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Multi-criteria filtering approach for comparison and analysis of scheduling alternative scenarios: case study on an open pit phosphate mine

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Abstract. Open-pit phosphate mine is characterized by a stack of layers with different chemical characteristics (Source qualities SQ). The extraction process involves various elementary operations performed by a dedicated or polyvalent machines. The tactical mining scheduling consists to define the blocs to be extracted and assign the machines over the planning horizon. However, the interdependencies and complexity characterizing this problem make the decision-making process so difficult. This paper proposes a multi-criteria approach integrated in an Interactive Decision Support System (IDSS) based on an original sequential approach selecting the most performant mining scenarios. Indeed, a discrete event simulation-based model developed and encapsulated in this IDSS proposes various scenarios. With a developed multi-criteria filtering approach, each scenario is approved by a feasibility study to verify that a scenario can satisfy the demand for merchantable qualities (MQ). Then, the feasible scenarios are analyzed based on their robustness when facing disturbed demand vectors and compared by other effectiveness and efficiency criteria. To preserve only the two or three most performant scenarios.

Keywords: Mining scheduling, Interactive Decision Support System IDSS, alternative scenarios, multi-criteria decision making.

1 Introduction

The planning of ore mining in an open-pit mine is widely studied in the literature since the 1960's based on optimization and/or simulation approaches. Researchers have focused on the long-term mining planning issue [1]. However, studies based on medium- and short-term scheduling are relatively limited [2]. The spatiotemporal interdependencies and the various characteristics of the mining sector make the decision-making process more difficult.

Our field of study is based on an open-pit phosphate mine from the OCP group, whose supply chain is made up of several entities allowing the transition from ore to a

finished or semi-finished product. The sedimentary nature of the mine means that the extraction of a layer can only be carried out if the upper level is already removed. From a transverse view, the mine is divided into panels, each of which is divided into blocs, the blocs on the same line represent the trench [3, 4]. The extracted SQ are transported to the down-stream mechanical processing units to subsequently enter a mixing or blending process [5] to constitute the MQ. A discrete event simulation-based (DES) model was developed considering the different constraints (geology, qualities, machines, etc.) of the mine to reproduce the extraction process and propose the extraction planning (scenario) [2]. The integration of the priority indexes of the extracted SQ as control parameters in the simulation, led to the possibility of generating various scenarios in a rapid and coherent way, based on a variation of parameters.

This paper aims to answer the following research question: How can we evaluate a set of generated scenarios, considering a multi criteria filtering approach, to select 2 or 3 most performant scheduling programs for the planning team to choose from and apply in the field? To answer this question, we have started by exposing the research works proposed in the scenario concept and the multi-criteria analysis approaches in section 2. Then, section 3 will propose the multi-criteria filtering approach developed. Thereafter, section 4 will be dedicated to the case study illustrating the experimental results based on real field data before concluding in section 5.

2 Literature review

The scenario analysis has been widely applied in several sectors and disciplines [6, 7]. Defining a scenario has been a challenge [8]. Bell affirmed in [9] that “scenario” gives methodological unity to futures studies. Today a diverse group of decision-makers, consultants, and researchers develop and use scenarios in a variety of ways [7, 10]. The scenario-based research methodology is considered among the most used in various fields and is used for many purposes as highlighted by [11]. Notten et al. proposed [12] an updated typology and explain how the typology was tested for its robustness in a comparative analysis of recent scenario projects. Borjeson et al. [13] regroup and reconcile several typologies, to distinguish three main categories based on the main questions asked by a decision-maker: *i*) what will happen? (Predictive), *ii*) what can happen? (Exploratory), *iii*) how to achieve a specific objective? (Normative).

Information about the past and the present lead to different alternative possibilities about the future. Thus, a need for evaluation and comparison to perceive to what extent each alternative is plausible, desirable and beneficial for the decision-maker is necessary [9] p.317. The complexity of analyzing and comparing multidimensional alternatives scenarios leads to considering explicitly several criteria and objectives to be optimized simultaneously in the analysis of preferences. Thus, defining a Multi-criteria decision problem consisting on the comparison of solutions and the determination of one or more optimal solution (s). Several approaches are used to guide the decision-making process in this case, by offering an analysis allowing to deepen the reflection on the studied scenarios and identify a consensus on the choice of one or more best scenarios.

