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A Simulation-based Optimization Approach for Material Dispatching in Continuous Mining Systems

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Abstract—This paper examines a problem related to dispatching materials to spreaders in coal (lignite) mines operated under the paradigm of continuously excavated material flow. In the real world, complexity in analyzing such systems emerges from numerous factors, including several random variables and frequent changes of extracted materials. Most of the mathematical programming approaches are limited by the amount of the decision variables. Indeed, simplifying assumptions should be made about these factors to develop a manageable mathematical model. In this study, a new simulation-based optimization approach is proposed that can accommodate most of these factors. This approach consists of running alternately a deterministic optimization model and a stochastic simulation model. It combines simulation, transportation problem, and job-shop scheduling problem. The transportation problem provides a mechanism to optimize dispatch decisions. In other words, it finds optimal connections between excavators and spreaders. Because of the nature of the transportation problem, it is possible to have multiple connections for an excavator. Therefore, the job-shop scheduling problem deals with the allocation of spreaders to different excavators over time. Its objective is to find the processing sequences and starting times of each operation on each spreader, in order to minimize the total weighted tardiness. Finally, the simulation uses the dispatch decisions generated by optimization and computes particular performance indicators. The calculated values are then introduced into a control module. The control module suggests refinements to parameters of the optimization model (e.g., transportation costs, jobs order, and jobs weight). The iterative process ends after a stopping criterion is met. The proposed approach is tested on a large continuous mine under given different dumping sequences, and results are reported. The merits and limitations of the proposed approach as pinpointed and farsighted operations management are discussed.

Keywords: simulation-based optimization, dispatching, opencast coal mining, mining, short-term scheduling.

1. Introduction

Short-term production scheduling of a continuous mining system generates a sequence of extraction and dumping operations over time within a predefined production plan. This schedule is seen as the operational guide to meet the long or medium-term objectives of the mine developed under current operating conditions and constraints. It outlines extraction and dumping stages in terms of weeks or days. The optimization of short-term production scheduling is guided by the life-of-mine or long-term mine planning and it is conventionally optimized in two distinct steps, (Hustrulid and Kuchta, 2006). The first step optimizes the physical sequence of extraction of materials. The second step optimizes the dispatch decisions based on the dumping sequences, equipment capacity, performance, and availability. The focus of this study is on the second step of the optimization.

In the real world, there are limitations to the above mentioned distinct optimization steps, which may result in non-optimal or infeasible short-term production schedules. First, uncertainty in input parameters is not considered in the optimization steps. Second, the optimization of the extraction sequence of material ignores operational considerations and equipment availability, and thus can be unrealistic. Lastly, Most of the mathematical programming approaches are limited by the amount of the decision variables. Indeed, simplifying assumptions should be made to develop a manageable mathematical model. The performance of the production scheduling can be adversely affected by these limitations and this may lead to: (a) increased operating costs due to the unscheduled downtimes; (b) uncertainty in equipment performance and lower utilization of equipment; and (c) inability to meet expected production targets. This paper proposes a new simulation-based optimization approach that can accommodate these limitations. This approach consists of running alternately a deterministic optimization model and a stochastic simulation model. It combines simulation, transportation problem, and job-shop scheduling problem. The transportation problem provides a mechanism to optimize...
dispatch decisions. In other words, it finds optimal connections between excavators and spreaders. Because of the nature of the transportation problem, it is possible to have multiple connections for an excavator. Therefore, the job-shop scheduling problem deals with the allocation of spreaders to different excavators over time. Its objective is to find the processing sequences and starting times of each operation on each spreader, in order to minimize the total weighted tardiness. Finally, the simulation uses the dispatch decisions generated by optimization and computes particular performance indicators. The calculated values are then introduced into a control module. The control module suggests refinements to parameters of the optimization model (e.g. transportation costs, jobs order, and jobs weight). The iterative process ends after a stopping criterion is met. The proposed approach is tested on a large continuous mine under given different dumping sequences, and results are reported. The merits and limitations of the proposed approach as pinpointed and farsighted operations management are discussed.

In the following sections, a literature review and a brief background about continuous mining systems will be given. It continues by defining the problem. Then, the solution strategy is discussed in detail. After that, the computational framework and its implementation are presented. Finally, the description of a real-size case study is given and the obtained results are reported. The last section concludes the findings of this study.

