Randomization Control in Heuristics and Metaheuristics Applied to the Optimal Path Search in Open Pit Mines

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ABSTRACT

The main contribution of the article is the presentation of a control of randomness on the Nearest Neighbour heuristic and the GRASP metaheuristic, in order to explore the capacity of local minimums found in their search processes. These structures have been analysed, readjusted, and verified for a database containing the location of several mines located in the territory of the United Kingdom. New algorithms are compared in terms of results based on reference datasets.

KEYWORDS. Nearest Neighbour. GRASP. Open Pit Mine.

Introduction, Methodology, Results, Conclusion, References

1. Introduction

It is possible to assist the search process of heuristics and metaheuristics, in a way that allows the algorithm to leave local minimums. This proposal considers a control of randomness over those structures. With this contribution, such algorithms become better able to treat problems such as optimum paths for trucks operating in open pit mines. More economical paths have implicit benefits to the analysis of the processes in open pit mines, such as savings in truck operation time and fuel,also contribution to the decrease in the demand for maintenance due to the lower wear of the trucks.

By definition, an open pit is the type of mine that is exposed on the surface and is composed of a set of mining fronts (for extraction of sterile ore), a fleet of trucks (each with its characteristic capacity and speed) and load equipment [Mendes et al., 2014]. In addition, trucks have the function of transporting the ore (for crushers) and the barren (for the barren pile). According to Bastos et al. [2011], the dispatch of trucks is a very important activity for an open pit mining area, since the cost of transporting the materials can reach 60% of the extraction operation in an operation in real situations. Dispatch is a type of problem that involves several issues (such as fuel consumption, tires, emergencies and so on). However, the model that is described in the present work aims at the search for the optimal way to attend (visitation) of several mines, starting from a certain initial mine. The truck should visit and attend to the various mines of a given set and return to their point of origin, thus, as Layeb et al. [2013]. At the end of the visitation process, the total distance traveled by the vehicle will be determined.

The context of transport in open pit mines has several aspects of analysis and research, some of them focused on the concept of analysis with heuristics, as it is portrayed in Section 2 of this article, with a complexity analysis.

In section 3, the algorithms used, both the reference as those proposed by this article are described. For constructive heuristics, the algorithms of Clarke-Wright and Nearest Neighbour were used. With these two algorithms, a new proposal was developed to be compared, the NN*. The new proposed constructive heuristic is based on the algorithm of Nearest Neighbour. In the metaheuristic studies, the proposal is derived from a GRASP (Greedy Randomized Adaptive Search Procedures) approach, called GRASP*.

The experiments were defined in section 4 the results of the tests performed and the conclusions are presented in Section 5.

2. The Problem

The problem of optimization of routes directed to the environment of mining companies that operate the process of extraction in the open pit mines that approached in the present article, can be referenced like a problem of routing of vehicles. This problem has several optics, such as those described in the previous section, one of them is the visitation of the truck to the open mines of service, which can also be considered as an instance of a TSP (Traveling Salesman Problem).

According to Lenstra [2003], the TSP is an issue where a set of cities $C = \{c_1, c_2, ..., c_N\}$ is presented for each pair $\{c_i, c_j\}$ of distinct cities with a distance $d(c_i, c_j)$. The objective is to find a π order of cities that minimizes the total distance travelled, such as model 1:

$$\begin{array}{l} \text{minimize} \sum_{i=1}^{N-1} d(c_{\pi(i)}, c_{\pi(i+1)}) + d(c_{\pi(N)}, c_{\pi(1)}) \\ \text{Subject to} \\ d(c_{\pi(i)}, c_{\pi(j)}) \geq 0; \forall i \in N, \forall j \in N, i \neq q \\ 1 \leq i, j \leq N \end{array} \tag{1}$$

