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Simheuristic-based decision support system for efficiency improvement of an iron ore crusher circuit

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ABSTRACT

The production rate of an ore crushing circuit depends on the amount of equipment in operation. If the amount of active equipment is less than the optimum level, the reduced ore flow paths restrict the production rate. However, if the amount of active equipment is greater than the optimum level, the excess circulating load ore and extra energy consumption reduce the circuit efficiency. In addition, the optimum amount of active equipment can change over time due to changes in the ore characteristics, such as hardness and particle size. In this paper, a decision support system is proposed for optimizing the amount of active equipment for maximum crushing production considering changes in the circuit feed rate. The proposed solution is based on a simheuristic approach in which a simulated plant model is used to evaluate the production rate. Real production scenarios at a Brazilian mining plant are used in computational experiments. The results show that the simheuristic solutions generate a higher production rate and result in less energy consumption. Production is increased by up to 9%, and energy consumption is reduced by up to 59%, demonstrating the efficacy of the proposal.

1. Introduction

Crushing circuits decrease the size of ore extracted from a mine until it is suitable for the next mineral processing steps. The sequential primary, secondary, tertiary, and quaternary crushing stages compose a crushing circuit. Each stage is composed of dozens of pieces of equipment, such as crushers, screens, and feeders. The processed ore size defines the type and position of each stage. For instance, the primary crushing stage receives the extracted iron ore directly from the mine, where the iron ore diameter may reach 1 m. In the quaternary crushing stage, the size of the ore that feeds the crushers is less than 20 mm. Screens classify the ore by size and therefore divide the flow of ore among the stages.

The flow of coarse ore retained in one stage of the crushing circuit is called the circulating load. The efficiency of a crusher is not 100%; hence, some of the ore crushed in one stage does not satisfy the size specification for proceeding to the next stage. This thicker material is retained in the screens and returns to the same crushing stage. The circulating load occupies space in silos and conveyor belts that should contain fresh new ore from the mine, which causes a decrease in production.

The amount of active equipment at each crushing stage has a significant impact on production. A circuit that works with considerably fewer crushers than the optimum value limits the production flow rate by restricting the number of lines in which the ore can flow. However, an excessive and poorly distributed number of crushers can increase the circulating load. Generally, the plant operator in the control room decides the amount of active equipment in the crushing circuit. This decision is subjective and dependent on the experience of the responsible plant operator during the work shift.

Choosing the amount of active equipment is a complex problem due to inevitable changes in ore features. The ore hardness and particle size distribution generally change over time. Additionally, the conveyor belt and silo capacity limits must be taken into account. Such characteristics of dynamic and stochastic processes make it challenging to apply exact optimization methods to solve the problem of choosing the amount of active equipment in a crushing circuit.

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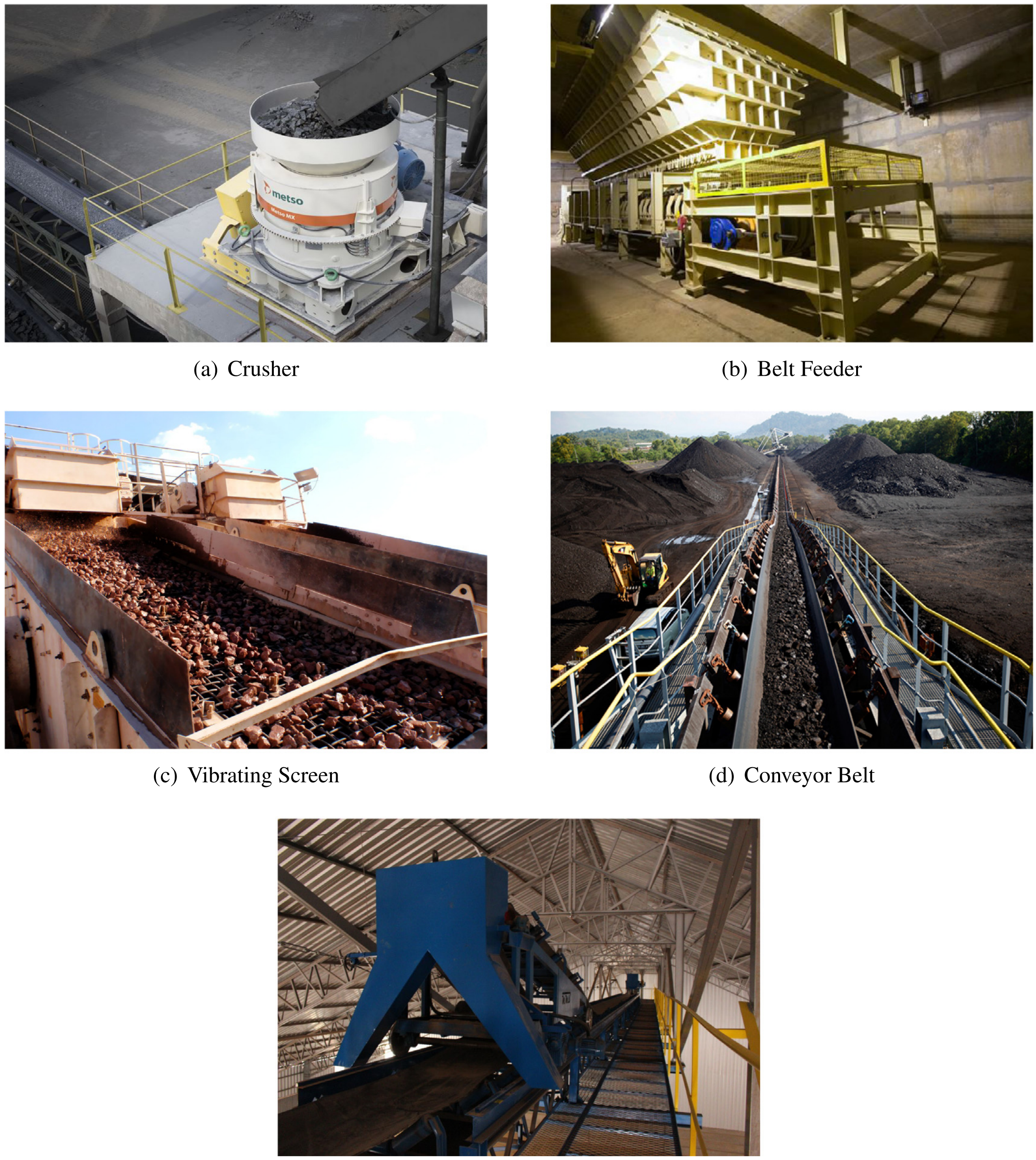


(a) Crusher

(b) Belt Feeder

(c) Vibrating Screen

(d) Conveyor Belt

(e) Tripper

Fig. 1. Crushing circuit equipment.

An artificial-intelligence-based decision support system is required to address this problem. In the literature, several artificial intelligence methods have been applied in decision support systems, such as machine learning, fuzzy logic, artificial neural networks and deep learning (Abbasi et al., 2020; Ji et al., 2020; Si et al., 2019; Vo et al., 2019). In addition, heuristic optimization techniques based on simulators, known as simheuristics (Juan et al., 2015), have also been successfully applied to solve several stochastic optimization problems in which predicting the operation of the process is a complex task. One advantage of using a simulation approach is that it enables the emulation of real situations encountered in the industrial process. Simheuristics have been applied for problems such as vehicle routing (Gonzalez-Martin et al., 2018; Gruler et al., 2018, 2020), waste collection in cities (Gruler et al., 2017a,b), airport flight planning (Guimarans et al., 2015), machine scheduling (Gonzalez-Neira et al., 2017; Hatami et al., 2018), facility location (de Armas et al., 2017), and financial investments (Panadero et al., 2020).

To our knowledge, there have been no reports in the literature on the application of simheuristics or other artificial intelligence techniques to address problems involving decisions on the amount of equipment required in production processes. Thus, this work aims to fill this gap by presenting a simheuristic-based decision support system for choosing the optimal amount of active equipment in each stage of a crusher circuit. The solution is obtained by solving an optimization problem, in which the goal is to maximize the total production. Local-search- or population-search-based metaheuristics can be used for this purpose (Gendreau and Potvin, 2010; Tian and Zhang, 2017; Tian et al., 2018; Zhongda Tian and Ren, 2019). The algorithm proposed in this work is inspired by the iterated local search (ILS) (Lourenço et al., 2003) metaheuristic integrated with a crushing circuit simulator. Metaheuristics based on local search methods, such as ILS, have been successfully applied to treat single-objective combinatorial optimization problems in a number of studies (Cota et al., 2014; Diniz et al., 2019; Lourenço et al., 2019). The results are applied to the crushing circuit of Vale S.A. at the Conceição II plant, Itabira-MG.

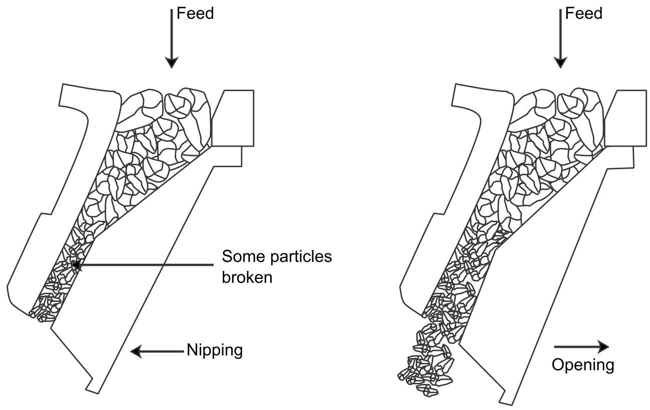


Fig. 2. Opening and nipping cycles in the crusher.
Source: Adapted from King (2012).