2. Review of Literature

A considerable amount of literature has been published on the optimization of short-term production scheduling. These studies in early attempts have focused on evolving concepts and related formulation for finding extraction sequences based on mathematical programming, e.g. (Wilke and Reimer, 1977, Wilke and Woehrle, 1980, Gershon, 1983). Their objective function is set to minimize production deviations from the long-/medium-term production targets. While allocating resources, the conventional optimization process considers mining direction and fleet capacity. Nevertheless, it does not integrate the fleet management, i.e. dispatching of mining equipment and uncertainty in equipment availability. More recent attentions thus focus on the provision of real-time fleet allocation for short-term production scheduling (Alarie and Gamache, 2002, L’Heureux et al., 2013) and stochastic optimization of short-term production scheduling (Topal and Ramazan, 2012, Matamoros and Dimitrakopoulos, 2016). They have been successfully applied for over three decades to find optimal solutions for real size case studies. However, a large and growing body of literature has mainly investigated the applications that are in the discontinuous block mining with the diffuse deposits.

In simulation-based optimization literature, Figueira and Almada-Lobo (2014) review the current research on its developments. They provide a taxonomy that gives an overview of the full spectrum of current simulation-optimization approaches. In the field of mining, little research to date has been carried out on this area. Mena et al. (2013) presented a simulation-optimization modeling framework based on the Arena and the LINGO software. Their objective is to maximize the overall productivity of the fleet in a truck-shovel system. In their model, trucks are allocated to transportation routes according to their operating performances. Improvements when using in realistic case are reported. Nageshwaranuyier et al. (2013a) investigated a two-level hierarchical simulation-based planning framework for a coal mining system consisting of multiple pits, using trucks and trains to transport the material and silos to blend it. The Arena software is used for building the simulation model. The problem is divided into sub-problems reducing the decision space of the complex problem. The train-loading problem is at the top level while the machinery-scheduling problem (defining working schedules for machinery at the mine for loading each customer train) is at the lower level. To maximize the revenues of the mine in each shift, the problems are solved using the OptQuest software. Nageshwaranuyier et al. (2013b) proposed a robust simulation-based optimization approach for a truck-shovel system in surface coal mines. It is based on a detailed simulation model created with the help of the Arena software. Response Surface Methodology (RSM) is applied to derive an expression for the variance of revenue. Their objective is the maximization of the expected value of revenue obtained from customer trains.

Since there are few applications of the simulation optimization approach in mining, it seems wise to focus on related fields, such as process system engineering and supply chain management, to build upon their findings. A supply chain management problem under demand uncertainty was presented by Jung et al. (2004) whereby safety stock levels were determined using simulation-based optimization method in a rolling horizon manner. Their proposed approach consists of running alternately a deterministic planning model and a stochastic Monte-Carlo based simulation model in a loop structure. Their algorithm ends when the difference between the estimation and the target values of the customer satisfaction level is equal to very small number.

3. Background

Continuous mining systems, usually known as opencast mines, consist of excavators, belt conveyors, and spreaders operating in series and under the paradigm of continuously excavated material flow.

Figure 1 shows a schematic section view of a continuous mining system. The operation starts with the excavation of materials by excavators at the extraction side. It continues by the transportation of the extracted materials from mining benches to dumping benches or a coal bunker. The transportation process includes a network of conveyor belts consisting of face conveyor belts, main conveyor belts, and a mass distribution center. Finally, lignite is stacked at the bunker or waste materials are dumped at the dumping side. In such a paradigm, the excavators can be seen as supply points and the spreaders together with the coal bunker can be considered as demand points.
The production planning in an opencast mine covers various periods, namely long-, medium-, and short-term planning horizons. The long-term planning affects an opencast mine across its entire life, all the way to the end of mining supervision after the land reclamation. The medium-term planning often covers the next five-year period. Finally, the short-term planning is a yearly seam-focused detailed plan.

Besides operational and economical parameters that are necessary for any production planning process, the major input here is the geological block model. It is divided into two separate block models namely, the extraction block model and the dumping block model. The former includes the geological strata, quality parameters, volumes-tonnages, and material types. The latter includes dumping profiles and volumes.

As mentioned earlier, the short-term plan is guided by medium and long-term plan. Forasmuch as the complex deposit formations require selective mining of coal as well as overburden on different benches. The objective of short-term planning is to find the sequence of blocks, known as extraction sequence, that meet the defined targets under current operating conditions and constraints. After the creation of the extraction sequence, basically, the first step of the optimization of the short-term scheduling is completed. The created extraction sequence can be used as a guide to create the dumping sequence. It is also an input for the second step of the optimization, which is the focus of this paper. The next section describes the problem with the defined objectives.

