Optimization of truck allocation in open pit mines using differential evolution algorithm

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Abstract

The allocation of trucks in open pit mines is a field with great potential for optimizing resources and applying advanced computer modeling techniques, mainly because many companies still choose to use manual allocation, which is premised on the decisions made by the operator, being subject to common failures and not reaching the maximum potential that the equipment can provide. Therefore, this work focuses on optimizing the allocation of trucks in order to increase production, reducing queue time and keeping ore grades within proper limits. The proposed algorithm was based on the differential evolution technique, where two types of mutation operators were used: rand/1/bin and best/1/bin, thus verifying the most suitable to solve the problem. The trucks were allocated in the ore loading and unloading process, aiming to improve the production capacity in a virtual mine. The results brought a convergence to the maximum global production, in addition to which, the allocation of unnecessary transport equipment to the planned routes was avoided. The two mutation operators compared had certain advantages and disadvantages, each better adapting to certain types of situations. The proposed technique can still be extended to other areas, for example, in the transport of grain on the road network or in the implementation of an allocation in freight cars that transport grain.

Keywords: Differential evolution; truck allocation; mines; optimization.

1. Introduction

Optimizing resources and cutting expenses are no longer a trend and are now necessary for a company to achieve the goals to achieve success and generate profits. With the increasing complexity of operations, it became necessary to allocate resources more rationally.

This new organizational culture has changed many business practices in recent years. The great technological revolution made processes more dependent on the implementation of automation and the development of new technologies. Process studies became more thorough and periodically revised. In the mining area it was no different, as companies invested heavily in research and innovation within their industrial processes. However, the mining area did not receive as much attention from organizations as the ore treatment sectors. For this reason, interest in this area has been aroused for some years, resulting in massive research and investments to optimize the production and extraction of ore (DE MELO et al, 2013).

According to Ibram (Brazilian Mining Institute) (2021), mining should receive investments in the order of R$ 38 billion between 2021 and 2025. This investment enables the implementation of new production and transport methodologies. The manual allocation of trucks at the mine is still widely used in ore transport, often generating losses in production due to queue time and idleness of transport equipment. Optimizing the dispatch of trucks on routes in open pit mines has become a new focus of investments to reduce costs and increase production.

According to some statistics, transport costs are believed to account for more than 50% of the total operating costs in mines that use trucks for transport (ZHANG; XIA, 2015). Aiming at the high costs associated with problems in the dispatch of trucks, the creation of an algorithm based on differential evolution was proposed in the present work, aiming at increasing production and reducing expenses, resulting in a reduction in queue time and a smaller number of idle trucks.

Differential evolution (DE) is an artificial intelligence method that seeks evolutionary optimization through natural selection mechanisms and population genetics, and uses mutation, crossing and selection operators to generate new individuals in search of the most adapted. It was proposed by Storn and Price in 1995 in a series of articles and, since then, it has attracted the interest of researchers and professionals. (OPARA; ARABAS, 2019).

To develop the study of allocation of trucks in open pit mines, the mine characteristics and statistical production data were studied, such as capacity of ore fronts, loading and unloading time of trucks, mixture contents, among others. An algorithm was proposed with the main objective of increasing the production of ore fronts in tons per hour, but respecting the existing restrictions such as minimum and maximum quality of mineral content, maximum amount of trucks per route, mineral production ahead of mining, among others.

With the developed mathematical model, a differential evolution algorithm was applied, obtaining results such as maximum number of production, maximum allocation of trucks and number of trips per route. Furthermore, more than one mutation operator was compared within the evolutionary algorithm.

The proposed model can serve as a basis for implementing the automation of the entire process. Using embedded technology, the variables can be captured by sensors on trucks and transmitted to a central controller whose processing will use the mathematical model developed to determine the optimal point of operation of the equipment.

2. Literature Review

The optimization of truck dispatch in mines has attracted the interest of several researchers and companies in the area of logistics and optimization, aiming to reduce costs. Some optimization models for this problem have already been developed, using different methodologies, such as heuristic methods, or models based on artificial intelligence taking as reference the reduction of queues, costs and increased production. Some of these works are already consolidated and serve as a basis for future projects.

Chanda and Deagdelen (1995) propose a Linear Programming model with the objective of maximizing economic gains and minimizing deviations in ore quality and tonnage.