The remainder of this paper is organized as follows. The crushing circuit is detailed in Section 2. In Section 3, the problem is defined. In Section 4, the cone crusher efficiency is discussed in terms of the cavity level. The simulation is presented in Section 5. The proposed algorithm is introduced in Section 6. In Section 7, the results of computational experiments are reported and discussed. Finally, Section 8 presents the conclusions and future works.

2. The crushing circuit

A crushing circuit typically consists of five types of equipment: crushers, feeders, conveyor belts, tripper cars, and screens. Sections 2.1 to 2.5 provide details of these equipment types, and Fig. 1 depicts them.

2.1. Crusher

Crushers are designed to reduce the ore size to a particle size that is suitable for the next stage of the circuit. The operation of a crusher is periodic. Each period consists of a nipping action and an opening action. During the opening period in the cycle, the material moves down the crusher, and a portion of the material exits the equipment. Meanwhile, a certain amount of feed enters the crusher. Fig. 2 illustrates this process.

According to King (2012), Eq. (1) determines the particle size distribution of the ore at the crusher output:

$$p_i = \frac{1 - c_i}{1 - c_i b_{ii}} \left(p_i^F + \sum_{j=1}^{i-1} c_j \frac{M m_j}{W} b_{ij} \right), \tag{1}$$

where p_i is the fraction of the product in size class i, p_i^F is the fraction of the feed in size class i, M is the mass of material held in the crusher, b_{ij} is the fraction of particles breaking in size class j that end up in size class i, m_i is the fraction of material in the crusher in size class i, c_i or $c(d_i)$ is the fraction of material in size class i retained for breakage during the next nip of the crusher, and W is the mass of total feed accepted during a single opening.

As reported in King (2012), the parameters of the classification function c_i and the breaking function b_{ij} are specific to each type and size of crusher. Few studies have used predictive equations to establish the values of these parameters within a range of real operating conditions. In practice, it is common to estimate these values using the particle size distribution of operational crusher products. An experiment to model conical crushers was proposed by Atta et al. (2019).

2.2. Feeder

The feeder is essentially a conveyor belt used for short distances. It regulates the rate of ore transfer from one piece of equipment to another. For example, in a crushing circuit, feeders commonly feed screens and crushers by transferring ore stored in silos. In this paper, the authors modeled the feeders as a constant that represents the transfer rate from one piece of equipment to another.

2.3. Screen

Screens are responsible for segmenting the processed ore. A screen separates coarse material from fine material and redirects only the former to the crusher. The material retained by the screen is called oversize, and the material that passes through the screen surface is called undersize. Vibrating screens are the most important screens for ore treatment applications. The main reason for the use of such screens in crushing circuits is that the vibration increases the efficiency, as it reduces clogging and induces the segregation of the fed material.

The classification function $c(d_{p_i})$ defines the probability of an individual particle entering the oversize stream. The value of this function expresses the feed material mass fraction of size class i that will be present in the overflow. In this paper, the classification function was determined using the model from Karra (1979).

From the classification function, the particle size distributions of undersize and oversize streams are, respectively,

$$p_i^U = \frac{[1 - c(d_{p_i})]p_i^F}{\sum_i [1 - c(d_{p_i})]p_i^F}, \tag{2}$$

$$p_i^O = \frac{c(d_{p_i})p_i^F}{\sum_i c(d_{p_i})p_i^F}, \tag{3}$$

where p_i^U is the fraction of the underflow stream in size class i, p_i^O is the fraction of the overflow stream in size class i, and p_i^F is the fraction of the feed stream in size class i.

2.4. Conveyor belt

Another essential type of equipment in the crushing process and mining is the conveyor belt . The conveyor belt continuously transfers the material under the influence of frictional force. The conveyor belt is composed of a simple structure, and it is easy to maintain. This transport mechanism is commonly responsible for carrying millions of tonnes of minerals at mining plants and ports (Ribeiro et al., 2019); for instance, one conveyor belt in the Vale South system has a length of 9600 meters and transports 4000 tons per hour.

2.5. Tripper car

Mineral processing plants often use trippers. The purpose of trippers is to distribute ore coming from previous stages of the process to a silo with several hoppers. A tripper consists of a movable metal structure that physically supports a discharge point of a conveyor belt. Steel wheels located under the structure of the tripper drive the car. Metal rails support and guide the tripper along with the silo, allowing it to distribute among all subdivisions. The positioning of trippers above the silos is a scheduling problem that determines the position of the equipment through the divisions of silos over time.

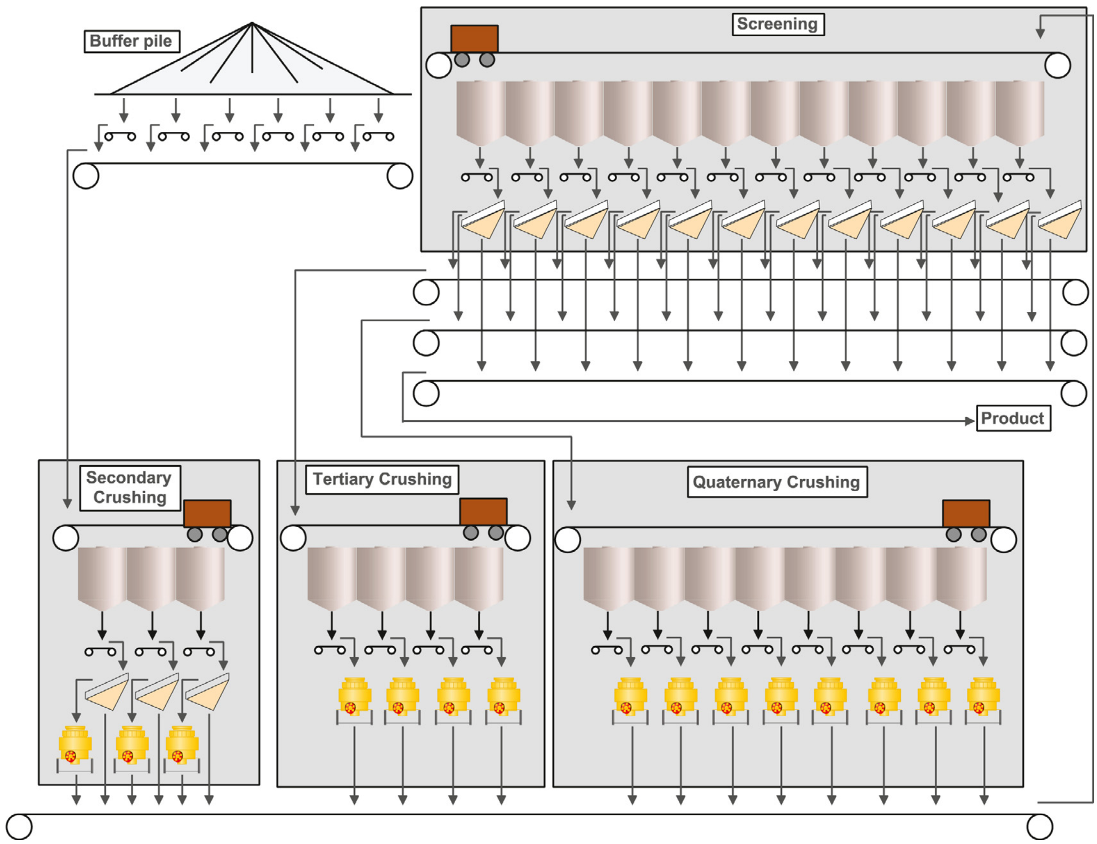


Fig. 3. Conceição II plant crushing circuit.