4. Problem Description

Figure 2 presents the flow diagram of the short-term production scheduling in continuous mining systems. Three major processes can be seen in the diagram namely, short-term planning, dumping sequence creation, and material dispatching. These should be completed in the presented logical order to have a short-term schedule. Here, there are two underlying assumptions; the first is that the extraction block model, the dumping block model, and the extraction sequence are given as discussed in the previous section. Stable dump construction needs different material types with special sequences; while these materials are distributed unevenly at the extraction side, the second underlying assumption becomes very important. It is defined as that the problem should be relatively a balanced problem. In a sense, the difference between the total amounts of different overburden materials at the extraction side with the amounts of available spaces at the dumping side should be a small number. In the presence of finite available space for a material type, when the extraction of that material type becomes sufficiently large, then for any given dumping sequence it will no longer be possible to meet the defined production targets. The optimization of dispatch decisions thus must involve the dumping capacity constraints. Furthermore, uncertainty is associated with input parameters, equipment availability, and their performances thus the resulting problem is a constrained stochastic optimization problem.

The different ranges of the ratio of the expected amount of materials at the extraction side to the dumping capacities of the same materials give rise to three different scheduling scenarios. In scenario I, when the extracted to dumped capacity ratio is sufficiently small, the dumping side has sufficient spare capacity to cope with abrupt changes in the extracted materials due to the uncertainty involved. Therefore, in this scenario, challenges are mostly located on the optimization of the dispatch decisions. In scenario II, characterized by an intermediate range of the extracted to dumped capacity ratio, the production capacity may be quite constrained by the dumping capacity when the extraction of different materials spike at some point in time. In this scenario, even with optimal dispatch decision, the production for some excavators may fail to reach their targets due to the downtimes. Finally in scenario III, the extracted to dumped capacity ratio is sufficiently large that most of the extracted materials simply cannot be dumped and thus excavators will compete for dumping spaces. In this scenario, dispatch decisions and dumping spaces must be assigned strategically to meet the demands of some excavators in preference to others. In this paper, the optimization problem that is under scenario I and II will be addressed. The
optimization of short-term scheduling for the case of scenario III involves strategies for the prioritization of excavators. Such strategies, while of considerable interest, are beyond the scope of this study.

Figure 2. Flow diagram of short-term production scheduling in continuous mining systems.

To formulate the problem, the following problem context is assumed:

- An opencast mine has multiple extraction benches which only one excavator operates on each bench. Different excavators may have different production capacities and each can extract any type of materials. Furthermore, the mine has multiple dumping benches which only one spreader can operate on each bench. Similar to the excavators, different spreaders can have different dumping capacities.
- The units at different benches cannot send material to a same destination at the same time.
- Daily/Weekly schedule known as the task schedule is an external input for the short-term scheduling problem. This schedule includes the planned availabilities and downtimes (i.e. planned maintenance) of the equipment.
- Each excavator can supply any spreaders and the transportation network is always available. Hence, in the first part of this study, namely optimization, availability of the transportation network is not explicitly considered. Later, in the simulation part, it will be added to the problem as a feedback from the simulator.

The objective is to minimize downtimes of equipment by effective resource allocations. This will result in decrements in overall costs, including extraction costs, dumping costs, and penalties for deviating from the predefined targets. There are two types of decisions, on the excavator and on the spreader side:

- Decision on the excavator side:
  - Production rate of each excavator (between 0% and 100%)
  - Connection to the spreader
- Decision on the spreader side:
  - Dumping sequence (depending on material type available)

5. Solution Strategy

To address the above-mentioned problem this paper proposes a new simulation-based optimization approach that relies on the use of deterministic optimization model and a stochastic simulation model. The deterministic model is built using a certain feasible dumping sequence and incorporates transportation problem and job-shop scheduling problem. The transportation problem provides a mechanism to optimize dispatch decisions. In other words, it finds optimal connections between excavators and spreaders. Because of the nature of the transportation problem, it is possible to have multiple connections for an excavator. Therefore, the job-shop scheduling problem deals with the allocation of spreaders to different excavators over time. Its objective is to find the processing sequences and starting times of each operation on each spreader, in order to minimize the total weighted tardiness. A discrete event simulation of the system is executed implementing the dispatch decisions obtained via the deterministic model for a given dumping sequence. The results of multiple simulation replications serve to provide an estimate of a particular performance measure (e.g., utilization). The calculated values are then introduced into a control module. The control module suggests refinements to parameters of the deterministic optimization model (e.g., transportation costs, jobs order, and jobs weight). The iterative process ends after a stopping criterion is met. The strategy uses two aspects of “Sim-Opt” architecture, (Subramanian et al., 2001). Figure 3a-b presents the configuration of the discussed simulation optimization approach.

