling is below the productivity of the available equipment.

CPLEX software was used to optimize the production scheduling formulation. It took approximately 9.9 h to solve the production scheduling formulation with a 2.56 GHz, 4 GB RAM machine with the solution approach mentioned in Section 3. For the purpose of measuring the efficiency and accuracy of the proposed solution approach, the linear relaxation of the production scheduling formulation was also solved and the results obtained are given in Table 3. The percentage of gap was calculated by comparing the results from the proposed approach with the linear relaxation of the original formulation. Table 3 represents three different cases, i.e. 3 years, 5 years and 20 years, for which the relaxed production scheduling problem was solved. For these three different cases the results of the proposed solution approach were compared with the relaxed problem formulation. Case I represents a gap of 2.327% from the optimal solution. The solution for the relaxed problem was achieved within 2053 s compared to 6251.92 s for the proposed solution approach. However, Case II clearly depicts the use of the aforementioned solution approach, since for the same problem formulation it took about 12.17 h to achieve an optimal solution compared to 6.55 h for the proposed solution approach. Case
Table 4. Results of the holistic solution approach compared with the sequential solution approach for small pushback.

| Problem no. | No. of blocks | Production period (years) | % Gap | Holistic solution approach | Sequential solution approach |
|-------------|---------------|---------------------------|-------|---------------------------|-----------------------------|
| 1           | 1649          | 2                         | 1.86  | 10.02                     | 0.95                        |
| 2           | 2400          | 3                         | 2.34  | 3327.52                   | 3.7                         |

III clearly demonstrated the necessity of the proposed solution approach. While it took around 9.9 h to solve the production scheduling formulation with the proposed solution approach, no solution was reached even after 96.26 h, even with the relaxed problem. It is worth mentioning here that although the linear relaxation provides the optimum solution, it does not provide a schedule; rather, it provides only the upper bound solution of the actual problem. The applicability of the proposed solution approach to real-life mine production scheduling problems is unquestionable, since large mining production scheduling problems contain millions of ore and waste blocks which need to be solved within a reasonable timeframe and with acceptable accuracy.

The efficiency of the proposed solution approach was validated by designing small problems from the original data for periods of 2 years (1649 blocks) and 3 years (2400 blocks) and using these smaller data sets to obtain the objective function value for a holistic solution approach and a sequential solution approach, as shown in Table 4. The holistic solution means that the exact mixed-integer linear formulation was solved using the branch-and-cut algorithm. It can be observed that the percentage gaps between the holistic approach objective function value and sequential approach objective function value are 1.86 and 2.34 for 2 years and 3 years, respectively, which are not significantly different. However, the time required to solve the problem has significant difference for 2400 blocks, as the sequential approach was able to solve the problem within 3.7 s while the holistic solution approach took 3327.5 s. Considering that mining blocks are usually numbered in thousands and millions, the sequential approach proposed herein is able to solve those problems within a realistic time-frame, as observed with the original data presented in Table 3.

It is worth mentioning that the proposed sequential approach cannot provide the optimum solution for the production scheduling problem (as observed in Table 4, there is always some gap). However, it is also true that no algorithm exists that can solve the large-scale real case production scheduling problem optimally (Table 3 shows that the Case III relaxed problem cannot be solved after 9 days). Therefore, it is difficult to judge how far the sequential solution is from the true optimum solution.

Figure 5 shows the NPV and year-wise discounted cash flow generated over the production scheduling period. The NPV of the proposed production scheduling formulation with the defined solution approach is US $4.09 × 10^9 over a scheduling period of 20 years. It was observed from the discounted cash flow graph that the proposed method generates more discounted cash flow in the initial production periods than in the later periods. This ensures that the proposed method extracts the high-quality coal during the initial periods, after satisfying the geotechnical constraints.

Maintaining the quality parameter of supplied coal is a crucial aspect of any production scheduling formulation. Figure 6 represents the coal quality parameter average CV for extracted and stockpiled coal over the scheduling period, which is within the specified bounds of coal-fired power plants. The production schedule, which includes stockpiled coal, has a maximum CV of 5400 kcal/kg and minimum of 5100 kcal/kg, which is within the operating range of the captive power plant.

The graph in Figure 6 shows that the upper and lower bounds of the CV parameter for stockpiled coal are stringent because the current case study imposed constraints on maintaining a high-grade stockpile to ensure homogeneity in the quality of supplied coal in periods of low-grade coal production, and also to reduce the probability of spontaneous combustion in stockpiled coal. The average CV of stockpiled coal is within the upper and lower bounds, signifying that the constraints are not
violated. It can be clearly seen from Figure 6 that a high-quality stockpile increases the average grade of supplied coal to power plants by blending from the stockpile.