Merschmann (2002) developed a model in two modules. In the first of these, a Linear Programming problem is solved and in the second, the simulation that allows using the Linear Programming solving data as input to the simulation is presented. The objective of the simulation is to optimize the process of blending the ore from various ore fronts, according to the plant's quality targets, and allocating vehicles to the appropriate fronts.

In Alexandre's work (2010) a multiobjective optimization was proposed, where it was possible to evaluate the performance of two optimization algorithms in several different scenarios generated by the virtual simulation system, which allowed their validation and performance analysis. In addition to computational modeling, the simulation environment was also developed.

Chang et al (2015) proposes a mixed integer programming model, in a heuristic approach with two improvement strategies considering the different yields and capacities of trucks. In Morad et al (2019) the truck allocation problem is analyzed through the development of the simulation-based optimization method (SBO), this method provides an integrated structure by the simultaneous combination of optimization and stochastic simulation of discrete events.

The work by Liu and Chai (2019) addresses a special problem of optimizing truck routes in open-pit mines, based on minimizing time-varying transport energy consumption. A mixed-integer programming model is formulated to clearly describe the engineering problem and a series of constraints are deduced to strengthen the model.

Based on some optimization concepts of the previous models, mainly on the restrictions to which the transport vehicles will be submitted, the optimization of the mineral total production will be addressed using the differential evolution as a method of resolution, determining the number of trucks needed and trips in each ore front and route.

3. Metodology

In this section, some general characteristics of open pit mines will be discussed, as well as some prerogatives and restrictions of the developed mathematical model and, finally, some aspects of the evolutionary evolution model that was used.

3.1 Mine characteristics

To develop the model, first you must know the characteristics and loading cycle of the truck to be allocated. The loading and transport cycle involves activities from the extraction of material to the point of unloading the material from it. The equipment involved is moved according to the production of the mining front, which is the material extraction point.

In the truck's loading and tipping cycle, they are allocated to different routes depending directly on the method of choice and management of the appropriate routes for each one of them. The truck can be directed to the primary crusher or to a secondary feed point. This secondary feed point shortens unloading queues and reduces truck travel at points away from the crusher.

The paths of the trucks will be allocated according to the DMT (Average Transport Distance). The DMT can be partial, the distance that the truck will travel between loading (Mining fronts) and unloading (Criller, Sterile Stacks), or per cycle, which represents the total distance presented in a Loading - Weighing -

Loading cycle . Figure 1 presents the description of the operating and idle times of trucks inside the mine, surveyed in the work by De Melo et al, (2013).

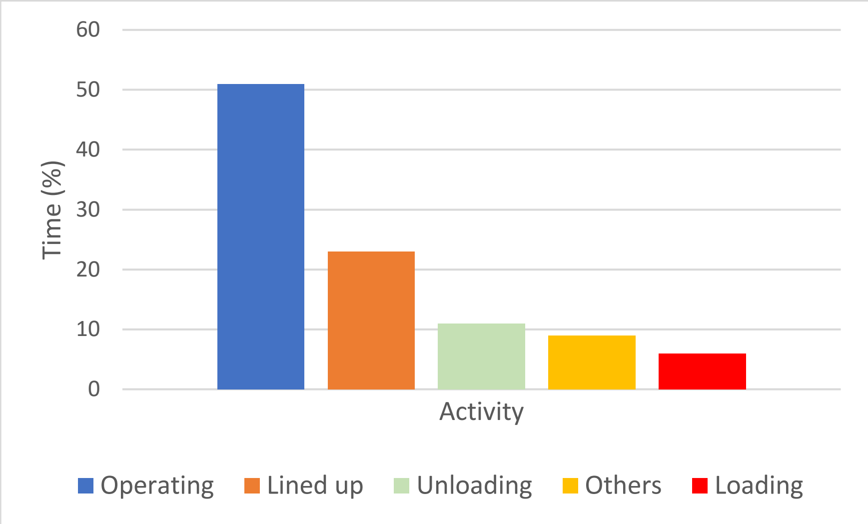


Figure 1 – Time spent per activity in the truck loading cycle

Based on the graph presented, it can be seen that the time spent queuing trucks in the mine is high compared to the total cycle, being equivalent to almost a quarter of the total truck time in the mine. This formation of queues becomes one of the main problems in the mine's operation, as it reduces the productivity of the ore fronts and alters the cycle time of the trucks.