The following will discuss the three key sub-problems, the creation of random dumping sequence, the transportation problem, and the job-shop scheduling problem. In the
subsequent section, the various computational details that are needed to link these sub-problems and to drive the computations to obtain the desired short-term plan will be discussed.

(a) Simulation Optimization

(b) Deterministic Optimization Model

Figure 3. Configuration of simulation-based optimization approach.

5.1. Random Dumping Sequences

If the dumping benches with their special profiles were discretized in a defined sections (e.g. every 50m), then the evolution of the random dumping sequences over time can be represented by the tree-like structure presented in Figure 4. Starting from each node, a large number of possible dumping options at the next dumping stage are expressed as branches stemming from that node. Assuming \( m \) possible next-stage dumping options at each node, the total number of scenarios will amount to \( m^S \), where \( S \) is the total number of dumping stages. Each scenario as a feasible dumping sequence is an input for the transportation problem as is shown in Figure 3b.

5.2. Transportation Problem

The transportation problem (TP) is concerned with shipping a commodity between a set of sources (e.g. excavators) and a set of destinations (e.g. spreaders). Each source has a capacity dictating the amount it supplies and each destination has a demand dictating the amount it receives, (Winston and Goldberg, 2004). TP is a subset of network models and the set of resources and destinations can be illustrated, respectively, by a set nodes. Nodes are connected to each other via arcs; each arc has two major attributes namely the cost of sending a unit of a material from one node to the others and the maximum capacity of the arc, Figure 5.

Figure 4. Schematic diagram of evolution of random dumping sequences.

Figure 5. A transportation problem with \( m \) sources and \( n \) destinations.
An opencast mine extracts material at \( m \) different benches \((i = 1, \ldots, m)\). The amount of material to be extracted at bench \( i \) is \( a_i \). The demands for the extracted materials are distributed at \( n \) different dumping benches \((j = 1, \ldots, n)\). The amount of material to be dumped at bench \( j \) is \( b_j \). The problem is to find connections between excavators and spreaders at minimum cost. Linear programming (LP) formulation of the problem is as follows, (Winston and Goldberg, 2004):

Objective function:

\[
\text{Minimize } \sum_{all \text{ arcs}} C_{ij}X_{ij} \quad (1)
\]

s.t.

\[
\sum_{j=1}^{n} X_{ij} \leq a_i \text{ for } i = 1, \ldots, m \quad (2)
\]

\[
\sum_{i=1}^{m} X_{ij} \geq b_j \text{ for } j = 1, \ldots, n \quad (3)
\]

\[
X_{ij} \geq 0 \text{ for all } i \text{ and } j, \quad (4)
\]

where, \( X_{ij} \), number of units of materials sent from node \( i \) to node \( j \) through arc \((i, j)\); \( C_{ij} \), cost of transporting one unit of material from node \( i \) to node \( j \) via arc \((i, j)\). The objective function, denoted by Eq. (1) involves a deterministic optimization in which the total cost of sending materials from supply points to demand points is minimized. In constraint (2), the sum of all shipments from a source cannot exceed the available supply. Constraint (3) specifies that the sum of all shipments to a destination must be at least as large as the demand. Constraint (4) is a binding constraint.

Consider the feasibility of the problem. The only way that the problem can be feasible is if total supply exceeds total demand \((\sum_{i=1}^{m} a_i \geq \sum_{j=1}^{n} b_j)\). Two conditions can be implied from this:

- When the total supply is equal to the total demand (i.e. \( \sum_{i=1}^{m} a_i = \sum_{j=1}^{n} b_j \)) then the transportation model is said to be balanced.

- A transportation problem in which the total supply and total demand are unequal is called unbalanced. If there is excess demand, a dummy source is introduced (i.e. a fictitious bench). The amount shipped from this dummy source to a destination represents the shortage quantity at that destination. If there is excess supply, a dummy destination is added to the network. Likewise, the amount received from this dummy destination from a source represents the excess quantity at that source.

Due to the nature of the transportation problem, it is possible that an excavator has to send materials to multiple spreaders. The next section will discuss the job-shop scheduling problem, which deals with the allocation of spreaders to different excavators over the time.