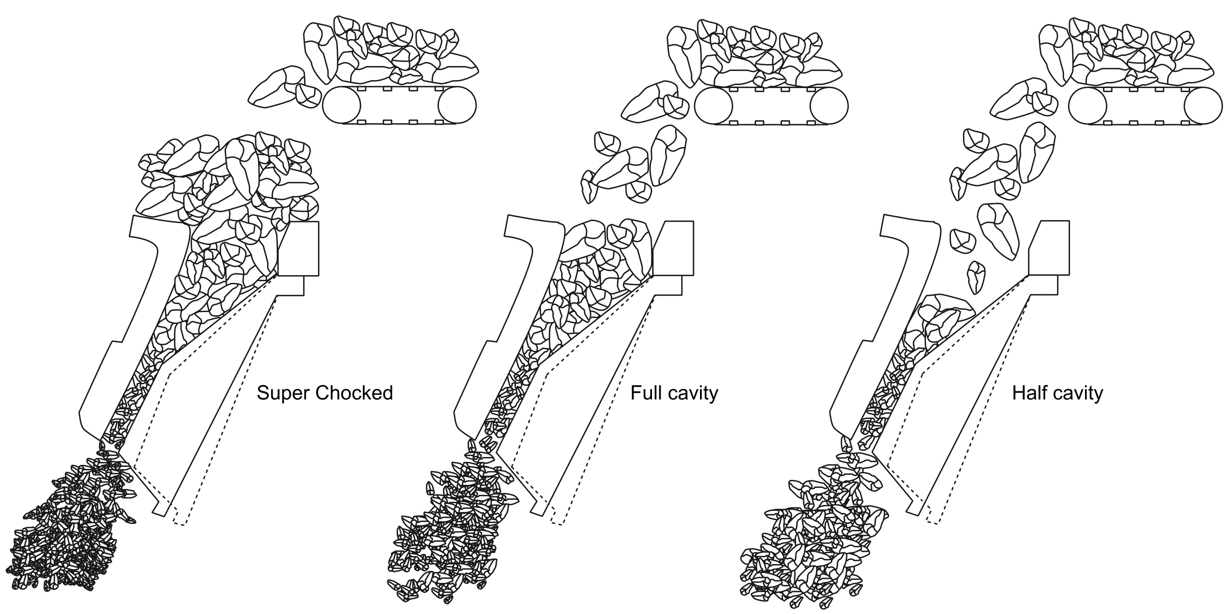
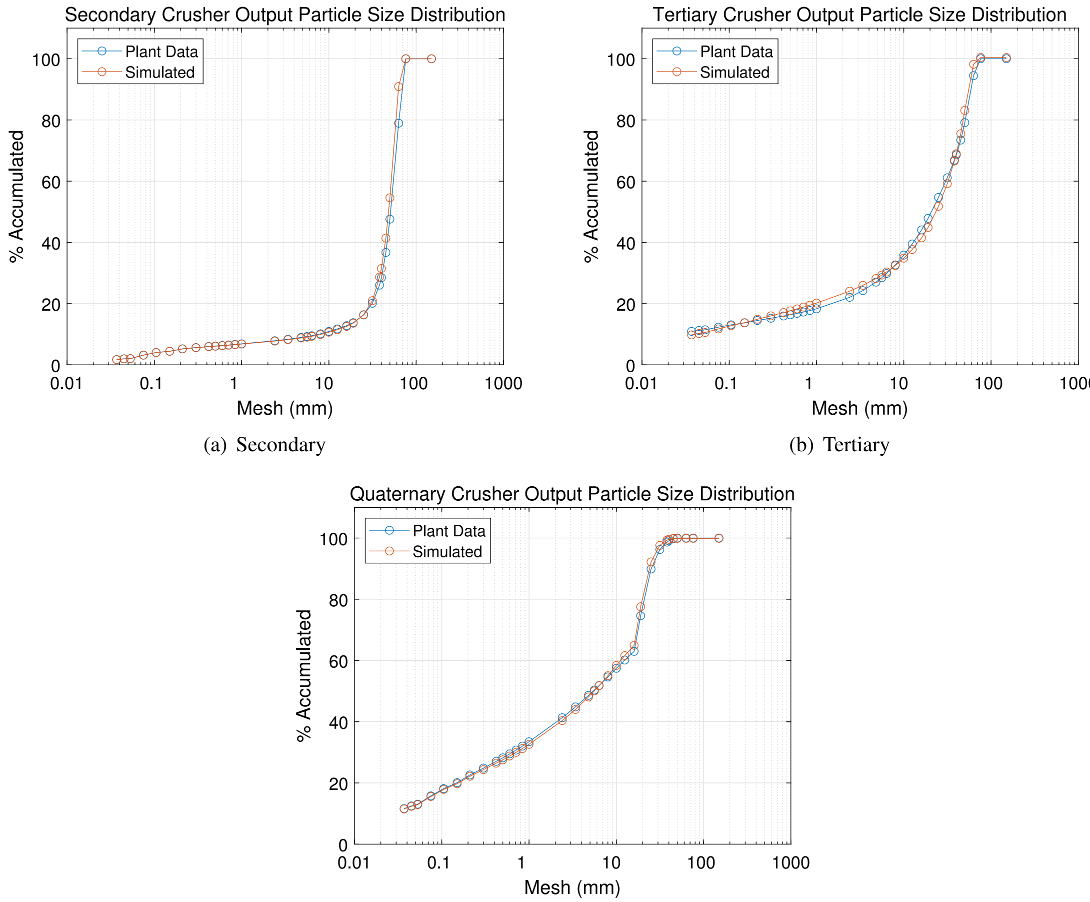


Fig. 4. Illustration of cavity levels.

3. Problem statement

The problem under study concerns the crushing circuit of Vale S.A. at the Conceição II plant, Itabira-MG, and has the following characteristics:

1. There is a set C of 15 cone crushers, which are used to reduce the ore block size;
2. There are 3 sequential crushing stages to gradually reduce the particle size of the iron ore: secondary, tertiary and quaternary;
3. The secondary crushing aims to reduce the material size to 63 mm or smaller;
4. The tertiary crushing aims to reduce the material size from the range of 63–50 mm to 50 mm or smaller;
5. The quaternary crushing is the last stage and aims to reduce the material size from the range of 50–38 mm to 38 mm or smaller;



(a) Secondary

(b) Tertiary

(c) Quaternary

Fig. 5. Crusher model validation.

6. There is a set S of 15 screens, which separate the material according to particle size;
7. There is a set F of 33 feeders, which represent a complete line of equipment (feeder–screen or feeder–crusher);
8. The product generated must have a particle size smaller than 12 mm after crushing. All ore with granulometry greater than 12 mm is returned to tertiary or quaternary crushing;
9. The efficiency of each cone crusher depends of the cavity level. That is, cone crushers that operate at low cavity are less efficient than crushers operating at super chocked or full cavity. Therefore, this behavior must be simulated. Section 4 treats this issue and Section 5 details the simulator developed for evaluating the crushing circuit;
10. There is a circuit feed rate (r), in t/h, which must be defined to obtain a production flow per hour, which must respect minimum and maximum previously established limits.

The objective of the problem is to maximize the production of the crushing circuit in a time cycle of tc = 6 h. Fig. 3 shows the crushing circuit under study.

Trucks transport ore extracted from the mine and unload it into the primary crusher. The primary crusher reduces ore blocks with sizes of up to 1 m to a maximum size of 150 mm. Conveyor belts transport the primary crusher throughput to the buffer pile. In our study, we consider that the crushing circuit begins from the buffer pile.

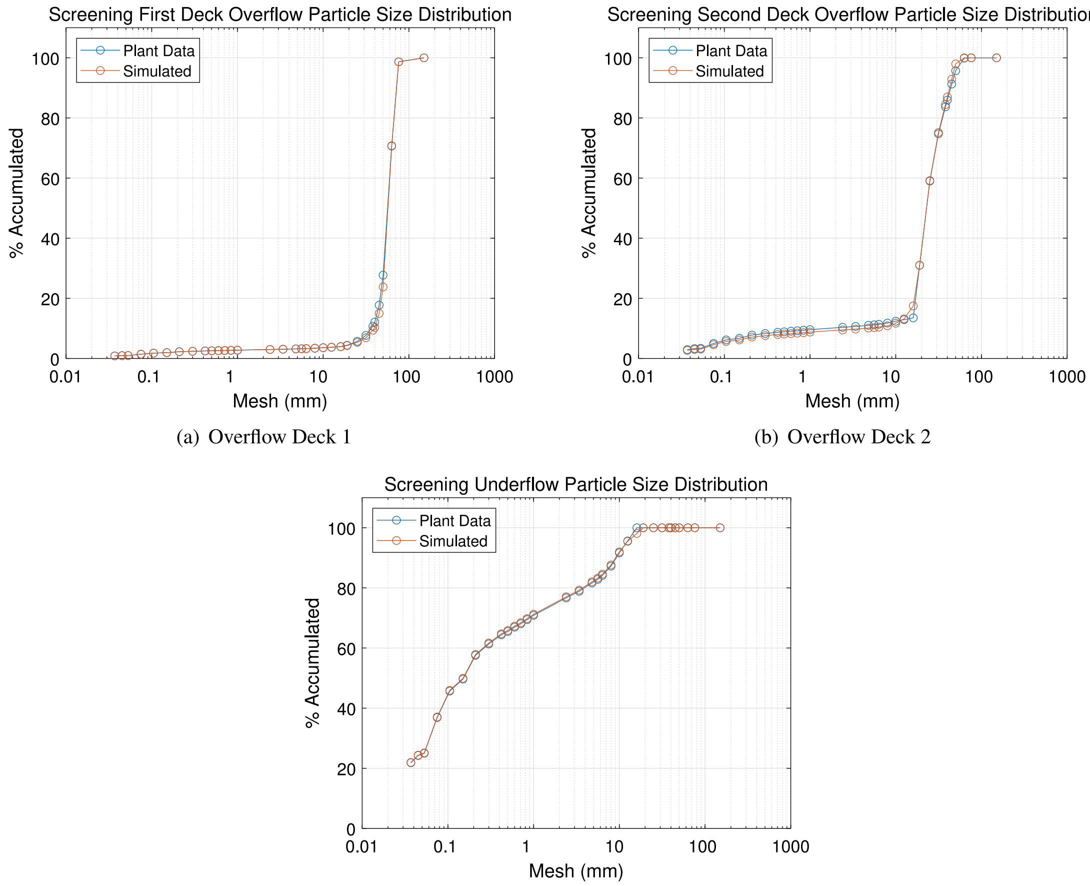
The buffer pile has an approximate volume of 56,000 m^3. It permits the secondary, tertiary and quaternary stages of the crushing circuit to operate despite moments in which the primary crusher stops. Vibratory feeders located under the buffer pile remove the ore and transport it to the conveyor belt, which is responsible for transferring it to the secondary crushing area.

There are three lines in the secondary crushing stage that operate independently. Each line has a silo division, a feeder, a sloped vibrating screen, and a standard cone crusher. The feeder extracts ore from the corresponding silo division at a controlled speed to maintain a stable load on the crusher. From the screen, the oversize stream feeds the crusher, and the undersize stream goes to a conveyor belt that feeds the silos of the screening stage.

Similar to the secondary crushing stage, the tertiary and quaternary crushing stages have four and eight lines, respectively. These lines operate independently and are composed of a silo division, a feeder, a standard cone crusher for the tertiary crushing stage and a short head crusher for the quaternary crushing stage. The throughput of the tertiary and quaternary crushers flows to the screening stage silo.