3.2 Model development

The main objective of the model will be to maximize the mine's production, increasing the mining rate (tons/hour), and respecting production restrictions, among some, ore quality and maximum feed to the discharge point. The material will be transported by a heterogeneous fleet of trucks, which have two different load capacities.

For the development of the model, data collected from a part of the mine that undergoes an automation process will be used, which consists of five mining fronts and three material discharge points, one discharge point being the primary crusher and the other two pile points of secondary power. The Equation 1 presents the objective function used:

$$\max \sum_{f \in F} \sum_{j \in J} Cap * X_{ij} \quad \forall f, \forall j \ \in F, J \tag{1}$$

Where F is the set of ore fronts, X_{ij} is the number of truck trips from front f to pile j and Cap is the transport capacity of the allocated truck. As previously mentioned, there will be 5 ore fronts connected to 2 feed piles and 1 primary crusher, these paths being carried out by 9 different routes. Thus, route 1, which represents the displacement from front 1 to feed point 1, will be equivalent to variable X11. Similarly, Front 1 - Primary Crusher (X12), Front 2 - Feed Point 1 (X21), Front 2 - Primary Crusher (X22), Front 3 - Feed

Point 1 (X31), Front 3 - Primary Crusher (X32), Front 4 - Primary Crusher (X42), Front 4 - Feed Stack 2 (X43) and Front 5 - Feed Stack 2 (X53).

From the optimization of the number of trips carried out by the allocated trucks, the total production of the mine is obtained, as well as the production taken from each ore front. The calculation basis for the work will be one hour.

The first restriction addressed is related to the quality of the ore, which expresses the limit in which it is possible to exploit the material in a given pile. This type of restriction limits large differences in travel on a given front in relation to others, ensuring a mix of the ore within the appropriate quality limits so that it reaches the beneficiation plant with maximum utilization. This restriction has a lower and upper quality limit. In other words, the homogenization of the ore must take place in a way that it does not have a quality below what is required, but also does not have a high ore content, which may indicate a high exploitation of rich rocks, and a decrease in the mine's useful life. The restriction can be seen in Equation 2, for lower limit and Equation 3, upper limit:

$$\sum_{f \in F} V_c P_f - VM_c \sum_{f \in F} P_f \geq 0 \tag{2}$$

$$VZ_c \sum_{f \in F} P_f + \sum_{f \in F} P_f V_f \geq 0 \tag{3}$$

Where VZc is the maximum admissible grade for the ore, V_f is the forward ore grade f, P_f is the mining rate for the f-th front, V_c is the ore grade for path C and VMc is the grade minimum allowable.

Another restriction used limits the number of trucks in front of ore with the main function of reducing the queue time during loading and unloading. For this calculation, it is necessary to know the unloading, loading, cycle times, among others. Each route has a cycle time different from the other due to the equipment allocated and transport distances.

This restriction is defined by two equations, the maximum number of simultaneous trucks on the same path, Equation 4, and the maximum number of trucks and trips per hour respecting the production limit of the mining front, Equation 5. This restriction was derived from the model of Pinto (2007).

$$N_{cmf} \leq \frac{T_{des}}{T_{carg}} \tag{4}$$

$$Cap * \frac{3600}{T_c} N_{cmf} H_{il} - P_{ft} \geq 0 \tag{5}$$

Where Cap is truck loading capacity, T_{carg} is truck loading time, Tc is cycle time, N_{cmf} is maximum number of trucks for each front f, T_{des} is total travel time, P_{ft} is production from the front by path, H_{il} is the vehicle allocation i to route l.

The restriction associated with the material discharge limit is related to the maximum material capacity that the crusher or the feed point can process, that is, this restriction will, in a way, limit the rate of extraction of ore from the mining fronts. The restriction can be expressed by Equation 6:

$$P_t - \sum_{f \in F} P_f \geq 0 \tag{6}$$

Where P_t is the maximum allowable mining rate, and P_f is the mining rate for the f-th front.