5.3. Job-Shop Scheduling Problem

The job-shop scheduling problem (JSP) consists of a finite set of jobs \( J = \{1, \ldots, n\} \) and a finite set of machines \( M = \{1, \ldots, m\} \). In this paper, excavators are defined as jobs and spreaders are defined as machines. The aim is to find a schedule of \( J \) on \( M \) under the below mentioned conditions:

- For each job \( j \in J \), a list \((O^j_1, \ldots, O^j_h, \ldots, O^j_m)\) of the machines which represents the processing order of \( j \) through the machines is given. Note that \( O^j_h \) is called the \( h \)-th operation of job \( j \) and \( O^j_m \) is the last operation of job \( j \).

- The processing order for each job is fixed, thus, machine-sequencing problem for every job should be taken into account.

- For every job \( j \) and machine \( i \), a non-negative \( P_{ij} \) is given, which represents the processing time of \( j \) on \( i \).

- Each machine must always be available and can process at most one job at a time, and once a job starts on a given machine, preemption is not allowed.

- Every job \( j \) has an assigned release time \( r_j \geq 0 \) so that the first operation cannot start before \( r_j \). In this paper, \( r_j \) is given in the task schedule.

- An additional attribute of a job \( j \) is its weight \( w_j \), which represents the relative importance of \( j \) in comparison to other jobs.

- Furthermore, every job \( j \) has a due date \( \tau_j \geq 0 \) which should, but does not necessarily have to, be met in a schedule.

In this study, the objective is to minimize the total weighted tardiness, as defined \( TWT = \sum_{j=1}^{n} w_j \cdot t_j \), where \( t_j = \max\{0, c_j - d_j\} \) is the resulting tardiness of job \( j \) in a schedule, and \( c_j \) its completion time. From then, this problem is referred to as JSPTWT. (Ku and Beck, 2016) investigated the size of problem that can be solved by Mixed Integer Programming (MIP) formulation. For a moderate sized problem up to 10 jobs and 10 machines, with the recent technology, MIP finds the optimum solution in a very reasonable amount of time. They also compared the performance of the four MIP models for the classical JSP. They concluded that the disjunctive MIP formulation with the use of Gurobi Optimization v6.0.4 solver (Gurobi Optimization, 2016) gives the fastest result for a moderate sized problem. The below is the disjunctive MIP formulation of JSPTWT is based on Manne (1960)’s formulations. The decision variables are defined as follows:

- \( X_{ij} \) is the integer start time of job \( j \) on machine \( i \)

- \( \tau_{ij} \) is equal to 1 if job \( j \) precedes job \( k \) on machine \( i \)

Objective function:

\[
\text{Minimize } \sum_{j=1}^{n} w_j \cdot t_j \quad (5)
\]

s.t.

\[
X_{ij} \geq X_{i,j-1} + P_{ij} \quad \forall j \in J, i = 2, \ldots, m \quad (6)
\]
\[ X_{ij} \geq X_{ik} + p_{ik} - V \cdot Z_{ijk}, \quad \forall j, k \in J, j < k, i \in M \]  
(7)

\[ X_{i} \geq X_{ij} + p_{ij} - V \cdot (1 - Z_{ijk}), \quad \forall j, k \in J, j < k, i \in M \]  
(8)

\[ t_{j} \geq x_{mj} + p_{mj} - d_{j}, \quad \forall j \in J \]  
(9)

\[ t_{j} \geq 0, \quad \forall j \in J \]  
(10)

\[ X_{ij} \geq t_{j}, \quad \forall j \in J \]  
(11)

Constraint (6) is the precedence constraint. It ensures that all operations of a job are executed in the given order. The disjunctive constraints (7) and (8) ensure that no two jobs can be scheduled on the same machine at the same time. \( V \) has to be assigned to a large enough value to ensure the correctness of (7) and (8). In this paper, it is defined as \( V = \sum_{j \in J} \sum_{m \in M} p_{ij} \), since the completion time of any operation cannot exceed the summation of the processing times from all the operations. Constraint (9) and (10) measure the resulting tardiness of each job. Finally, constraint (11) ensures that a job cannot start before its release time, and thus, captures the non-negativity of the decision variables \( X_{ij} \).

As an example, Figure 6 shows a simple JSP that three jobs J1, J2, and J3 are to be scheduled on three machines M1, M2, and M3. The graph on the top represents the precedence constraints. The Gantt chart on the bottom displays a feasible schedule that satisfies the precedence constraints.