Coal-fired power plants typically function for specified ranges of coal properties. Deviation from the bounds of these ranges may incur huge losses and damage to the power plant. The ash and moisture content of coal determines the useful heat value of the coal. Figure 7 illustrates the average
Figure 7. Coal quality parameter: average ash + moisture (AA + AM) content in the extracted and stocked coal for the scheduling period.

The graph in Figure 7 shows that the maximum ash + moisture percentage value permitted for the specific captive power plant is 40%; however, the resultant production scheduling formulation ash + moisture parameter has a maximum value of 38% and 33% is the lowest value. Also, the graph shows that the average value of the ash + moisture parameter over the scheduling period does not fluctuate significantly, resulting in a homogeneous coal supply to the coal-fired power plant. Figure 7 clearly demonstrates that the stockpiled coal helps to maintain the coal ash + moisture content of the supplied coal under the required upper bound by blending coal from the stockpile.

Consistency in the quantity parameter of coal determines the smooth and steady functioning of the power plant and prevents rehandling of the extracted coal. Figure 8 represents the total ore production compared with the requirements of the power plant over the scheduling period. The maximum amount of coal that can be mined in a year is 20 Mt. However, since for the first year there was no coal in the stockpile, production was increased to 22 Mt, i.e. including the capacity of the stockpile. So, it is demonstrated from Figure 8 that no constraints associated with quantity were violated throughout the production scheduling period.

Stockpiles buffer the quantity of coal supplied to the end users and also play a vital role in maintaining the quality parameter of the coal supplied to a power plant. Figure 9 shows the amount of material assigned to the stockpile over the scheduling period. It is clear from Figure 9 that no constraints associated with the stockpile quantity are violated. The use of the stockpile is more significant during periods of low coal production. In these periods the coal from the stockpile helps to reduce fluctuations in the quantity of supplied coal. Stockpiles are generally associated with the problem of spontaneous combustion, which is also tackled in the problem formulation proposed in this article.

The production scheduling technique being used at the case study mine (which will be referred to as the ‘present scenario’) is a heuristic method with a 5 year pushback design using mining software. Pushbacks refer to small pit shells for the whole deposit. Different pushbacks for the life of mine are generated and used to produce a life-of-mine production schedule. However, as observed above with the small data set of 3 years and 4 years, the time required to solve even small pushbacks (2400 blocks)
Figure 8. Coal quantity parameter: ore production yearly for the whole scheduling period.

Figure 9. Material assigned to the stockpile for the scheduling period.

is significantly higher than when using the sequential solution approach. Production scheduling with pushbacks does not produce the optimal solution to the production scheduling problem for the life of the mine. Production scheduling decisions for the present scenario are currently based on CV. The moisture and ash content of coal are not used in the production scheduling formulation in the
present scenario. Also, a stockpiling option was not incorporated within the formulation; rather, it has been determined as an on-site decision based on the functioning of the processing unit, power plant and equipment performance. The incubation period concept is being tackled for the stockpile with on-site inspection, which is neither convenient nor accurate. The production scheduling formulation proposed herein will help to maintain the desired quality of coal supplied to the power plant, thus increasing the efficiency of the power plant. All the decisions regarding stockpiling and blending are formulated within the production scheduling formulation to facilitate quick and efficient decision making. Moisture and ash content are also included as the driving variables for the production scheduling decision to make the schedule more effective with respect to power plant operation. The proposed production scheduling formulation will help the coal mining industry to optimize the production schedules, while making stockpiling decisions efficiently, considering the spontaneous heating problem, and enhancing the performance of power plant operations by maintaining consistency in the quality and quantity of supplied coal.

5. Summary and conclusion

The application of production scheduling formulations in the mining industry requires efficient and effective solution techniques. Since application sizes are large, sometimes up to tens of thousands of blocks, it becomes extremely difficult to solve these problems within a reasonable time. In this article, a new production scheduling formulation for coal mines was reviewed, with a stockpiling and blending option, and a period-wise solution approach was utilized, considering the application of this formulation in large open-pit coal mines. To make the problem more realistic, a penalty term associated with the quality and quantity parameters of coal was added, while formulating the problem along with the stockpiling and blending options. The accuracy of the proposed solution approach was then assessed by measuring the gap value from the optimal solutions of the relaxed production scheduling formulation. The results indicated that the proposed solution approach was able to solve the problem within a realistic time and with acceptable accuracy.

The case study illustrated an application of the proposed production scheduling formulation in large open-pit coal mines, and gives valuable insight about the importance of stockpiling and blending options for maintaining homogeneity and consistency in the quality and quantity of coal supplied to coal-fired power plants, outlining the penalty incurred owing to violation in these parameters. Furthermore, a stockpiling and blending option in the production scheduling formulation makes the problem more realistic and the concept of incubation period within the formulation makes the production schedule more user friendly. The findings of this work will help to optimize the production schedule of an open-pit coal mine, while effectively maintaining the homogeneity in the quality of supplied coal as per the demands of the end user.

Disclosure statement

No potential conflict of interest was reported by the authors.

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