The problem analysed in this work is the visitation of a truck operating in the proposed environment, traversing each of the open pit mines belonging to a set C of cities along the territory of the United Kingdom, forming a Hamiltonian cycle during the service process . According to Pichpibul e Kawtummachai [2013] the TSP is classified as an NP-Hard (Non-deterministic Polynomial-time

hard) problem.
In Golden e Wong [1981] it is said that the proof on the issue of a problem being NP-complete is very relevant because the problem is intractable. Although a problem is NP-Hard, if there is a polynomially limited algorithm for such a problem, it implies the existence of a polynomially limited algorithm for all NP-complete problems. Also according to Golden e Wong [1981], the problem that was addressed, the CARP (Capacitated Arc Routing Problems) was validated as NP-Hard.
According to Lenstra [2003], the following test condition can be presented: Taking E as an NP-Hard optimization problem (minimization) and A as a polynomial time algorithm to solve it. Then an instance J of the corresponding decision problem D is the form (I, c), where I is an instance of E, and c is a number. Then the response to D for instance J can be obtained by running A on I and checking whether the cost of the optimal solution exceeds c. Then there is a polynomial time algorithm for D and NP - completeness implies $P = NP$. Thus the complexity of the problem to be treated, like the TSP is NP-Hard [Golden e Wong, 1981].
It should be noted that several experiments were performed about transports in open pit mines, some of them based on heuristics and metaheuristics. These approaches collaborate with the affirmation that several studies are directed to this type of problem, besides confirming the potential and use of heuristics and metaheuristics for the treatment of the same.

2.1. Transport in Open Pit Mines Approaches

The context of transport in open pit mines has several aspects of analysis and research. White e Olson [1986] presents an algorithm was proposed that is the basis for the DISPATCH system, which operates in many mines around the world. A two-step solution is obtained. The first one, based on linear programming, deals with the problem of optimization of the ore mixture, minimizing costs considering the mining rate, the quality of the mixture, the feed rate of ore to the beneficiation plant and the handling of materials. The second step of the algorithm, uses a similar model to White et al. [1982], differing from this using a decision variable for the volume of material transported per hour in a given route, rather than the work rate of the Truck per hour. Also considered is the presence of storage batteries. In this second stage of the algorithm, the goal is to minimize material transport in the mine.
In Sgurev et al. [1989], an automated system was described for the real-time control of truck transport in open pit mines (TRASY) and is intended to improve the technical and economic indices of the loading and unloading process in open pit mines, where trucks are used as vehicles. The authors described the two ways of organizing the work of trucks: in a closed circuit system and in an open circuit system, called a dynamic allocation system. The authors concluded that increasing the productivity of the operation in open pit mines can be achieved by improving the efficiency of load-transport process control, so that the introduction of automated systems for the control of transport vehicles is one way to achieve this goal.
Alvarenga [1997] proposes the best dispatch of trucks in the iron mining of an open pit mine, in order to minimize the queuing time of the trucks in the fleet, increasing productivity and improving ore quality extracted. In the work, which is the basis of the SMART MINE system widely used in several Brazilian mines, a stochastic optimization technique was applied, using the genetic algorithm with parallel processing. Basically, the problem is to indicate the best tilt or load point and the trajectory for the movement, when there is a choice situation to be made. The author pointed to productivity gains of 5-15%, proving the validity of the proposal.
Guimaraes et al. [2007] presents a computational simulation model is demonstrated to validate the results obtained by the application of a mathematical programming model to determine the mining rate in open pit mines. LINGO solver, version 7.0, was used to optimize the problem and ARENA, version 7.0, simulated the solver solution. The modeling showed that by increasing the number of vehicles, the production goal was not met and was further deterred by the increase in queuing time.
There is the treatment of truck dispatch, in Bastos et al. [2011], as a combinatorial problem of

assigning trucks to blades in order to optimize a specific objective, taking into account various constraints and uncertainties. This study addresses the stochastic question that must be considered, due to inherent uncertainties to the problem, that are present in most real-world problems. The article cites, in particular, that the dispatch of trucks in open pit mines is subject to uncertain behavior, such as variations in fuel consumption, unexpected equipment stops (failures, flat tires, emergencies, etc.) and lasting actions.

In Riquelme Rodríguez et al. [2014], a problem is described in which the edges of a network represent the customers and a quantity of material is delivered to them, so that each reaches a desired level of inventory when finding the route of least cost of delivery. Routing and inventory decisions are made at the same time. The application example of this problem is the suppression of dust in open pit mines. A fleet of trucks sprays water along the roads of a mine. Moisture increases the effectiveness of dust particle retention. As the humidity level decreases, refueling is done periodically.

In Agamennoni et al. [2011] apud Ahmed et al. [2015], an approach was performed that estimates the set of major curves on the input routes in a constructed map. A machine learning method was used to represent the map in open pit mines.

These are some examples of approaches that consider the context of transport in open pit mines.