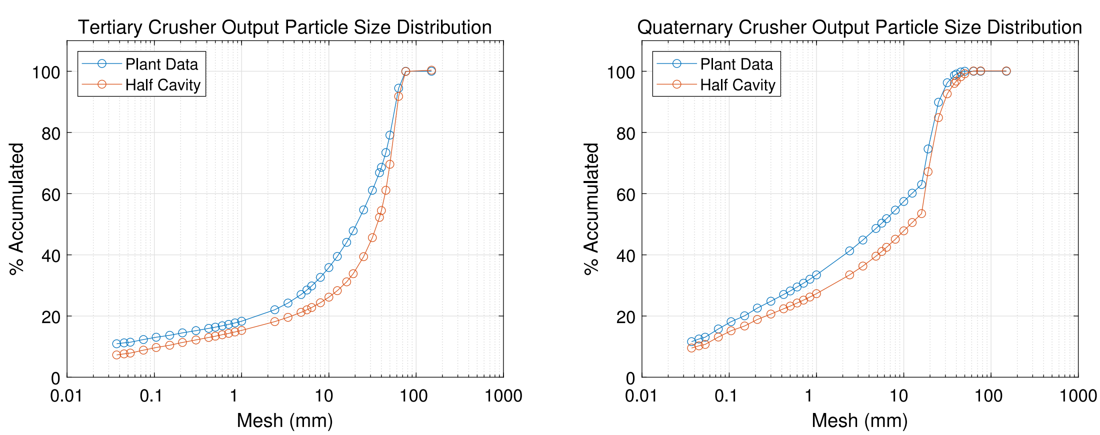
There are twelve lines within the screening stage, and each line operates independently. Each line is composed of a silo division, a feeder, and a sloped two-deck vibrating screen. The oversize stream of the upper deck proceeds to the tertiary crushing stage, the oversize stream of the lower deck flows to the quaternary crushing stage, and the undersize stream goes to the milling courtyard.

The set of equipment that constitutes the crushing circuit consumes approximately 2534 MWh per month. In Brazil, hydropower generation systems provide 86% of the electrical energy consumed (Zhang et al., 2017; Li et al., 2018, 2019). The Conceição II Plant is fully powered by electrical energy from hydropower systems. Therefore, the energy efficiency of circuit operation is an important issue.



(a) Overflow Deck 1 (b) Overflow Deck 2 (c) Underflow

Fig. 6. Screening stage screen model validation.



(a) Tertiary (b) Quaternary

Fig. 7. Crushers with half cavity.

4. The cone crusher efficiency problem

The cavity level has a strong effect on cone crusher efficiency. Fig. 4 shows three different scenarios of cone crusher operation.

According to Jacobson et al. (2010), filling the crushing cavity is vital for three reasons:

1. It allows for interparticle crushing to begin at a higher level in the crushing chamber;
2. The additional weight of the material above the particles receiving compression strokes enhances the downward flow through the cavity and increases particle density in the crushing zones;
3. It increases the probability of nip and improves the mass flow rate and throughput.

Moreover, Jacobson et al. (2010) shows that cone crushers that operate at half cavity are 17% and 14% less efficient than crushers operating at super chocked or full cavity, respectively. Therefore, it is better to work with only one active crusher with a super chocked cavity

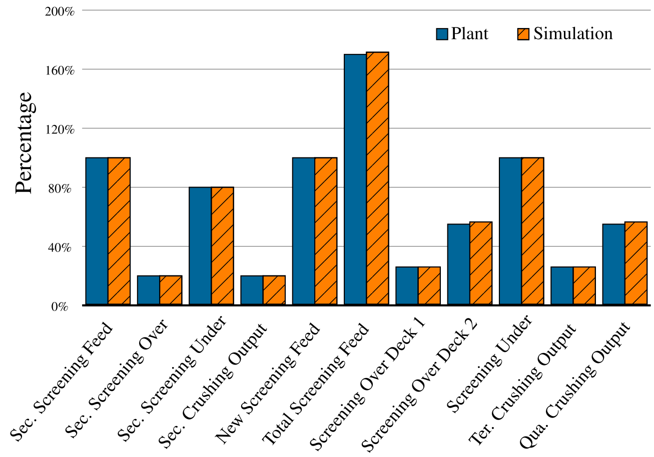


Fig. 8. Mass balance of plant and simulation.

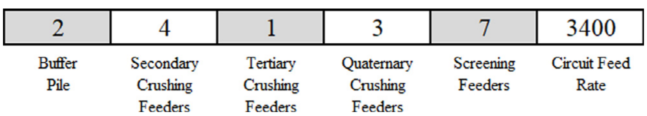


Fig. 9. Representation of a solution.

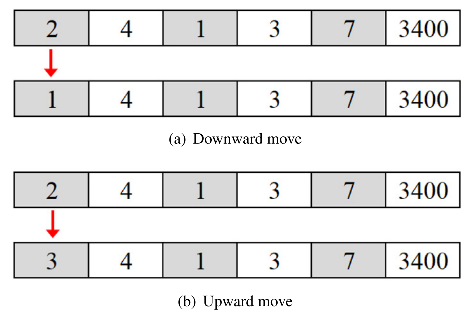


Fig. 10. Examples of moves.

level than to work with two or more crushers operating with half cavity levels.

Usually, low-level silo interlocks are applied to avoid crushers operating at half cavity level. That is, the feeder turns off while the level in the silo is under a low limit and turns on when the level in silo is above a threshold. However, this strategy leads to feeders turn-on and turn-off repeatedly switching, which still leads to temporary half cavity level operation. Thus, a correctly chosen number of active crushers is necessary for higher production in complex crushing circuits.

5. Simulation

In this section, the simulation results for the Conceição II crushing plant shown in Fig. 3 are presented. The simheuristic approach requires the simulated crushing circuit model to test combinations of active equipment to identify the combination that results in maximum production. Therefore, it is essential that the simulation results are consistent with the actual dynamics of the circuit.

The models of crushers and screens used are described in King (2012). The dynamics of these types of equipment are represented by Eqs. (1), (2) and (3), presented in Section 2. These are the most important types of equipment in the circuit because they are responsible for the reduction and classification of processed ore. Simulator implementation was performed in MathWorks MATLAB® version R2016b. Figs. 5 and 6 illustrate the real and simulated processed ore particle size distributions at the output of the crusher and at the overflow and underflow of the screen. The results demonstrate the representativeness between the simulated model and the operational plant data.

In the simulation, the conveyor belt was considered to be an ore flow adder. An essential conveyor belt feature in the simulation is its maximum load limit. The simulator discards any solution that violates this characteristic. In operation, the particle size of the material that feeds the crushing process varies. The simulation considers a random range of 3 mm in the size of particles that feed the circuit. This range is compatible with the crushing circuit addressed.

The tripper car is not included in the simulation. Hence, the ore distribution among the silos is considered to be homogeneous. This approach is not far from reality because existing control solutions make the level variability among silos negligible. In the literature, some papers, including Caldas and Martins (2018) and Albuquerque et al. (2019), are dedicated to level control systems through manipulation of the tripper car position.

A condition was created to represent a 20% decrease in the efficiency of tertiary and quaternary crushers if they are operating below their capacity to represent a crusher working with a low cavity level. In practice, this penalty results in thicker material at the output compared to the same crusher working with a full chamber (Jacobson et al., 2010). Fig. 7 illustrates the change in output particle size compared to the full chamber crusher.

Fig. 8 shows the mass balance of the crushing circuit in percentages, comparing the design values of the crushing site with the values obtained by the simulator. Note that the results of the model were close to the project values. Additionally, note that values above 100% exist in the screening feed because, in addition to the new feed coming from secondary crushing, the circulating load is coming from tertiary and quaternary crushing.

6. Proposed algorithm

In this section, the proposed simheuristic algorithm is presented. The representation and evaluation of a solution are described in Section 6.1. In Section 6.2, the proposed algorithm is detailed. The local search is shown in Section 6.3. Finally, in Section 6.4, the simheuristic-based system is presented.

6.1. Representation and evaluation of a solution

An array of six positions represents a solution. The first five positions identify the number of active feeders in each circuit stage. The feeders represent a complete line of equipment (feeder–screen or feeder–crusher). The last position represents the circuit feed rate.

Fig. 9 illustrates the representation of a solution s by the following configuration: (i) two feeders in the buffer pile, (ii) four feeders in secondary crushing, (iii) one feeder in tertiary crushing, (iv) three feeders in quaternary crushing, (v) seven feeders in screening, and (vi) use of a circuit feed rate of r = 3400 t/h.

The objective function of the problem is to maximize the production of the crushing circuit. The evaluation of a solution is performed by the simulator.

6.2. SILS-SIM algorithm

The proposed algorithm is based on the ILS metaheuristic (Lourenço et al., 2019). This metaheuristic explores the solution space of an optimization problem through perturbations in local optima. To apply an ILS algorithm, four components need to be specified: (*i*) the *InitialSolution*() procedure, which generates an initial solution s_0 to the problem; (*ii*) the *LocalSearch*(·) procedure, which returns a possibly improved solution; (*iii*) the *Perturbation*(·) procedure, which modifies the current solution to produce an intermediate solution; and (*iv*) the *AcceptanceCriterion* procedure, which decides the criterion for accepting a solution.

The proposed simheuristic algorithm, called SILS-SIM, uses the developed crushing circuit simulator to evaluate the objective function. The version of ILS used is Smart ILS (SILS) (Reinsma et al., 2018). SILS differs from ILS in regard to the perturbation mechanism. Whereas in ILS, the level of perturbation increases whenever there is no improvement in the solution, in SILS, some attempts are made to perform a local search at the same level before the perturbation is increased. The pseudocode of SILS-SIM is shown in Algorithm 1.