Every existing mining front in a mine has a maximum production rate. One of the main reasons for this restriction is the limit on the mining rate that the loading equipment can generate. This restriction is represented by the model of Equation 7:

$$P_f - Ym_f \leq 0 \quad \forall f \in F \tag{7}$$

Where Y_{mf} is the maximum plowing rate for the fth front. All 5 ore fronts that are part of the problem addressed have their own limits and each one has a specific rhythm.

We still have restrictions on the allocation of cargo and transport equipment depending on the model and cargo capacity. Loading equipment will be allocated at each loading point compatible with its production and loading characteristics. In addition, each type of truck will operate on a single front where the loading equipment is compatible with its capacity. Equations 8, 9 and 10 have the restrictions:

$$\sum_{q \in Q} J_{qf} \leq 1 \qquad \forall q \in Q \tag{8}$$

$$\sum_{f \in F} J_{qf} \leq 1 \qquad \forall f \in F \tag{9}$$

$$\sum_{f \in F} H_{il} \leq 1 \qquad \forall f \in F \tag{10}$$

Where H_{il} is the representation of truck i allocated to route l, Q is the set of load equipment and J_{qf} is the load equipment q operating in front f. The first two equations show that only one cargo equipment compatible with each front will be allocated for loading. The variable H_{il} takes value 1 if the truck is correctly allocated to its route. If the transport equipment is not compatible with the allocated route, this variable will assume a value of 0.

3.3 Differential evolution

From the mathematical model with the objective function and restrictions, and using the collected data, an evolutionary algorithm model for the optimization of the problem will be proposed. The DE adjustment is based on the so-called hyperparameters, which are adjustable variables necessary for the model, and the main ones are: the weight of the difference used (F), the probability of occurrence of recombination (CR), the number of individuals/vectors maintained in the population (Np) and the number of generations carried out during the process. (ZINI, 2009).

In solving the problem, methods based on penalizing infeasible individuals, who are not able to meet the conditions, were used. Therefore, less able individuals are penalized according to violations of the restrictions.

In the case of the mutation operator, results from two different operators will be compared. The first is random mutation, which operates by randomly choosing three distinct individuals among all the N that make up the initial population. This combination gives rise to new individuals, called donor vectors, by adding the weighted difference between two randomly chosen individuals from the initial population to a third individual who is also randomly chosen with uniform distribution from the original population, given by the equation:

$$V_q = X_\alpha + F(X_\beta - X_\gamma) \tag{11}$$

In this equation V_q is the created vector, F is the factor that weights the difference of individuals, and X_α,X_β and X_γ are the random individuals chosen from the population. We also have the crossover process that uses for comparison the best candidate of the current generation (X_{best}), to be added and result in the individuals of the next generation:

$$V_q = X_{best} + F\left(X_\beta - X_\gamma\right) \tag{12}$$

After the mutation occurs the crossing operation, where the donor vectors are combined with the components of another vector chosen randomly, called the target vector, in order to generate the vector called experimental. At the end of this operation, all crossed individuals will form a new population of the same size and dimension as the populations obtained previously. For crossing the binary method was used. This method consists of crossing individual I_o, selected from the original population, and I_m, selected from the fined population, resulting in a new individual I_c, and the crossover coefficient (Cr) will be the threshold value to determine the origin of the gene that will be transmitted to the new individual. The crossover equation is defined by:

$$I_c^{ij} = I_m^{ij} \, se \; rand_i \leq Cr \; ou \; j = k \tag{13}$$

$$I_c^{ij} = I_o^{ij} \, , caso \; contrário \tag{14}$$

In which (j, k = 1,2,...,N) and Cr $\in$ [0,1] . From the equation we can see that every time the random value is greater than the crossover coefficient, the gene that will be chosen is that of the fined individual Im, otherwise the gene of Io will be passed on. The combination of these random mutation methods with binary type crossover is known as rand/1/bin and, similarly, the combination of best and binary method is best/1/bin. After defining the mutation and crossing methods, the algorithm was developed and implemented, and the results are presented in the next section.

4. Results

To simulate the created algorithm, a graphical interface was developed using the Matlab® appdesigner, where it is possible to adjust the hyperparameters of the genetic algorithm. The interface makes it possible to choose the population, the number of generations, the crossover coefficient (Cr), the differential F value for mutation and choice of mutation and crossing methods. Tests were performed with the rand/1/bin and best/1/bin mutation method. For comparison purposes, the same crossing method was used, for both the binary.