2.2. Heuristics Approaches

With regard to the use of heuristics for the problem, it can be mentioned three can be noted. First, Ezawa e Silva [1995] describes a dynamic truck allocation system was developed with the objective of reducing variability in ore levels and increasing transport productivity. The system uses a heuristic to sequence the trucks in order to minimize changes in levels. For validation, the authors used a simulation and graph theory for the mathematical modeling of the mine. Deployment of this system transport productivity increased by 8% and management achieved more accurate data in real time.

As in Riquelme Rodríguez et al. [2014], Golden e Wong [1981] analyses the routing for water trucks. They are used in open pit mines for dust suppression and maintenance of the haul road. Well-maintained transportation roads extend the life of the main component and the tire and reduce the maintenance costs of the transport truck. In order to minimize the sum of running and irrigation delay costs, the scheduling problem is modeled as a trained arc routing problem with an infinite horizon.Golden e Wong [1981] uses the minimum cost stream and partitioning-based heuristics to solve the problem of locating water truck refueling stations. A case study is presented for a large copper / gold open pit mine in Australia. Golden e Wong [1981] shows in its results that, under certain circumstances, building a new refueling station is a better option than buying a truck.

In Arelovich et al. [2010] an algorithm is proposed to make real-time dispatch decisions in open pit mines based on discrete position information. The methods in Arelovich et al. [2010] are presented to estimate the probability density function for the position of each vehicle through the mine. New heuristic rules are then presented using current local data collected by peer-to-peer (P2P) communication systems and vehicle position estimates to select the ideal destination for the travel plan for each vehicle. A comparison of the algorithm with the existing approaches based on the global information of the truck's position is presented. The results show that performance improves using discrete information, and there are significant improvements in case of accidents or queues.

2.3. Metaheuristics Approaches

On the metaheuristics, to obtain the Hamiltonian cycle of lower cost can be cited in mining problem, other lines of articles presents relevant experiments.Yu et al. [2011], that describes an adaptive hybrid AG, along with a Tabu search (GA-TS), was used for optimum routing resolution. The algorithm combines AG parallel computing and global optimization with Tabu Search (TS) ability for faster local search. This technique was experienced in the routing of mine material transportation vehicles in China Zhengzhou Coal Mine and Power Supply Co. Ltd. Through experience,

optimal economic routing was created and economic costs were reduced.
Layeb et al. [2013] presents a GRASP algorithm based on a new random heuristic is presented to solve the problem of trained vehicle routing. The problem is characterized by a fleet of homogeneous capacity of the vehicle that will start from a tank, to serve a number of customers with demands that are smaller than the capacity of the vehicle. The proposed method is based on a new constructive heuristic and a Simulated Annealing procedure as an improvement phase. The new constructive heuristic uses four steps to generate feasible initial solutions, and Simulated Annealing operates on these solutions found to achieve the best.
In Souza et al. [2010] is researched the problem of Open Mine Operational Planning with dynamic truck allocation. The objective is to optimize mineral extraction in mines, minimizing the number of mining trucks used to meet production targets and quality requirements. It is presented a hybrid algorithm that combines characteristics of two metaheuristics: GRASP and General Variable Neighborhood Search. The proposed algorithm was tested using a set of real data problems and the results were validated by running the CPLEX optimizer with the same data. This solver used a mixed integer programming model (also developed in this work). Computational experiments show that the proposed algorithm is very competitive, finding almost optimal solutions (with a gap smaller than 1%) in most cases, requiring short computing times.

3. Algorithms

The experiments used concepts of constructive heuristics and metaheuristics methods to treat the proposed problem.
According to Barr et al. [1995], a heuristic method (also called an approximation algorithm, an inaccurate procedure, or simply a heuristic) is a well-defined set of steps to quickly identify a high quality solution for a given problem, where a solution is a set of values for the problems and quality is defined by a metric or declared evaluation criterion. The solutions are generally assumed to be feasible, meeting all constraints of the problem. The purpose of heuristic methods is to identify solutions to problems where time is more important than quality of solution, or knowledge of quality.
According to Semančo e Modrák [2012] there are two well-known types of heuristics. The first type is the constructive heuristic, which starts its search process and adds one step at a time (in a TSP, a city or vertex visited at a time). The second type is based on metaheuristics (they use local searches in their processes).
For the experiment to be carried out with constructive heuristics, two algorithms of the literature, Clarke-Wright and Nearest Neighbor were tested. The others experiments has used GRASP.