Algorithm 1: *SILS-SIM*

input : $iter_{max}, t_{exec}, attempt_{max}$
output: s
$level, attempt, iter_{withoutImp} \leftarrow 1$;
$s_0 \leftarrow$ *InitialSolution*();
$s \leftarrow$ *LocalSearch*(s_0);
Update $t_{current}$;
while $(t_{current} \leq t_{exec}) \land (iter_{withoutImp} \leq iter_{\max})$ **do**
  $s' \leftarrow$ *Perturbation*($s, level$);
  $s'' \leftarrow$ *LocalSearch*(s');
  if $f(s'') > f(s)$ **then**
    $s \leftarrow s''$;
    $level \leftarrow 1$;
    $attempt \leftarrow 1$;
    $iter_{withoutImp} \leftarrow 1$;
  end
  else
    $attempt \leftarrow attempt + 1$;
    $iter_{withoutImp} \leftarrow iter_{withoutImp} + 1$;
    if $attempt > attempt_{\max}$ **then**
      $attempt \leftarrow 1$;
      $level \leftarrow level + 1$;
    end
  end
  Update $t_{current}$;
end
return s;

Algorithm 1 has two stopping criteria: a time limit and a maximum number of executions without improvement in the objective function. It has the following parameters: (i) t_{exec} represents the time limit, (ii) $attempt_{\max}$ defines the allowed number of attempts at a particular perturbation level to search for better solutions, and (iii) $iter_{\max}$ is the maximum number of iterations without improvement in the objective function.

An initial solution s_0 is built with two distinct strategies, each giving rise to a different version of the algorithm, respecting the bounds of the parameters. In the first version, named SILS-SIM-R, the initial solution is built randomly as follows. In the first five positions of the solution, the amount of equipment is randomly chosen among the number of available feeders, and in the last position, the circuit feed rate is randomly selected within the minimum and maximum limits. As an example, suppose that there are 8 feeders available in the quaternary crushing; then, we randomly select a number between 1 and 8 to represent the number of feeders that should be active in this crushing stage. Likewise, assuming that the circuit feed rate varies between 3000 and 4015 t/h, we choose a random integer within this range. In the second version, named SILS-SIM-G, the initial solution is greedy, that is, all available feeders are activated and the circuit feed rate is maximum. Once the initial solution is generated, it is submitted to a local search for refinement. The algorithm performs the following steps in each iteration.

1. *Perturbation*: A perturbation is applied to the solution s. This perturbation consists of selecting a random position and changing its value upward or downward while respecting the bounds for each position of the solution. The $level$ variable defines the number of times this strategy is applied;
2. *Local Search*: A local search is applied on the perturbed solution s' to generate a new solution s'';
3. *Acceptance Criterion*: If the solution s'' is better than the current solution s, then s is updated; otherwise, the variable $attempt$ is incremented. If $attempt_{\max}$ is exceeded, $level$ is incremented and $attempt$ is set to 1;
4. *Stopping Criteria*: When one of the stopping criteria is reached (t_{exec} or $iter_{max}$), the search is finalized, and the best solution is returned.

6.3. Local search procedure

The local search procedure uses the first improvement strategy and a neighborhood structure based on upward or downward moves. If the analyzed position is one of the first five, then the move consists of increasing or decreasing the number of pieces of active equipment in the circuit stage by one. If the last position of the array is analyzed, the circuit feed rate is increased or decreased by $flowVariation$ units. The $flowVariation$ is defined as the minimum rate variation that generates some significant change in production. There are upper and lower bounds for each position of the solution. In the first five positions, the bounds define the amount of active equipment permitted. In the last position, the bounds define the allowed circuit feed rate. The upper and lower bounds are represented by two arrays, u and l, respectively.

Fig. 10 shows an example of two moves in a solution. The bounds are $l = (1, 1, 1, 1, 1, 3000)$ and $u = (3, 5, 2, 5, 7, 3800)$. In Fig. 10(a), the amount of active equipment is decreased, and in Fig. 10(b), it is increased.

Because there are two possible values for each position of the solution, the size of the neighborhood can be defined easily. Each solution has $2(n + 1)$ neighbors, where n represents the number of positions of solution s. For $flowVariation = 1$, all neighbors of the solution $s = (2, 4, 1, 3, 7, 3400)$ are presented as follows.

$s_1 = (\mathbf{1}, 4, 1, 3, 7, 3400)$
$s_2 = (\mathbf{3}, 4, 1, 3, 7, 3400)$
$s_3 = (2, \mathbf{3}, 1, 3, 7, 3400)$
$s_4 = (2, \mathbf{5}, 1, 3, 7, 3400)$
$s_5 = (2, 4, \mathbf{2}, 3, 7, 3400)$
$s_6 = (2, 4, 1, \mathbf{2}, 7, 3400)$
$s_7 = (2, 4, 1, \mathbf{4}, 7, 3400)$
$s_8 = (2, 4, 1, 3, \mathbf{6}, 3400)$

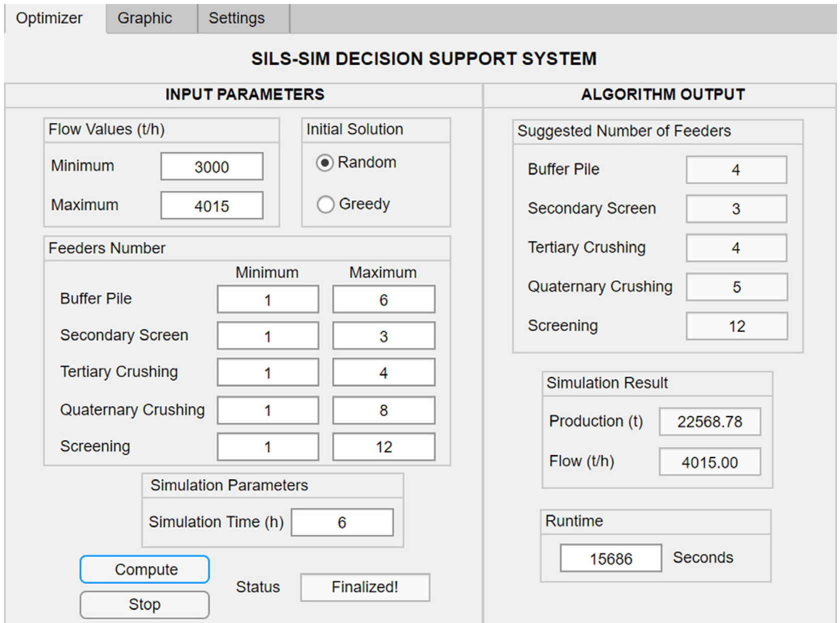


Fig. 11. Decision support system user interface.

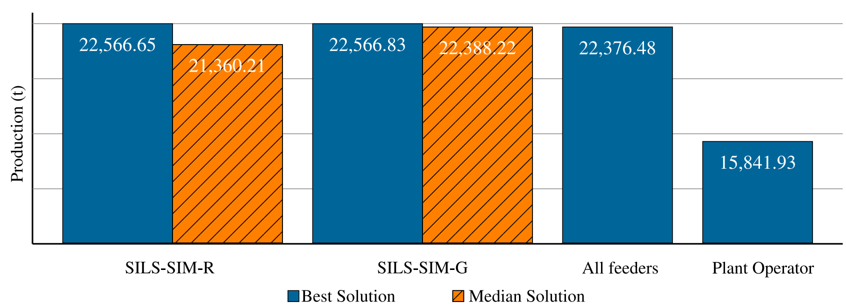


Fig. 12. Accumulated production over 6 h for Example 1.

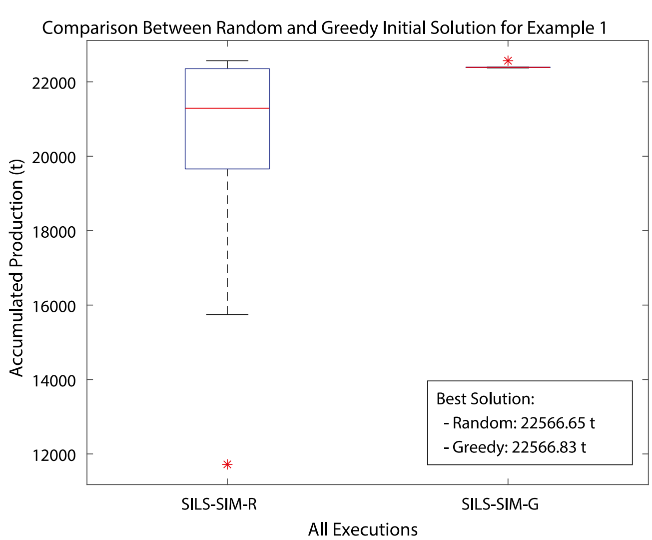


Fig. 13. SILS-SIM algorithm results box plot diagram for Example 1.

$s_9 = (2, 4, 1, 3, 7, \mathbf{3399})$

$s_{10} = (2, 4, 1, 3, 7, \mathbf{3401})$

The solutions $(2, 4, 0, 3, 7, 3400)$ and $(2, 4, 1, 3, 8, 3400)$ are not considered because the bounds are extrapolated.

The pseudocode of the local search procedure is presented in Algorithm 2.

In Algorithm 2, the search starts from a solution s'. In each step, a neighbor is visited. If the neighbor is better than the current solution s'', then s'' is updated. The evaluation of the objective function is performed by a simulation that measures the production rate. Only for the circuit feed rate (last position) can the increase or decrease in the value be greater than 1 because the circuit feed rate amplitude is extremely large. At the end of the search, an improved solution is returned. This solution is a local optimum for the neighborhood analyzed. Note that there are $2n$ neighbors to be evaluated, where n is the size of the array that represents the solution. Therefore, the time complexity of the local search procedure is $O(n)$.

6.4. Implementation of the decision support system

The SILS-SIM algorithm was implemented using MathWorks MATLAB® version R2016b. The software interface was generated in

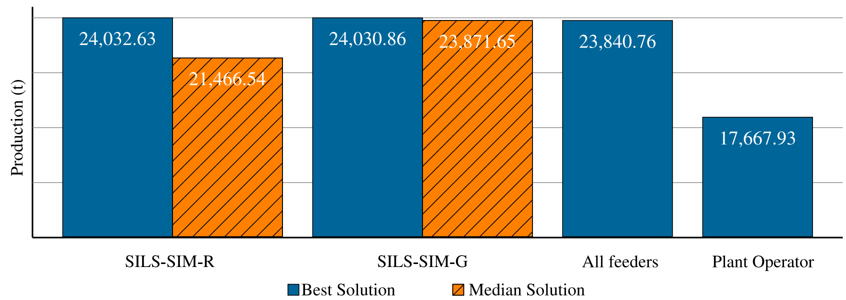


Fig. 14. Accumulated production over 6 h for Example 2.