![Figure 6. A simple job-shop scheduling problem, (Ku and Beck, 2016).](image)

6. Computational Framework

In this section, the overall computational approach is described. First, input parameters are explained. Then, the computational logic with the details of the integration of the sub-problems together and with the discrete event simulation is discussed. After that, the simulation based optimization framework is presented.

6.1. Input Parameters

The second step of the optimization of short-term scheduling starts with the assignment of input parameters. The definitions and their functionalities are as follows:

- **Start points** of dumping in different benches, i.e. the start locations of spreaders on benches at the beginning of the working shift. This is an input for the creation of random dumping sequences.
- **The allowed range of movement** for spreaders, i.e. in what range it is allowed to transport spreaders and start a new dumping profile. This is also an input for the creation of random dumping sequences.
- **Transportation costs**, these costs are used to distinguish between different destinations for a source in the transportation problem.
- **Machine sequencing**, the Earliest Due Date (EDD) sequencing method is used to create processing orders of the jobs in the JSP.
- Finally, **job weights** are some other input parameters for the JSP. For instance, they can be used to prioritize an excavator if a bottleneck is seen after the simulation.

The aim is to find the best combination of these parameters using simulation based optimization approach to achieve the optimum short-term schedule.

6.2. Deterministic Optimization with Embedded Simulation

The following describes the details of the integration of the sub-problems together and to the discrete event simulation in walk-through steps.

Step 1: start with arbitrary set of input parameters.

Step 2: create a sufficient number of random dumping sequences, \( \{ 1, \ldots, R_{d} \} \).

Step 3: for a certain dumping sequence, \( d = 1, d \in R_{d} \), optimal connections can be found using the transportation problem.

Step 3.1: check the availability of the equipment based on the given task schedule and create the nodes.

Step 3.2: start with first blocks in the given extraction sequence and assign their volumes as \( a_{i} \) to supply nodes in the TP formulation.

Step 3.3: assign the volumes of the first sequence of blocks in the given dumping sequence as \( b_{i} \) to demand nodes in the TP formulation.

Step 3.4: check if problem is balanced, if not dummy nodes will be added to the network.

Step 3.5: create arcs between supply and demand nodes. Only the nodes get connected that have the same type of material.

Step 3.6: add a capacity to the arcs. In the TP, the capacity is set to be infinite for all the arcs.

Step 3.7: add costs to the arcs. In an open cast mine, the potential costs can be:

- Excavators and spreaders on the same level (altitude) get lower cost of transportation.
- Length of belt conveyors between supply nodes and demand nodes, the closer the equipment the lower the costs.
• Difference between the production capacity and dumping capacity of the equipment, the lower the difference the lower the costs.

Step 3.8: build the LP model with the help of Eqs. (1)-(4) and solve it by Gurobi solver.

Step 3.9: calculate the residual volumes and add them to the next iteration of the optimization.

Step 3.10: go to the step 3.1 and repeat steps 3.1–3.10 until all the blocks are extracted in the given extraction sequence.

Step 3.11: check for feasibility of the schedule, if there is residual volume left on the extraction side, set \(d = d + 1\) and go to the step 3 until \(d = R_x\).

Otherwise, continue.

Step 4: create the input for the JSPTWT and build MIP model using Eqs. (5)-(11) and solve it by Gurobi solver.

Step 5: create the Gantt chart. The output of the JSPTWT is the optimum short-term schedule for the given extraction and dumping sequence \((d)\).

Step 6: run the discrete event simulation for the given short-term schedule.

Step 7: record the state (utilizations, amounts) at the end of the time horizon.

Step 8: set \(d = d + 1\) and go to the step 3 until \(d = R_x\).

6.3. Simulation based optimization framework

A more detailed flow diagram, which summarizes the overall computational framework, is presented in Figure 7. It combines the deterministic optimization with the stochastic simulation in a closed loop. Most of the steps are explained in detail in the previous section. As can be seen, the simulation is implicitly built over the embedded optimization. Once the computations over the simulation loop are completed, a number of best schedules based on the user-defined targets such as shorter makespan, higher utilization of equipment are selected.

These are analyzed in the control modules; if the stopping criteria are met, the algorithm stops otherwise a new set of input parameters are introduced to the optimizer. The following section presents more details about the interactions between the components over a simulation-optimization platform.

7. Implementation of the computational framework

The implementation of the proposed simulation-based optimization approach consists of following major components: the computational control module, the databases, the three modules for the creation of random dumping sequences, transportation problem and job-shop scheduling, the discrete event simulation with its interface, the post-processing module, and finally the control module, Figure 8.