In this literature review, we studied three main approaches: the statistical response surface methodology (RSM), the aggregated and Pareto methods as main categories of multi objective optimization (MOO).

The RSM aims to evaluate the impact of decision variables as inputs on the response obtained as output, in order to determine the set of optimal decision parameters allowing to lead to the best scenario in relation to an objective function [14] and providing an exact answer to an approximate problem [15]. Some authors [16, 17, 18], having used or compared the RSM method with other methods, explain that this technique also represents multiple limitations to consider. Concerning the MOO approaches, there is a general consensus that it can be broadly broken down into two basic categories: Aggregation methods and Pareto methods [19]. The formulation of the aggregate objective function requires the assignation of preferences or weights to criteria converging towards the choice of a single scenario. Guo et al. ensure in [20] that in the world of industrial production and when making decisions, it is common for several production objectives to be considered and achieved simultaneously. Some authors use the weighted sum method to transform multi-objective problems into single-objective problems like [21, 22]. However, it is difficult for some problems to determine the weight of the different lenses. It is also impossible to have a single solution that can simultaneously optimize all goals when multiple goals conflict. To deal with this problem, some researchers have used the concept of Pareto optimality to provide more feasible solutions (optimal solutions in the Pareto sense) to the production decision maker such as authors in [23, 24, 25] affirmed that the advantage of the Pareto method lies in the possibility of separately taking into account several conflicting criteria in the evaluation and the selection of the best scenarios, thus allowing a richer critical analysis of the potential scenarios.

Based on this literature review, we conclude that this paper deals with a specific problem that have not been yet studied in the context of multi-criteria decision making related to the short and midterm scheduling of ore extraction problem taking into account different criteria. Indeed, The RSM is not applied in our case given the weak link between inputs parameters, their interdependence, and the response. The aggregation method is also not adequate because of the absence of a synthetic indicator that can express the multidimensional complexity of a mining scheduling scenario. Thus, considering the conflicting efficiency and effectiveness criteria, the Pareto method seems to be the best to keep this complexity while determining a reduced subset of the best scenarios located on the Pareto front. Furthermore, it is necessary to note that considering the complexity of this problem, we will define other levels to our multi criteria approach before using the Pareto method at the end. All in all, this IDSS is an enriching contribution to the few decision support systems dealing with the mining industry, using a DES model as a resolution module and following an original problem tailored sequential approach instead of the classical traditional. This sequential approach will guarantee the consideration of all the technical mining constraints by encapsulating the SED model. On the other hand, it will ensure that significant criteria for the decision makers will be taken into consideration. Thus, we will guarantee an alignment with complex mining objectives and make our approach feasible in the practical case of the mine.

3 Multi-criteria approach: proposition and integration

In order to generate a set of technically feasible scenarios for ore extraction scheduling, we feed the DES model with real mine data. Then simulate a set of scenarios each based on distinct control parameters (priority indexes), on an annual scheduling horizon as presented in [26, 27]. The possibility of rapidly and coherently constructing extraction scenarios based on the variation of priority indexes of each SQ, made it possible to respect deposit, process and machines constraints but also explore several alternative scenarios. Thus, we were confronted with a decisional challenge to support the decision makers in their choice of the 2 or 3 most performant scenarios from a hundred alternatives. This decision making process goes beyond the technical coherence of the generated scenarios, by considering other criteria to evaluate different aspects of the alternatives scenarios. The first criteria as suggested in [27] focuses on the satisfaction of the client's demand on several scheduling horizons. We calculate the demand satisfaction rate (SR_s) per scenario such as:

$$SR_s = \frac{\sum_h F_{s,h}}{N} \quad (1)$$

s : Index of scenario.

h : Index of scheduling horizon.

N : Number of the scheduling horizon tested.

$F_{s,h}$: Binary variable which is equal to 1 if the scenario s tested on horizon h is feasible, and null otherwise.

Nevertheless, this criterion, alone, is not sufficient for decision makers to make a final choice. Because, even if a scenario is coherent and assures a satisfaction of the client's demand, it is acceptable as a viable solution, but is not necessarily the most efficient of the alternative scenarios. Thus, we integrate more significant criteria in our proposed multi-criteria approach, aiming to support the decision maker to choose the best scenario while taking into account the complex multidimensional nature of the latter.