Algorithm 2: Local search procedure

input : $s', l, u, flowVariation$
output: Refined solution s'

$s'' \leftarrow s'$;
$improve \leftarrow TRUE$;
while $improve$ **do**
  $improve \leftarrow FALSE$;
  for $i \in s'$ **do**
    $step \leftarrow 1$;
    if $i = 6$ **then**
      $step \leftarrow flowVariation$;
    end
    Let s'_+ be the result of adding the value $step$ in position i of solution s';
    if $l(i) \leq s'_+(i) \leq u(i)$ **then**
      if $f(s'_+) > f(s'')$ **then**
        $s'' \leftarrow s'_+$;
      end
    end
    Let s'_- be the result of subtracting the value $step$ in position i of solution s';
    if $l(i) \leq s'_-(i) \leq u(i)$ **then**
      if $f(s'_-) > f(s'')$ **then**
        $s'' \leftarrow s'_-$;
      end
    end
  end
  if $f(s'') > f(s')$ **then**
    $s' \leftarrow s''$;
    $improve \leftarrow TRUE$;
  end
end
return s';

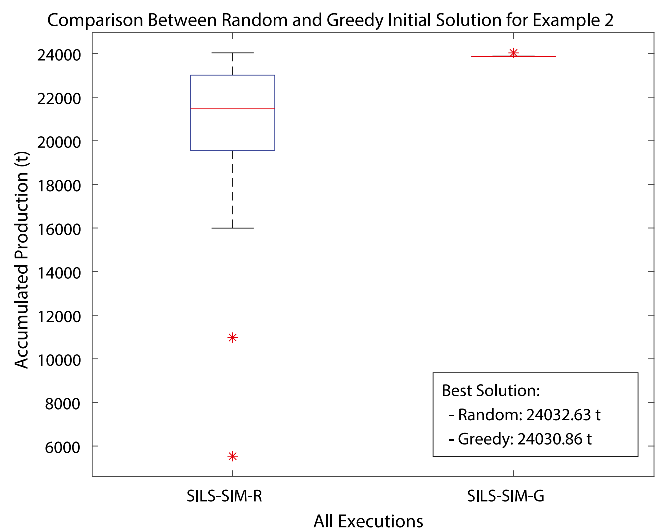


Fig. 15. SILS-SIM algorithm results box plot diagram for Example 2.

the App Designer tool. The parameters of SILS-SIM were empirically fixed to the following values: (*i*) t_{exec} = 10 minutes, (*ii*) $attempt_{\max} = 2$, and (*iii*) $iter_{\max} = 5$.

Fig. 11 shows the main screen of the decision support system. In this software, the plant operator defines the following parameters: (*i*) bounds of the circuit feed rate (t/h), (*ii*) bounds of the amount of active equipment, and (*iii*) the size of the crushing circuit cycle (h). Subsequently, the plant operator clicks the compute button, and the system suggests the amount of active equipment and the circuit feed rate that should be used for maximum production.

7. Computational experiments

The simulation experiments are based on a set of typical production scenarios at the Conceição II plant. The SILS-SIM algorithm results were compared with the results of two other strategies. The first strategy is to allow all equipment to be active. The second strategy is based on the actions of a plant operator for a similar situation. The plant operator chooses the minimum number of feeders in each stage capable of operating the plant with the maximum circuit feed rate of ore (the maximum circuit feed rate at Conceição II is 4015 t/h). The feeder capacity in each stage is (*i*) 1222 t/h in the buffer pile, (*ii*) 2037 t/h in secondary crushing, (*iii*) 373 t/h in tertiary crushing, (*iv*) 274 t/h in quaternary crushing, and (*v*) 647 t/h in screening. For instance, suppose that all feeders are available to operate and that the required production flow rate is 3000 t/h. The operator will likely to choose to run three feeders in the buffer pile, two feeders in secondary crushing, three feeders in tertiary crushing, six feeders in quaternary crushing and five feeders in screening. Notably, not all the material that feeds the circuit goes to secondary and tertiary crushing. According to Fig. 8, 27.5% and 47.2% of the material that feeds the circuit goes to tertiary and quaternary crushing, respectively. Despite its simplicity, the operator strategy fails to account for the particle size distribution of the ore in the pile and the circulating load in the circuit; thus, this strategy requires adjustments on the fly.

The tests were executed on a computer with an Intel Xeon E5-2670 2.3 GHz processor, 16 GB of RAM and the Windows Server 2012 operating system. The simulator considers a time cycle of 6 h. The following subsections show the results of the simulation experiments, an analysis of energy consumption and a convergence check of the algorithm.

7.1. Simulation experiments based on real production scenarios

The simulation experiments illustrate some real situations of the crushing circuit that frequently occur, such as unavailable equipment,

Table 1
Numbers of feeders suggested for Example 1.

Process stages	Number of feeders				
	Lower bound	Upper bound	Plant operator	SILS-SIM-R	SILS-SIM-G
Buffer pile	1	6	4	5	6
Secondary crushing	1	3	2	3	3
Tertiary crushing	1	4	3	4	4
Quaternary crushing	1	8	7	5	5
Screening	1	12	7	12	12

Table 2
Numbers of feeders suggested for Example 2.

Process stages	Number of feeders				
	Lower bound	Upper bound	Plant operator	SILS-SIM-R	SILS-SIM-G
Buffer pile	1	6	4	6	5
Secondary crushing	1	3	2	3	3
Tertiary crushing	1	4	3	3	3
Quaternary crushing	1	8	7	5	5
Screening	1	12	7	12	12

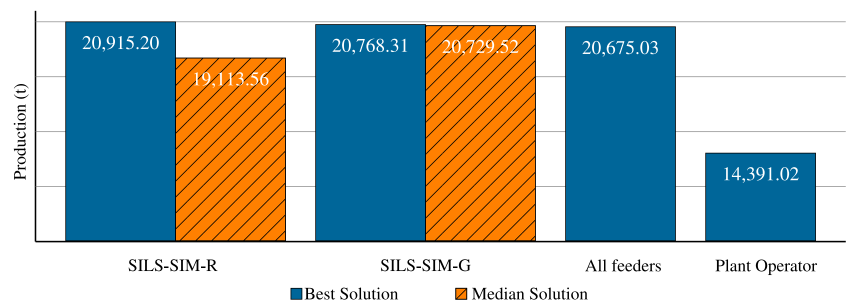


Fig. 16. Accumulated production over 6 h for Example 3.

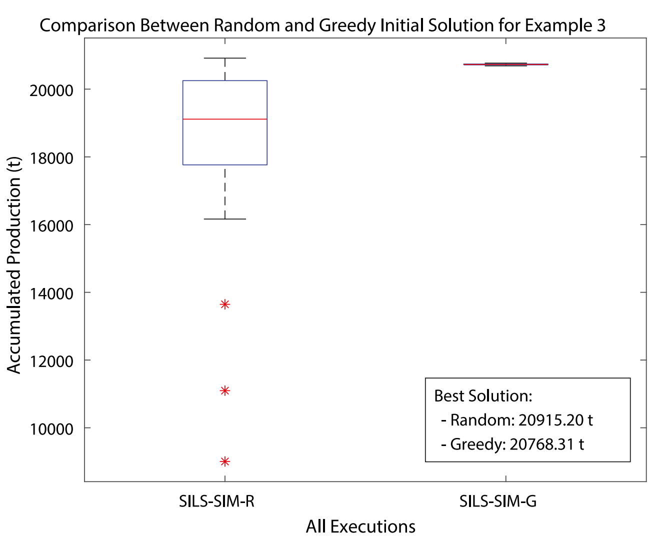


Fig. 17. SILS-SIM algorithm results box plot diagram for Example 3.

changes in particle size distribution, changes in type of minerals and variation in circuit feed rate. In all tests, the two versions of the SILS-SIM algorithm were each executed thirty times for each production scenario. The justification for executing the SILS-SIM algorithms thirty times is that the solutions they produce may vary among executions due to the stochastic components of the ILS metaheuristic and the simulator.

7.1.1. Example 1: Standard situation

This production scenario describes a regular situation at the plant. All feeders are available in the crushing circuit, and the feeding ore has a $D_{80} = 60.63$ mm, i.e., 60.63 mm is the diameter at which 80% of the feeding ore mass consists of particles with a diameter less than this value. Table 1 reports the best results for this example.

As can be seen, the SILS-SIM algorithms and the plant operator suggest a low number of active feeders. The recommended circuit feed rate is the same in both strategies: 4015 t/h. The best solution and the median solution of the four strategies (SILS-SIM-R, SILS-SIM-G, plant operator, and all feeders) are compared in Fig. 12.

This figure shows that the best SILS-SIM solution results in greater production than the other solutions do. Although the production corresponding to the solution with all feeders is similar to that of the SILS-SIM solution, the proposed algorithm suggests a considerably smaller number of active feeders, thus allowing a reduction in the numbers of operating crushers and screens, leading to energy savings.

The production rate suggested by the plant operator solution is the smallest for this scenario.

Fig. 13 shows a box plot diagram with the obtained solutions, comparing the random and greedy initial solutions for Example 1. As can be seen, the two initial solutions have similar best solutions, but the variation is greater during the thirty executions of the SILS-SIM algorithm with the random initial solution.