In the first test, the number of generations was set at 500, and the other variables were also set, at well-adjusted values, with a population of 100, the F factor of 0.5, rp (Weight of penalties) equal to $1x10^6$, and the Cr at 0.9. The values of F and Cr were chosen based on the suggestion of the work of Storn and Prince (1995) being appropriate to obtain a fast convergence. The test was performed 50 times and the average values of the variables were found. Using the rand/1/bin mutation method, an average value of 4337 tons per hour with a standard deviation of 6.81 was obtained as the maximum mine production, with the best value found being 4347 tons per hour. Table 1 brings the results of the average values for the allocation of trucks in the 9 available routes. Table 2 brings the results for the ore fronts and material discharge points.

Table 1. Production, number of trips and trucks per route using the rand/1/bin method

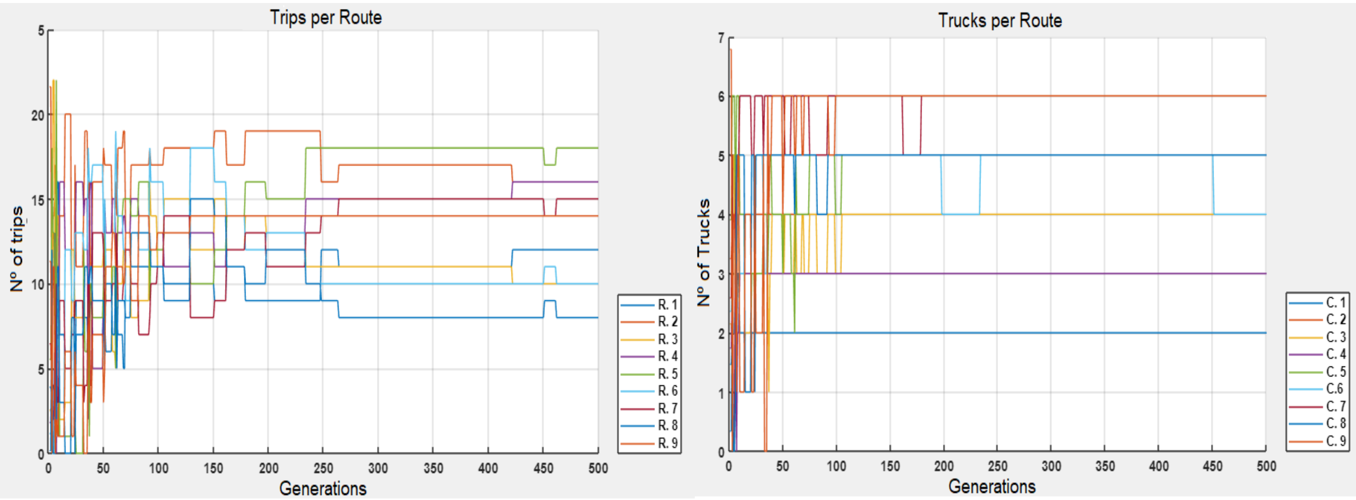
Routes	Average production (tons/h)	Number of trips (Average)	Number of trucks allocated (Average)
Route 1	444,00	12,00	2,00
Route 2	592,00	16,00	4,00
Route 3	350,00	10,00	4,00
Route 4	591,30	16,02	3,03
Route 5	661,30	17,89	5,20
Route 6	355,20	10,05	3,85
Route 7	554,20	15,15	6,13
Route 8	281,10	7,82	4,93
Route 9	516,40	14,12	5,91

Table 2. Results for material loading and unloading points using the rand/1/bin method

Loading or unloading point	Average production (tons/h)	Number of trips (Average)	Number of trucks allocated (Average)
Front 1	1036,00	28,00	6,00
Front 2	940,33	26,21	15,13
Front 3	1012,56	27,82	8,94
Front 4	837,42	23,14	11,04
Front 5	522,10	14,52	5,82
Feeding stack 1	1420,32	39,42	11,15
Primary crusher	2087,41	58,92	17,17

Feeding stack 2	831,24	22,31	10,79

From the values presented in the tables, it is possible to distinguish that the routes that are allocated to front 1 varied less and achieved greater repeatability. Overall, the variation in total production between trials was very small, around 0.7%, so the difference between trips and trucks allocated per route between simulations was minimal or sometimes identical. Routes 5 and 4 had a higher production and a higher number of trips and trucks allocated. To ensure that all restrictions were respected, the penalty coefficient used (rp) was relatively high. To verify the variation in the allocation of trips and trucks over evolutionary generations, the graphs in Figure 2 were drawn.