Fig. 1. depicts the proposed multi-level filtering approach serving the purpose of evaluating and comparing alternative scenarios. Level 1 consists on data wrangling, structuring and synthesizing important needed information from simulation output. Level 2 aims to study the feasibility of the scenario as explained in [27]. Level 3 deals with the study of scenario's robustness which is the important aspect to consider while deciding for the scheduling program to apply. In fact, the robustness of a scenario reflects its ability to deal with a stochastic MQ demand. In the mine, this fluctuation of the demand can disturb the execution of the scheduling program, leading to necessary perpetual adjustments. The integration of this aspect in the decision-making process will allow us to assess the robustness of the acceptable scenarios regarding a fluctuated demand character. Therefore, to avoid weaker scenarios that may satisfy the initially formulated demand but would fail meet it, if a fluctuation occurs.

In order to formulate level 3, we had to understand how the demand fluctuates then verify if a significant data history is available to quantify the disturbances in volume

and nature. The MQ demand fluctuates in two fundamental forms: temporal and quantitative. Four sub-types follows: *i*) temporal disturbance based on an anticipation of one or more MQ demand, *ii*) temporal disturbance based on delaying of one or more MQ demand *iii*) quantitative disturbance based on an increase of the required volume of one or more MQ over a specific period, *iv*) quantitative disturbance based on a reduction of the required volume of one or more MQ over a specific period. According the experience of miners, time anticipation (*i*) and quantity augmentation (*ii*) are the two most critical types of disruption. In this case, they may not be able to satisfy the demand if the SQ to produce it are not extracted yet or available in volume and nature. Note that the availability of SQ in a period is linked to the succession of elementary operations of the extraction process, to the assignments and availability of the extraction machines as well as to the time necessary to access and extract the desired SQ.

Another challenge we encountered during the formulation of this level, is the lack of a significant data history that can be exploited in the quantitative formulation of disturbances. To get around it, we decided to set up a Generator of Disturbed Demand vectors called GDD. The role of this component is to generate different types of disturbances to help us perceive the behavior of acceptable scenarios when facing disturbed demand vectors. In fact, based on the initial demand vector, the generator chooses each time: *i*) two MQs and two periods to be modified if it is a temporal disturbance or, *ii*) two MQs and one period in the case of a quantitative disturbance. In the first case, an addition or subtraction of the volume from one period to the next is introduced but the total volume required remains intact. However, in the second case we introduce two parameters α and β specific to the selected MQ's. These parameters serve to specify the percentage of increase or reduction of the initially requested volume applied to generate the disrupted demand vectors. We made it possible that these parameters can be specified by default between a minimum and maximum values or else defined by decision-makers if a more precise information is communicated ahead. The GDD allows us to create several sets of disrupted demand vectors, where each vector comprise the 4 types of disturbance, which we specify as test bundles. We try to test alternative scenarios on different test bundles, in order to evaluate and assess their robustness while dealing with disturbances that are different in nature.

So, the purpose of this robustness study is to test the capacity of feasible scenarios to respond to disturbed demand vectors, with the same SQ supplies proposed to satisfy the initial demand. It is based on the same formulation as the feasibility study (a linear programming blending formulation), but the demand is not fixed this time. Moreover, to analyze the results of the robustness study, it was necessary to synthesize a Robustness Rate (RR_s) per scenario, such as:

$$RR_s = \frac{\sum_k \sum_v F_{s,v,k} \cdot w_v}{N} \quad (2)$$

s : Index of scenario.

v : Index of perturbed demand vector.

k : Index of test bundle.

N : Number of tested bundles

$F_{s,v,k}$: Binary variable which is equal to 1 if the scenario s tested on perturbed demand vector v from test bundle k is possible, and null otherwise.

w_v : attributed weight for the perturbed demand vector v .

The scenarios are then ranked according to their RR_s , to select only the ones with a RR_s above 80% (a rate considered as an acceptable threshold according to the industrials).

At level 4, alongside the robustness study component, other criteria are synthesized from each scenario, to explore the multidimensional complexity of scheduling program through a Pareto method. This criteria are related to the displacement time and occupation of the extraction machines.