7.1.2. Example 2: Fine fresh ore

A scenario with fine fresh ore is described in this example. The input ore may be smaller for several reasons, such as extraction of less compact minerals or greater use of explosives in rock detonation. In this production scenario, all feeders are available, the range of the circuit feed rate is the same as in the previous production scenario, and the particle size is $D_{80} = 45.71$ mm. Table 2 shows the best results, and Fig. 14 illustrates the accumulated production for the best solution and the median solution. Note that the SILS-SIM algorithms show better performance than the other solution methods.

Table 3
Numbers of feeders suggested for Example 3.

Process stages	Number of feeders				
	Lower bound	Upper bound	Plant operator	SILS-SIM-R	SILS-SIM-G
Buffer pile	1	6	4	4	5
Secondary crushing	1	3	2	2	3
Tertiary crushing	1	4	3	4	4
Quaternary crushing	1	8	7	5	8
Screening	1	12	7	12	12

Table 4
Numbers of feeders suggested for Example 4.

Process stages	Number of feeders				
	Lower bound	Upper bound	Plant operator	SILS-SIM-R	SILS-SIM-G
Buffer pile	1	6	3	5	5
Secondary crushing	1	3	2	2	3
Tertiary crushing	1	4	3	2	4
Quaternary crushing	1	8	6	5	8
Screening	1	12	5	12	12

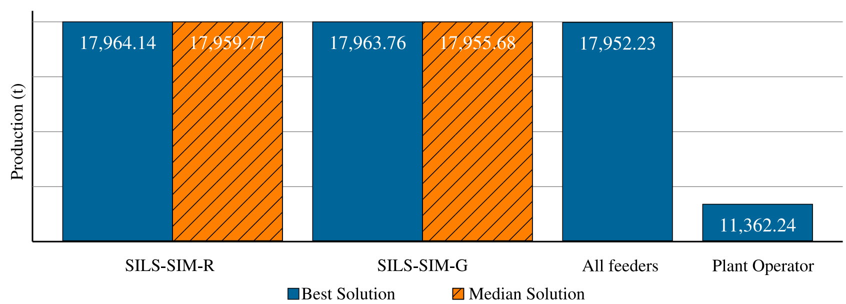


Fig. 18. Accumulated production over 6 h for Example 4.

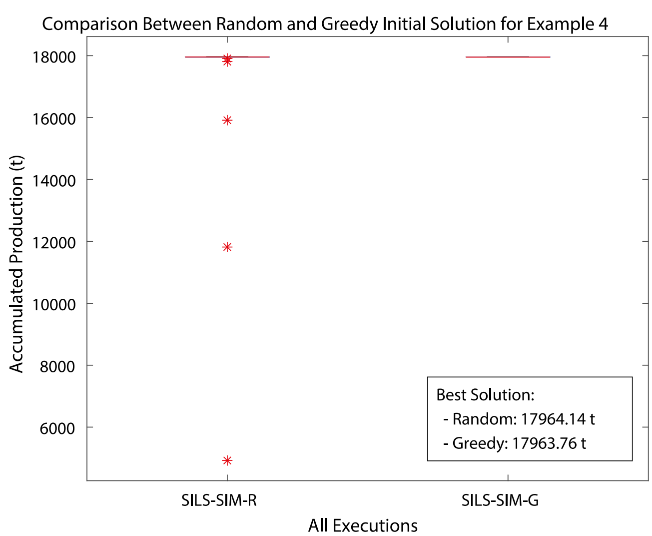


Fig. 19. SILS-SIM algorithm results box plot diagram for Example 4.

As in Example 1, the variability of production generated by the SILS-SIM-R algorithm is higher than that generated by the SILS-SIM-G algorithm, as seen in Fig. 15. The variability of SILS-SIM with a greedy initial solution is small because the greedy solution (all equipment active) is already a good solution.

7.1.3. Example 3: Thicker fresh ore

This production scenario specifies a thicker fresh ore. This situation depends on the type of ore explored in the mines and the amount of explosive used. The input material has a particle size of $D_{80} = 69.2$ mm. In this production scenario, all feeders are available, and the circuit feed rate is the same as that in the previous production scenario. Table 3 shows the numbers of feeders suggested by the best solution, and Fig. 16 illustrates the accumulated production for the best solution and the median solution.

In this production scenario, the solutions suggested by the SILS-SIM algorithms use fewer active feeders and generate more accumulated production. The variability of the SILS-SIM algorithm with a random initial solution is again larger than that with a greedy initial solution, as seen in Fig. 17. However, the best solution of the algorithm with a random initial solution results in greater production than that with a greedy initial solution.

7.1.4. Example 4: Limited flow rate

This scenario presents a situation in which there is a limitation in the ore flow rate. This may occur when there is damage to the conveyor belt or an interruption in mine exploration. The simulated circuit feed rate is 3000 t/h, the particle size of the material is the same as in Example 1 ($D_{80} = 60.63$ mm), and all feeders are available. Table 4 presents the number of feeders suggested by the best solution. In addiction, Fig. 18 shows the accumulated production for the best solution and median solution.

It can be verified that the SILS-SIM algorithm again achieves better performance in accumulated production. Furthermore, the algorithm suggests that fewer feeders are activated.

As shown in Fig. 19, both the random and greedy initial solutions lead to low variability and similar results. However, with a random initial solution, the SILS-SIM algorithm produces some outliers during execution.

Table 5
Numbers of feeders suggested for Example 5.

Process stages	Number of feeders			
	Lower bound	Upper bound	SILS-SIM-R	SILS-SIM-G
Buffer pile	1	4	4	4
Secondary crushing	1	2	2	2
Tertiary crushing	1	3	3	3
Quaternary crushing	1	7	5	7
Screening	1	10	10	10

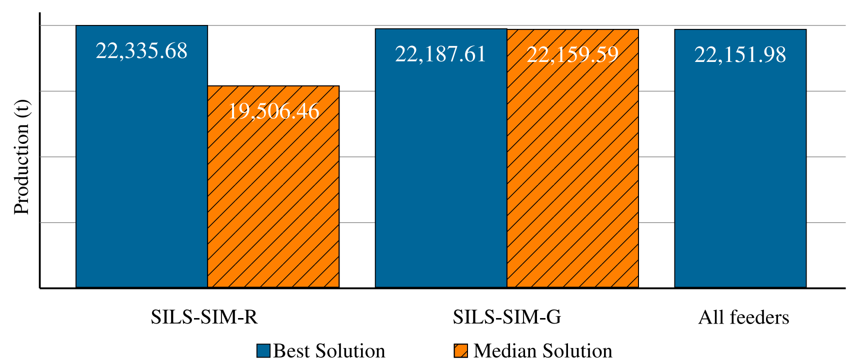


Fig. 20. Accumulated production over 6 h for Example 5.

7.1.5. Example 5: Random equipment unavailability

In this production scenario, five feeders are not available in the crushing circuit. Feeders may be unavailable for various reasons, such as maintenance stops in crushers or screens and interruptions in plant feeding. The particle size of the materials and the range of the circuit feed rate are the same as those in Example 1.

Table 5 presents the best results, and Fig. 20 illustrates the accumulated production for the best solution and the median solution. The plant operator solution is not considered because it is similar to that with all available equipment operating.

The SILS-SIM algorithm suggests fewer feeders in quaternary crushing and generates the highest accumulated production when running with a random initial solution. As in Example 3, despite the high variability and outliers generated during the execution of the algorithm with a random initial solution, the best result leads to higher production, as shown in Fig. 21.

7.1.6. Example 6: Half screening unavailability

In Example 6, six feeders for screening are not available. The screening stage is divided into two parts. Therefore, during some types of maintenance, half of the screening stage is stopped. For this production scenario, the best results are shown in Table 6, and Fig. 22 illustrates the accumulated production for the best solution and the median solution. As in Example 5, the plant operator solution is not considered.

The solutions from SILS-SIM suggest a reduction by 10 feeders in relation to the solution with all feeders, that is, a 37% reduction. The solution generated by the proposed algorithm also achieves better accumulated production (a total of 1298 tonnes or 9.38%). As shown in Fig. 23, in this example, the executions of the SILS-SIM algorithms present an insignificant difference in terms of the median solution value.

7.2. Analysis of energy consumption

The mineral industry is among the most energy-intensive sectors, mainly because of the comminution stage (Steyn et al., 2010; McLellan et al., 2012; Holmberg et al., 2017). An analysis of the energy consumption in all production scenarios is performed in this subsection.

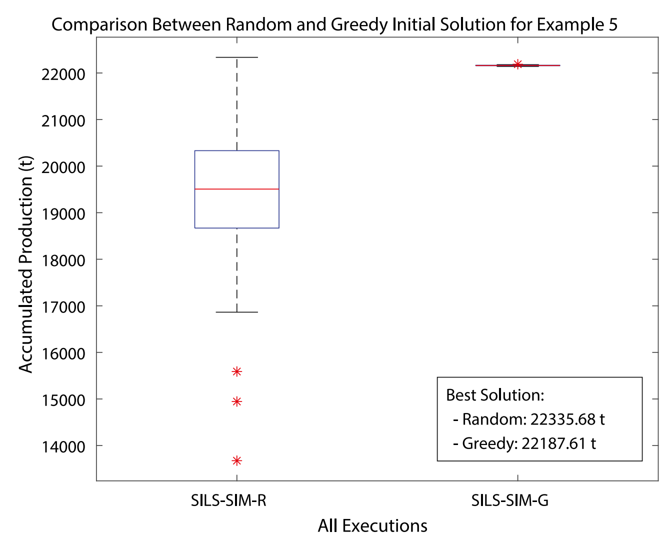


Fig. 21. SILS-SIM algorithm results box plot diagram for Example 5.

The energy consumption is verified only for the cone crusher for two reasons: (i) this equipment consumes the most energy in the crushing circuit, and (ii) considering the real plant, this is the only equipment that has a power measurement. The average power required of the cone crushers in each stage is (i) 40.52 kW in secondary crushing, (ii) 70.62 kW in tertiary crushing, and (iii) 82.68 kW in quaternary crushing. The screening stage does not have cone crushers.