(a) (b)

Figure 2. Graphs of the number of: (a) trips allocated per route and (b) trucks per route using the rand/1/bin method.

The graphs in the figure show great variability, especially within the number of trips allocated to each route. The numbers of allocated trucks converged first, promoting few changes from 250 generations onwards, with only route 6 showing significant changes. As for the allocation of trips, there was an intense change in values between the routes until around 250 generations and, from this point onwards, there were still some changes in travel between the routes, but with less intensity.

In the second test, the same hyperparameters were used for the differential evolution algorithm, with only the mutation method being changed to best/1/bin. This test was also repeated 50 times, resulting in an average value for total mine production of 4180 tons per hour, with a standard deviation of 275.1. The best result found was 4337 tons per hour. The results found varied on a much larger scale than those found in the previous test, and sometimes the algorithm stuck to some local maximum. Despite this, the best result found was very close to the method used in the first test. The results for the available routes and for the loading and unloading points are presented in Tables 3 and 4 respectively.

Table 3. Production, number of trips and trucks per route using the best/1/bin method

Routes	Average production (tons/h)	Number of trips (Average)	Number of trucks allocated (Average)
Route 1	450,30	12,70	2,21
Route 2	565,40	13,80	3,92
Route 3	343,20	9,50	3,75
Route 4	567,30	15,08	2,97
Route 5	641,30	16,39	4,89
Route 6	342,20	9,34	3,52
Route 7	518,20	13,10	5,89
Route 8	272,32	7,10	4,78
Route 9	501,20	13,00	5,75

Table 4. Results for material loading and unloading points using the best/1/bin method

Loading or unloading point	Average production (tons/h)	Number of trips (Average)	Number of trucks allocated (Average)
Front 1	1022,89	26,52	5,75
Front 2	930,26	25,44	14,33
Front 3	980,53	26,72	8,45
Front 4	826,47	21,89	10,55
Front 5	508,12	14,12	5,36
Feeding stack 1	1217,31	36,21	9,75
Primary crusher	2075,92	56,89	16,89
Feeding stack 2	774,40	21,50	9,89

For this mutation method, the results had a lower precision and a wider variability than the values obtained in the previous test. The values achieved for the average production of the allocated routes and ore fronts were lower, in addition to which, in some of the simulations, the values presented differed significantly from the average, being a point far from the convergence region. Some simulations reached values similar to those achieved with the mutation operator Rand, however, trucks were often allocated to routes that did not reflect at a point close to the global optimum region to maximize production. The analysis of the evolution of the allocation of routes and trucks over the generations is shown in the graphs in Figure 3.