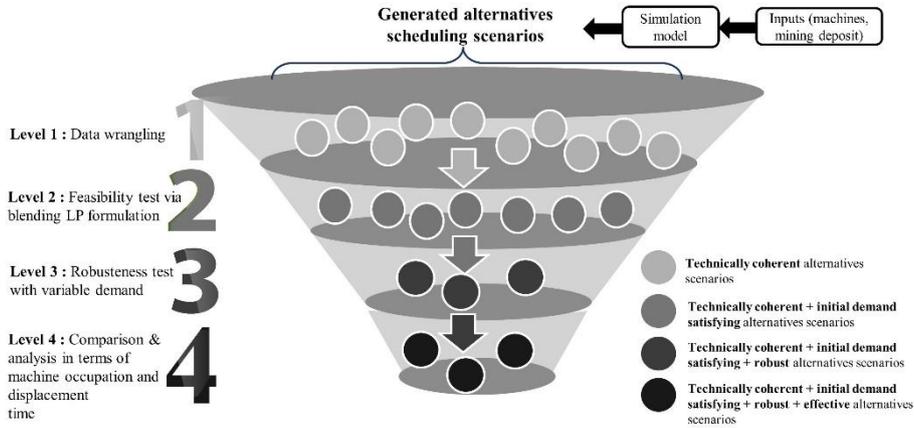


Fig. 1. Multi-level filtering approach

4 Experimental analysis

We have tested the relevance of the IDSS designed on real data in collaboration with the mine's planning and method team [27] of OCP group. We were able to generate and validate an acceptable scheduling program ensuring technical consistency and allowing the satisfaction of the annual demand for 2020 over all planning horizons. Subsequently, our vision turned towards the search for a scheduling program based on the approach proposed.

Therefore, we started by generating a set of 20 scheduling scenarios relating to the same 2020 demand data, by varying the control parameters. In order to have 20 different scenarios the control parameters related to the SQ were given each time a different value from 1 to 10, at the start of the simulation as. Then, we carried out the feasibility study presented in [27] for each scenario. The obtained results in Table 1 show that six out of twenty scenarios are efficient in the short term, but failed to meet the initial demand in the medium term. The black dots meaning the scenario is feasible on the scheduling horizon, the white dots insinuating the infeasibility. These six scenarios are

considered irrelevant ones and are therefore eliminated for the remainder of the study. Thereafter, we illustrate the creation of the disturbed demands via the GDD, through which behavior of the scenarios is studied.

Table 1. The satisfaction rate (SR_s) for the feasibility study per scenario i per month m

m/s	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S12	S13	S14	S15	S16	S17	S18	S19	S20	S21
M1	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
M2	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
M3	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
M6	•	•	•	•	•	•	•	•	•	•	○	•	•	○	•	•	•	•	•	•
M9	•	•	•	•	•	•	•	•	•	•	○	○	•	○	•	•	•	•	•	•
M12	•	•	•	•	•	•	•	•	•	•	○	○	○	○	○	•	•	•	•	○
SRs (%)	100.0	100.0	100.0	100	100.0	100.0	100.0	100.0	100.0	100.0	50.0	66.7	83.3	50.0	83.3	100.0	100.0	100.0	100.0	83.3

Table 2 shows the creation of two different vectors of disturbed demand. The first vector representing one-month time anticipation of the requested volume of MQ 2 and 3. The second vector reflecting a quantity increase of the initial demand by 15% and 10% respectively regarding MQ 1 and 4 on the 9th month.

Table 2. Example of demand disruptions

Cumulated demand	MQ 1	MQ 2	MQ 3	MQ 4	MQ 5
M1	190932	132682	13441	25641	1282
M2	381865	265364	26882	51282	2564
M3	572797	398046	40323	76923	3846
M6	1145596	796092	80645	153846	7693
M9	1718394	1194137	120968	230769	11539
M12	2291191	1592183	161290	307692	15385
Time anticipation	Anticipation of the requested volume of the 3 rd month on the 2 nd month				
M1	190932	132682	13441	25641	1282
M2	381865	398046	40323	51282	2564
M3	572797	398046	40323	76923	3846
M6	1145596	796092	80645	153846	7693
M9	1718394	1194137	120968	230769	11539
M12	2291191	1592183	161290	307692	15385
Quantity addition	Quantity addition of the initial demand by 15% & 10% respectively for MQ 1 and MQ 4				
M1	190932	132682	13441	25641	1282
M2	381865	265364	26882	51282	2564
M3	572797	398046	40323	76923	3846
M6	1145596	796092	80645	153846	7693
M9	1976153	1194137	120968	253846	11539
M12	2291191	1592183	161290	307692	15385

For this study we create 3 test bundles (Table 3), each one containing 16 vectors of disturbed demands of all four types, to maintain a heterogeneous nature of the disruptions in each test bundle. The weights attributed to each disruption nature is defined by the decision makers, taking in consideration the criticality factor. In fact, as we explained earlier time anticipation and quantity augmentation are considered most critical, since it requires more SQ in a specific period. We thus attribute a more important weight to the more critical disturbances.