3.1. Clarke-Wright Algorithm

The Clarke-Wright algorithm [Lenstra, 2003; Golden e Wong, 1981] is considered a savings heuristic (also named CW algorithm). It initiates the search process for the TSP problem with a pseudo tour in which an arbitrary city is called a hub and the Traveling returns to the hub after each visit to another city (ie, the process starts with a multiplier which Each non-hub city is connected by two arcs to the hub). Thus, for each pair of non-hub cities, savings are allowed to be the amount by which the tour would be ordered if the traveling salesman went directly from one city to another, passing over the hub (crossing, that is, a Bypass). In a sequence, passing through the non-hub cities pairs in a non-increasing order of economies, performing a bypass such that no non-hub vertex cycle is created or causes an effect of a non-hub vertex to become adjacent to more of two other non-hub vertices. The construction process ends when only two non-hub vertices (cities) remain connected to the hub, where there will actually be a tour.

3.2. Nearest Neighbor Algorithm

The Nearest Neighbor (NN) is an algorithm for the connection of the vertices with the neighborhood closest to the analyzed node [Du e He, 2012; He et al., 2010]. In this case, V^* will be taken as the set of unvisited vertices. An initial node (node 0) is taken and a path consisting of nodes $0, i_1, ..., i_j$, will be constructed, being:

$$i_j = arg(min\{c_{i_{j-1}k} : k \in V*\}) \tag{2}$$

Where $u \geq d_{i_1} + d_{i_2} + ... + d_{i_j}$, and any other node $s \in V*$ is such that $u < d_{i_1} + d_{i_2} + ... + d_{i_j} + d_s$. Repeating these steps until all nodes are visited, presenting a cost of $\Theta(n^2)$ [Lenstra, 2003].

In addition to the two basic algorithms (CW and NN), a constructive heuristic, called NN *, is proposed for comparative purposes. The change in NN * is very simple: in its structure, the NN chooses a city randomly and connects the neighborhood according to the lowest cost between them. The NN * maintains the randomness of the choice until the second city, that is, the first and the second city are chosen randomly .

It should be noted that NN * does not give the option of the nearest neighbor k as in Yang [1997], nor is it a NN with a search margin as in Weinberger e Saul [2009] or an analysis that considers a Fuzzy logic as in Keller et al. [1985]. Only one degree of randomness is added at the second moment of NN analysis (considering only valid answers).

3.3. GRASP Algorithm

According to Festa e Resende [2011], GRASP is a metaheuristic with multiple initial conditions, to produce good quality solutions for combinatorial optimization. Each GRASP interaction behaves as a building step, and a local search starts in a constructed solution and applies an interactive improvement, until it reaches a great location. The GRASP reference algorithm (which was also used to change and generate the so-called GRASP *) has the structure shown in detail in Algorithm 1.

Algorithm 1 shows that the analyzed parameters are based on the function $f(.)$, the graph to be analyzed $g(.)$, the maximum number of interactions $MaxInterations$ and the initial Seed of the response to be obtained. During the execution of the algorithm, the greedy solution process occurs and an analysis of the possibility that x is an acceptable response is performed. If the solution found is better than the one already proposed (line 8), there is the update process.

Algorithm 1 GRASP Pseudocode

1: **function** GRASP($f(.)$,$g(.)$,$MaxInterations$,$Seed$)
2:     $x_{best} \leftarrow \emptyset$; $f(x_{best}) \leftarrow +\infty$;
3:     **for** $k = 1, 2, ..., MaxInterations$ **do**
4:         $x \leftarrow ConstructGreedyRandomizedSolution(Seed, g(.))$;
5:         **if** (x not feasible) **then**
6:             $x \leftarrow$repair(x) ;
7:         **end if**
8:         $x \leftarrow$LocalSearch($x, f(.)$);
9:         **if** ($f(x) < f(x_{best})$) **then**
10:             $x_{best} \leftarrow x$;
11:         **end if**
12:     **end for**
13:     **return** x_{best};
14: **end function**

The algorithm 2 demonstrates the process of obtaining a greedy search [Festa e Resende, 2011]. In Festa e Resende [2011] we see some variations that GRASP present in the literature, such as:

1. *GRASP Reactive:* abstracts a learning mechanism, in a process without memory, in the construction phase of basic GRASP.

2. *Cost Disturbances:* Noise is attributed at the original costs. These perturbations are most effective in cases where the construction algorithm is not very sensitive to randomness. The disturbances can be by elimination or by changes of costs of the nodes.