Fig. 24 illustrates the energy consumption in each production scenario for three solutions: one solution from the SILS-SIM-R algorithm, one solution from the SILS-SIM-G algorithm and the solution with all feeders activated. Approaches that generated a higher production rate were analyzed. The data are expressed in MWh and correspond to a time course of 6 h (the time cycle used in the production scenarios).

The solutions of the SILS-SIM algorithms incur considerably less energy consumption in most cases. The SILS-SIM-R algorithm leads to

Table 6
Numbers of feeders suggested for Example 6.

Process stages	Number of feeders			
	Lower bound	Upper bound	SILS-SIM-R	SILS-SIM-G
Buffer pile	1	6	4	6
Secondary crushing	1	3	3	3
Tertiary crushing	1	4	1	1
Quaternary crushing	1	8	3	3
Screening	1	6	6	6

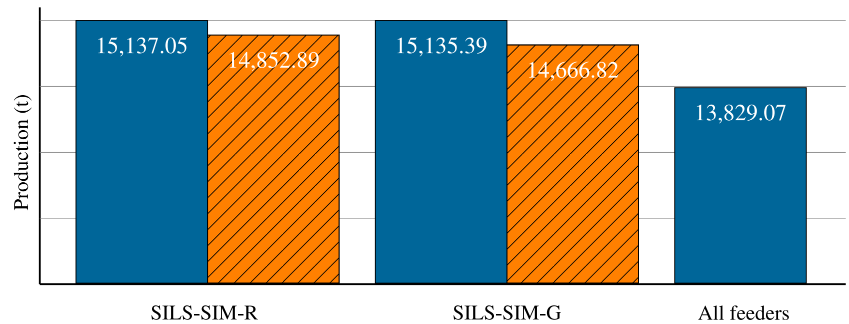


Fig. 22. Accumulated production over 6 h for Example 6.

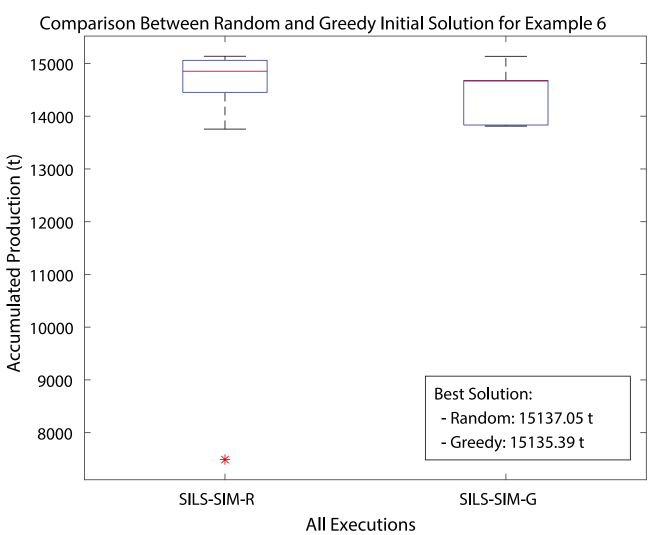


Fig. 23. SILS-SIM algorithm results box plot diagram for Example 6.

considerably less energy consumption in all cases; however, the SILS-SIM-G algorithm results in the same energy consumption as that with all feeders activated in Examples 3 and 5. In Example 6, there is a 59% savings in energy consumption with the SILS-SIM-R algorithm. These results are important and demonstrate the efficiency of the SILS-SIM algorithm.

7.3. Convergence check of the SILS-SIM algorithms

SILS-SIM is a heuristic algorithm; thus, there is no guarantee that the solutions found are optimal. To analyze the convergence of SILS-SIM, a brute force algorithm was implemented. This type of algorithm generates all possible solutions and returns the globally optimal solution to the problem.

A random production scenario with all feeders available and the same particle size from Example 1 (D_{80} = 60.63 mm) is used in the simulation experiment. The range of the circuit flow rate is 4000 t/h to 4015 t/h. Because the problem addressed is a real one-mine circuit, there is a lower bound and an upper bound for the number of feeders in every stage. Values that extrapolate these bounds are impossible to apply. Table 7 shows the bounds of the production scenario used.

The number of feasible solutions ($\#Solutions$) to the problem can be calculated using Eq. (4):

$$\#Solutions = \left(\prod_{i=1}^{5}(UB_i - LB_i + 1)\right) \times \left(rate_{\max} - rate_{\min} + 1\right), \tag{4}$$

where LB_i and UB_i are the lower and upper bounds, respectively, on the number of feeders in stage i and $rate_{\min}$ and $rate_{\max}$ are the minimum and maximum flow rates, respectively.

Thus, according to Eq. (4), the number of possible feasible solutions for this scenario is 10,368. The brute force algorithm required 18 h to find the optimal solution, for which the accumulated production is 22,579.61 tonnes. The optimal solution is (i) a buffer pile with 4 feeders, (ii) secondary crushing with 3 feeders, (iii) tertiary crushing with 4 feeders, (iv) quaternary crushing with 5 feeders, (v) screening with 10 feeders, and (vi) a flow rate of 4015 t/h.

To obtain a measure of how far the solutions are from this optimal solution, the optimality gap was calculated for a set of thirty SILS-SIM algorithm solutions. The results showed a gap of 0.06% for the best solution and an average gap of 9.05% considering all executions for SILS-SIM-R. SILS-SIM-G also showed a gap of 0.06% for the best solution and an average gap of 0.83% considering all executions. For the best solution, the gap was the same, but in terms of the average gap, the execution of the SILS-SIM algorithm with a greedy initial solution yielded a better result.

Table 8 presents the results of the convergence analysis for the SILS-SIM algorithms. For each of the 30 executions, the time and the iteration at which the best solution was obtained were recorded. The average time and average number of iterations were used as evaluation metrics.

Some general conclusions about the results of the SILS-SIM algorithms can be obtained as follows. SILS-SIM-G can find a good solution quickly, and the previous box plots show that the solutions have low variability. Both versions of the SILS-SIM algorithm result in increased production and reduced energy consumption in all simulated scenarios.

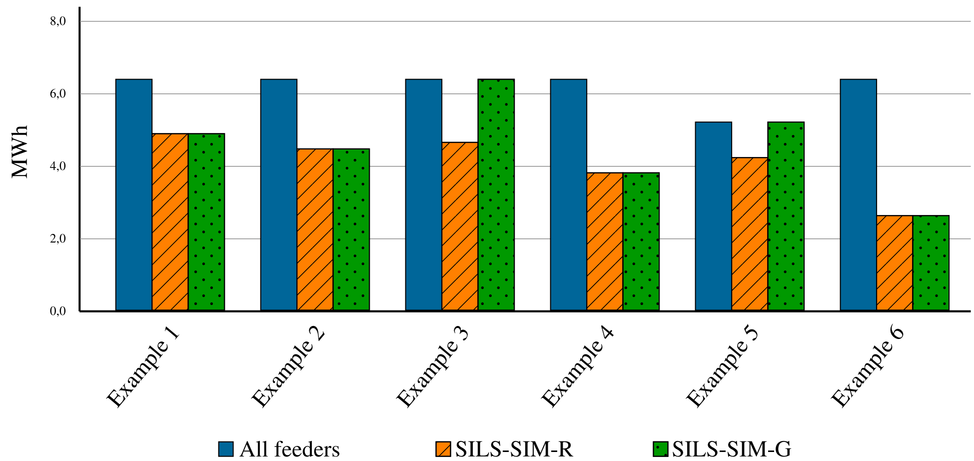


Fig. 24. Energy consumption in all production scenarios.

Table 7
Bounds on the number of feeders.

Stage index	Process stage	Number of feeders	
		Lower bound	Upper bound
1	Buffer pile	3	6
2	Secondary crushing	1	3
3	Tertiary crushing	2	4
4	Quaternary crushing	3	8
5	Screening	10	12

Table 8
Convergence analysis of the SILS-SIM algorithms.

Evaluation item	Methods	
	SILS-SIM-R	SILS-SIM-G
Average time (in seconds)	580.62 (± 104.71)	53.00 (± 9.61)
Average number of iterations	88.75 (± 63.88)	12.00 (± 9.09)

8. Conclusions

In this paper, a crushing circuit operation problem at a Brazilian mining plant was investigated. The amount of active equipment in each crushing stage has a significant effect on production, and the choice of the optimal amount of active equipment is complex due to inevitable variations in ore features, such as hardness and particle size distribution. A simheuristic technique was used to address this problem. The optimization heuristic is based on the iterated local search metaheuristic. The developed simulator includes all aspects of the crushing circuit, such as mass balance, active equipment, and material particle size properties. It enables the simulation of various scenarios that differ in the quantity of active equipment. Hence, it is possible to determine the optimal relationship between production and the amount of active equipment. The results demonstrated the effectiveness of the method, showing that it is possible to increase production with less active equipment than is currently in operation, thus contributing to better crushing circuit efficiency, lower energy consumption, and reduced equipment wear. In Example 6, energy consumption was reduced by approximately 59%, and production was increased by 9% (109,870 tonnes/month). Future work should employ improved crusher and sieve models. The problem should be extended to consider not only productivity and energy consumption but also issues regarding maintenance and varying equipment performance. In this way, new practical concerns for industrial operations can be addressed using the proposed decision support system.

CRediT authorship contribution statement

Mário S. Santos: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Thomás V.B. Pinto:** Methodology, Validation, Data curation, Visualization. **Ênio Lopes Júnior:** Methodology, Validation, Data curation, Visualization. **Luciano P. Cota:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Marcone J.F. Souza:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Thiago A.M. Euzébio:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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