The computational control module is responsible for controlling interactions of computational components. It has various functionality including:

- Issuing commands for retrieving information from the database.
- Generating/updating and releasing commands for executing the steps of the algorithm.

- Re-processing and controlling the output of each computational component before issuing the next command.
- Selecting a number of best schedules based on the defined criteria to proceed the algorithm to the simulation part.

The database contains information about geological block model, the given extraction sequences, and the task schedule. These data are stored in a Microsoft Excel Workflow file. Since the computational control module is coded in Python, a publicly available Pandas library (McKinney, 2010) is used to access each cell in the Excel sheets. Big datasets can be readily read and stored in DataFrames with the help of Pandas library.

The three major components of the deterministic optimization were explained in detail in the previous sections. It should be noted that to solve the LP or the MIP models, Gurobi Python interface is used. After the selection of a number of best schedules by the computational control module,
the data are recorded in two separate databases, namely, the block model and the schedule. These two are the major inputs for the discrete event simulation of an opencast mine.

The discrete event simulation model is built in Arena® simulation environment. The detail of the construction of the simulation model of an opencast mine can be found in Shishyev and Benndorf (2016). A process worth attention is the simulation model interface, which is situated between the computational control module and the Arena. This process is required because there is no direct way to interact with the Arena using, for instance, the command line. Instead, the program relies on automation via Visual Basic for Applications (VBA), a Microsoft technology for creating interconnection between applications. This technology is not available in Python, thus the simulation model interface is written in Visual Basic and compiled as an executable that can be controlled and run with the relevant parameters. When the simulation run is completed, the VB script releases a command to the controller.

The post-processing module processes the simulation outputs and creates plots and tables. Finally, the control module calculated the differences between the current results with the predefined targets. If another loop of simulation-optimization is required, the new input parameters are suggested to the computational control module.

8. Case study

To demonstrate the performance of the proposed simulation based optimization approach, a real case study has been developed. The Hambach mine is a large opencast coal mine and produces over 100 million tons of coal and over 500 million m³ of overburden materials per year.

8.1. Case Problem

8.1.1. Overview of the Production System

A schematic view of the Hambach mine is shown in Figure 9. In total eight bucket-wheel excavators (BWEs) have to be scheduled to serve continuously seven spreaders with waste materials and two bunkers with coal. Each BWE excavates either coal or waste in terrace cuts and transfers materials to the face conveyor belt, which carries it along the bench to the main conveyor belt. All excavated materials of the eight benches are distributed to their destinations at the mass distribution center. Based on a predefined daily schedule, waste is distributed to the seven spreaders for dumping, and lignite is forwarded to two coal-bunkers. Table 1 shows the technical specifications of the BWEs.
Figure 9. Schematic overview of the production system of the Hambach mine.

Figure 10. Placement of M2N materials in between a prebuilt polder, (Gärtner et al., 2013).

<table>
<thead>
<tr>
<th>Bench</th>
<th>BWE model</th>
<th>Discharge per min</th>
<th>Bucket capacity (m3)</th>
<th>Theoretical capacity (m3/h)*</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>259</td>
<td>44</td>
<td>2.6</td>
<td>5700</td>
</tr>
<tr>
<td>B1</td>
<td>260</td>
<td>38</td>
<td>3.5</td>
<td>5700</td>
</tr>
<tr>
<td>B2</td>
<td>291</td>
<td>48</td>
<td>5.0</td>
<td>12500</td>
</tr>
<tr>
<td>B3</td>
<td>287</td>
<td>43</td>
<td>5.1</td>
<td>10400</td>
</tr>
<tr>
<td>B4</td>
<td>290</td>
<td>48</td>
<td>5.0</td>
<td>12500</td>
</tr>
<tr>
<td>B5</td>
<td>292</td>
<td>48.6-72.0</td>
<td>5.0</td>
<td>12500</td>
</tr>
<tr>
<td>B6</td>
<td>293</td>
<td>48.6-72.0</td>
<td>5.0</td>
<td>12500</td>
</tr>
<tr>
<td>B7</td>
<td>289</td>
<td>48</td>
<td>5.0</td>
<td>12500</td>
</tr>
</tbody>
</table>

* 19.3 hours per day

The mine operates 24 hours per day and seven days per week. Regular maintenance is carried out on weekly, monthly, and annually based schedules. During the regular maintenance or an unscheduled breakdown, the production process ceases on the bench.