3. *Bias Functions:* builds on a RCL (Restricted Candidate List) without an egalitarian probability condition, a family function of probabilities functions that create a bias for candidate selection.

4. *POP Construction:*POP (Proximate Optimality Principle) is an idea where "good solutions at one level are likely to be found" close to "good solutions at an adjacent level." The scope of this additional local search application is the "iron-out" of the current solution and its "bad" components. However, the experimental research carried out in the literature showed that the application of the idea of POP in each iteration of construction is excessively time consuming.

5. *Path-relinking:* Proposal that seeks intensification, exploring trajectories, connecting elite solutions obtained by the search for tabu or search for dispersion. From one or more elite solutions, paths are generated and explored in the space of solutions that lead to other elite guidance solutions, in search of better solutions.

6. *Parallel GRASP:* Most parallel implementations of GRASP follow the multipath independent thread strategy, based on the distribution of iterations over the processors. Two approaches can be mentioned, the Search Space Decomposition (where the search space is divided into several regions and GRASP is applied to each in parallel) and Iteration Parallelization (GRASP iterations are partitioned and each partition is assigned to a processor).

7. *GRASP in Hybrid metaheuristics:* As improvements to its basic structure, different GRASP hybridizations with several other metaheuristics were studied and proposed in the literature, such as: hybridization with the Tabu Search, GRASP Reactive whose local search was strengthened by the Tabu Research, GRASP In conjunction with genetic algorithms;

Algorithm 2 GREED Pseudocode

procedure CONSTRUCTGREEDYRANDOMIZEDSOLUTION(Seed,$g(.)$)
  $x \leftarrow \emptyset$;
  Sort the candidate elements i according to their incremental cost $g(i)$;
  while x is not a complete solution **do**
    RCL←MakeRCL();
    v ←SelectIndex(RCL,Seed);
    $x \leftarrow x \cup \{v\}$;
    Resort remaining candidate elements j according to their incremental cost $g(j)$;
  end while
  return (x);
end procedure

In Marinakis et al. [2009], an interaction between the GRASP and the Artificial Bee Colony (ABC) is presented, to optimize the clustering of N objects in K clusters. The performance of the algorithm is compared to other popular metaheuristic methods such as classical genetic algorithms, tabu research, GRASP, ant colony optimization, particle swarm optimization and honey bees mating.With such a basis on GRASP's possibilities of action, a new approach to GRASP* has been proposed in this article.

The GRASP* is based on a procedure where the random construction of the response does not have 100% randomness. A condition that p of probability (between 0 to 100%) of choice of the nearest

neighbour during the construction of the answer by the Greedy search (Algorithm 2) was triggered. An example is that, at $p = 50\%$, that is, during the greedy search process, the response would have a 50% chance of, instead of adding to the solution (which was being constructed) a random neighbour, that neighbour would now have 50% chance of being the nearest neighbour, generating a semi-random response, conditioned to p.
As already discussed, the analysis of the randomness control of this article is done on constructive heuristics and metaheuristic structures aimed at obtaining the optimal path of a truck visitation process over a certain amount of open pit mines. A Hamiltonian cycle is sought where the truck can meet the N collection points and return to the point of origin with the shortest distance d. The mathematical model of the problem has the same structure as in expressions 1. Such modeling does not include elements such as fuel, passenger or resource constraints, it only contemplates the distance between mines in the United Kingdom. However, the element d (distance) is analyzed according to the dataset used.

4. Experiments Definitions

The experiments were based on two databases, the first account with 4 instances of the dataset available in Reinhelt [2014] to benchmark the algorithms to be used (CW, NN and the proposed NN* algorithm for constructive heuristics and GRASP and GRASP* for metaheuristics). The instances are berlin52, kroA100, kroA150, and kroA200. The distances d of such references between the points are calculated by a Euclidean norm between two distinct vertices (nodes).
The second dataset, in Schruben et al. [1994], has real latitude and longitude locations of open pit mines. For a more specific focus, only the UK information (as discussed above) was used, regardless of the type of ore mined. Since the information is in real geographical locations, a specific calculation was used to analyse distances d. For this, the Haversine distance calculation was used, in 3.
According Chopde e Nichat [2013], the Haversine formula is an equation important in navigation, where great-circle distances between two points on a sphere of radius R from their longitudes and latitudes (in this case, between two points on the Earth surface - in meters - specified in longitude and latitude) with latitudes φ_1 and φ_2, that generates a separation of Latitudes $\Delta\varphi$, where $\Delta\varphi = \varphi_1 - \varphi_2$, and with longitudes λ_1 and λ_2 with the separation $\Delta\lambda = \lambda_1 - \lambda_2$. The formula 3 demonstrates this:

$$d = 2Rsin^{-1}(\sqrt{sin^2(\frac{\varphi_2 - \varphi_1}{2}) + cos(\varphi_1) + cos(\varphi_2) + sin^2(\frac{\lambda_2 - \lambda_1}{2})}) \tag{3}$$