Table 3. The weight and disruption type for the generated disturbed vectors (V)

V/ S	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S17	S18	S19	S20	Weight	Disruption type
V1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.075	Time Anticipation
V2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.075	Time Anticipation
V3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0.075	Time Anticipation
V4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0.075	Time Anticipation
V5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.05	Time Retardation
V6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.05	Time Retardation
V7	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.05	Time Retardation
V8	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.05	Time Retardation
V9	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0.085	Quan Augmentation
...
V46	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	Quan Reduction
V47	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	Quan Reduction
V48	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.04	Quan Reduction

The robustness test is carried out for each scenario 48 times (the number of test vectors). As shown in Table 4, from the remaining 14 scenarios only 5 have a RR_s above 80 % that is considered acceptable for the decision makers.

Table 4. The results of robustness rate per scenario

Test (%) / S	S4	S3	S6	S8	S17	S9	S10	S18	S1	S2	S5	S7	S20	S19
Test_bundle_1	100.00	100.00	100.00	92.50	92.50	92.50	80.50	92.50	92.50	100.00	92.50	92.50	72.00	60.00
Test_bundle_2	100.00	85.00	85.00	76.50	76.50	63.50	76.50	76.50	76.50	70.00	76.50	56.50	76.50	50.50
Test_bundle_3	92.50	77.50	77.50	77.50	77.50	80.50	77.50	63.50	60.50	55.50	55.50	63.50	63.50	50.50
RRs (%)	97.50	87.50	87.50	82.17	82.17	78.83	78.17	77.50	76.50	75.17	74.83	70.83	70.67	53.67

Table 5. Synthesis of the results of each step per scenario

Scenario	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S12	S13	S14	S15	S16	S17	S18	S19	S20	S21
Respect of technical mining constraints	Green																			
Satisfaction of the initial demand	Green	Red	Red	Red	Red	Red	Green	Green	Green	Green	Red									
Acceptable robustness facing demand fluctuations	Red	Red	Green	Green	Red	Green	Red	Green	Red	Green	Red	Red	Red	Red						

In this case study, we explain how the first 3 levels of the proposed multi-level filtering approach permits us to guide the decision makers through the choice of 2 or 3 performant scenarios. We started by generating 20 technically coherent scenarios via a DES model. We proceeded to eliminate those not satisfying the initial demand on all planning horizons (1, 2, 3, 6, 9, 12 months). Then, we integrated the stochastic aspect of the demand and evaluated the robustness of the remaining scenarios, to end up with only 5 acceptable scenarios out of 20 as shown in Table 5. This approach helps the decision makers consider different aspects of a performant scenario, all while reducing the number of scenarios to be discussed.

5 Conclusion

The open-pit mine extraction process is characterized by a spatiotemporal constraints and a conflictual criteria who make the tactical scheduling complex. A DES model was developed to generate a feasible extraction program (scenario) considering technical constraints. The integration of priority indexes of SQ as control parameters made it possible to generate several technically coherent scenarios by means of variations of the latter. Consequently, an evaluation and comparison of the generated set of alternatives scenarios was necessary. Thus, this paper, presents a multi-criteria filtering approach integrated on an IDSS aiming to propose the two or three most performant extraction planning. The approach proposed was tested and experimented based on a real data from the phosphate mine. The results obtained show the significance of the approach making it possible to evaluate and compare the 20 generated scenarios. In addition to the respect of technical constraints assured by the simulation model, many scenarios failed to ensure the satisfaction of the client's demand in the short as in the mid-term (1,2,3,6,9,12 months) and thus they were be eliminated. Other scenarios, even if feasible, showed weakness while facing fluctuations of the demand. We continue working on the fourth level to integrate criteria giving decision makers insight on occupational, displacement time of the extraction machines and SQ stock residue. Exploring the complexity of a scenario and understanding the challenges of the mining decision makers, will help us guide the choice of the most performant 2 or 3 scenarios. The development of a visualization component based on advanced data analytic tools is on progress to facilitate the visualization and comparison of the different indicators.

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