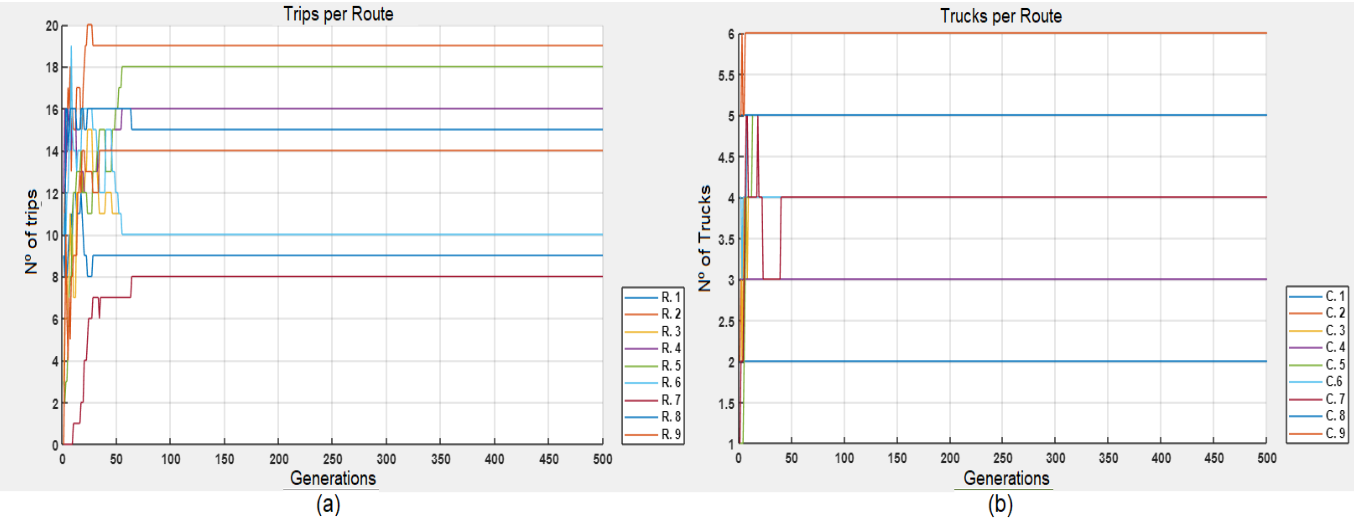


Figure 3. Graphs of the number of: (a) trips allocated per route and (b) trucks per route using the best/1/bin method.

From the graphs in Figure 4, it is possible to identify a faster convergence, in about 80 generations, where the algorithm stabilizes and there are no changes in the results. In some simulations values with more than 10% of difference from the mean were found, even in these cases behaviors of fast convergence of the variables were observed, showing no changes even with results significantly inferior to the optimal ones. Thus, this type of mutation was more likely to find local maximums and present worse results for both production and allocation of trucks.

In the third test, the behavior of the algorithm in cases of limitation in the number of trucks available in the mine was explored. Transport trucks will be allocated according to the model available for a given route, being adjusted according to their capacity. In this test, the number of allocated trucks ranged from 15 to 30, in increments of 5 in 5 trucks. To adjust the DE algorithm, the same parameters of the last tests were applied, modifying only the number of generations to 600, due to perceptible variations in the algorithm. The simulation was repeated 50 times to obtain a statistically significant mean value. The results are shown in Table 4.

Table 4. Comparative results between the quantity of available trucks and the methods used

Number of Trucks	DE Method	Average production(tons/h)	Standard deviation	Best value
15	Rand/1/bin	2055,14	385,15	2439
15	Best/1/bin	1996,06	303,48	2330
20	Rand/1/bin	2679,88	126,89	2840
20	Best/1/bin	2709,11	189,28	2986
25	Rand/1/bin	3189,33	135,08	3414
25	Best/1/bin	3312,12	148,88	3449
30	Rand/1/bin	3833,23	96,02	3961
30	Rand/1/bin	3737,45	188,08	4000

In this type of experiment, the standard deviation of production was decreasing while the number of allocated trucks grew, this behavior being more evident in the mutation of the rand type. This variability is great for smaller quantities of trucks due to greater freedom of choice without infringing restrictions. The best mutation type obtained better mean values for a smaller number of allocated trucks. With 30 trucks allocated the average rand/1/bin value became better and we also saw a standard deviation equivalent to half of the other average, resulting in better precision and reliability of the simulations compared to the best/1/bin method.

5. Conclusion

The open-pit mine truck allocation algorithm using differential evolution as an optimization method that brought significant results for maximizing production and allocation of trips and routes, achieving consistent convergence, with precision and reliability, for maximum production value.

Comparison of the mutation methods in the DE algorithm showed that each one has some benefits and disadvantages, and sometimes the rand/1/bin method achieved greater precision and lower standard deviation for simulations without restrictions for the number of allocated trucks. As for the best/1/bin method, some simulations achieved better results than the other method, but some simulations converged to results well below the average, more than 15% difference, being probably great locations, causing a significant increase in the value standard deviation and generating less reliability in the simulations. Despite this for limited values of the number of trucks available for allocation, this method achieved better results than the rand/1/bin method.

From the final model developed, it will be possible to apply it in an automated truck allocation system so that any real mining company can implement it in their mines. The development of an embedded technology system will enable total control over the process, and will assist in the exchange of data between equipment and between operators and controllers.

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