8.1.2. Problem in Mining

Waste materials at the Hambach mine are categorized in three types of mixed soils, dry mixed soils type1 (M1), semi-wet mixed Soils type2 (M2T) and wet mixed soils type2 (M2N). The extraction of M2 type materials is increasingly facing deficiencies in output due to difficult mining materials. This type of soil, specifically M2N, exhibits a high share of cohesive components and is difficult to drain. M2N material cannot be used for stable dump construction and needs to be filled in between prebuilt polders constructed of dry material (Figure 10). The fact that only a limited quantity of these unstable mixed soils can be placed in the waste dump causes downtimes and bottlenecks in the placement process on the dumping side.

Furthermore, historical data show that next to scheduled maintenance, breakdowns of the equipment occur in a random manner. Due to the “in series” system configuration, equipment units feeding or are connected to the ceased equipment are blocked and set out of the operation while the maintenance is
being done or the failure is being repaired. In addition, because of the multi-layer nature of the deposit, changes from one material type (e.g., M1) to another material type (e.g., M2N) or vice versa happens very frequently. Each time a material change takes place, the BWE stops excavating. The combined effect of random equipment breakdowns and frequent changes in extracted materials, makes the prediction of the exact material flow rate at any given future time span as a major source of uncertainty.

The objective is to optimize dispatch decisions to decrease downtimes/increase efficiency of excavators and spreaders by effective resource allocation while ensuring stable dump construction using the proposed simulation based optimization approach. Here, decisions on the dumping side are the length of polders to be built while on the extraction side, decisions are production rates of excavators and their connections to spreaders.

### 8.1.3. **Input Data**

The following presents the data for a day of production. The objective is to find the optimum daily schedule that maximizes the utilization of equipment.

**Extraction Sequence**

Figure 11 shows the given extraction sequence for one day of production. This model is also called the slice block model.

**Task Schedule**

The given task schedule for a day is presented Table 2. The number “0” denotes that the equipment is unavailable and “1” vice versa. Thus, the transportation problem will have six supply nodes and eight demand nodes.

<table>
<thead>
<tr>
<th>Bench</th>
<th>First Shift</th>
<th>Second Shift</th>
<th>Third Shift</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>B1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>B2</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>B3</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>B4</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>B5</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>B6</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>B7</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>I1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>I2</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>I3</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>I4</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>I5</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>I6</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>I7</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

### 8.2. **Results**

As explained in section 6, the initial set of parameters is set and 1000 random dumping sequences are created. The transportation model is built; in the first and second iterations of simulation-optimization, there was no feasible solution. After 10-th iteration, which in every iteration input parameters have been altered, 464 feasible production schedules were found. For the demonstration purpose, one of the Gantt-Charts is presented in Figure 12.

![Figure 11. An extraction sequence given for a day.](image-url)
Figure 12. A feasible Gantt-Chart.

Figure 13. Utilizations of nine different feasible schedules, output of optimization block.
Figure 14. Utilizations of nine different feasible schedules, output of optimization block.

Figure 15. Utilization of excavators after running in Arena for the best schedule.
Out of these many feasible solutions, based on the below mentioned performance measures, a number of solutions are chosen as n best-solutions to be tested in Arena®:

- Gantt-Charts,
- Utilizations of excavators (Figure 13),
- Utilizations of Spreaders (Figure 14),
- Busy and total available hours.

The aim of this selection is to find solutions with higher and realistic utilization. This is due to that if the utilization is equal to 97%, for instance, there is a high chance that this will not happen in the reality when the unscheduled breakdown behavior is added to the model in the simulation. This can be true for spreaders as well. The selected schedules are run in Arena® and the result of the best schedule is presented in Figure 15.

9. Conclusions

Throughout this study, a new simulation-based optimization approach has been proposed. The approach is capable of optimizing the dispatch decisions in an open-pit mine operated under the paradigm of continuously excavated material flow. A deterministic optimization and stochastic simulation models were combined. The transportation problem and the job-shop scheduling problem composed the optimization model. The performance of the proposed approach was tested in a real-size case study. For this case, 1000 random dumping sequences were created. The results showed that for a given extraction sequence and the random dumping sequences, the optimum dispatch decisions were obtained after 10-th iteration. 464 out of 1000 were found as feasible production schedules. In every simulation-optimization loop, the 10 best schedules based on the defined criteria were selected to be run in Arena. In two steps optimization approach of short-term production scheduling, the scheduling elements, physical sequencing and equipment utilization, are artificially separated so that they do not benefit from their simultaneous optimization. As a future work, a single step optimization approach is recommended, i.e. physical sequencing can be merged into the deterministic optimization.

Acknowledgement

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References