The tests were done in two steps. The first step counts on the comparison between the constructive heuristic methods. At this moment, the tests are performed with the algorithms CW, NN and NN*. In the second stage, tests are performed with GRASP and GRASP* representing the tests with metaheuristics. In all tests, the 4 reference bases and the base that represents the problem worked are tested by the algorithms of each step and compared the results.

5. Results

The first step of the tests results in the data of table 1, which shows the result of Benchmark, comparing the two algorithms tested (CW and NN), the type of distance that each one used and the optimum value available in the literature. Note that the CW algorithm has a better ability to abstract the problem because it presents values closer to the optimal one. The Table 1 shows the best values obtained by CW, NN and NN*, and the last two were executed 100 times, due to the presence of random elements during the constructive process of the best path response.
The Table 2 presents the best case of each of the algorithms, with a improvement of the NN* over the others (overcoming the CW in some situations, as shown in berlin52 in table 2) and presenting a valid answer. Note that despite the randomness (which implies an acceptable execution cost to

obtain a response that presents a competitive value), the responses can be considered as a real implementation option, coherent and executable. According to the results presented in table 2, it can be verified that a small randomness added to the NN algorithm allowed the exploration of possibilities that brought a gain (around 16%), to the process of construction of the original algorithm. However, the price paid for the new structure reflects on the need for a certain amount of executions so that randomness can have a positive effect.

Benchmark Results				
Dataset	**Distance**	**Global**	**CW**	**NN**
berlin52	Euclidean	7542	8376	9251
kroA100	Euclidean	21282	22568	26259
kroA150	Euclidean	26524	28770	33530
kroA200	Euclidean	29368	31895	36448
USGS	Haversin (Km)	-	4965	6207

Table 1: Benchmark Comparison

Results - NN* Tests					
Dataset	**Distance**	**Global**	**CW**	**NN**	**NN***
berlin52	Euclidean	7542	8376	9251	8181
kroA100	Euclidean	21282	22568	26259	24698
kroA150	Euclidean	26524	28770	33530	31479
kroA200	Euclidean	29368	31895	36448	34543
USGS	Haversin (Km)	-	4965	6207	5212

Table 2: Results for modified NN (NN*)

It can be seen, still in table 2, that the gains between the 4 reference bases, at least once, the NN* presented a better result than the other two classic algorithms simultaneously (in berlin52). In the second stage of the experiments, directed to the proposal, denominated GRASP*. The table 3 shows a comparison of GRASP* with the other algorithms already tested in table 2. Both GRASP and GRASP* have a $MaxInterations = 100$. Table 3 shows a large difference between GRASP* responses (characteristic of a local minimum) and that these responses present a much worse quality than the optimal response in the benchmark databases. Considering the database of the problem in question there was a worse response than the other results (with an average of approximately 142% worse than the best CW response to the USGS database).

Results - GRASP* Tests						
Dataset	**Distance**	**Global**	**CW**	**NN**	**NN***	**GRASP*(50%)**
berlin52	Euclidean	7542	8376	9251	8181	14286
kroA100	Euclidean	21282	22568	26259	24698	68714
kroA150	Euclidean	26524	28770	33530	31479	110127
kroA200	Euclidean	29368	31895	36448	34543	148116
USGS	Haversin(Km)	-	4965	6207	5212	11707

Table 3: Results for modified GRASP (GRASP*)

Other tests performed with the change from p to 0 % (symbolizing the reference GRASP) and 75%, with the results presented in table 4 and the path proposed by the lower value GRASP* is shown.

Results - GRASP* Tests II					
Dataset	**Distance**	**Global**	**GRASP**	**GRASP*(50%)**	**GRASP*(75%)**
berlin52	Euclidean	7542	24931	14286	9578
kroA100	Euclidean	21282	149292	68714	42690
kroA150	Euclidean	26524	236565	110127	60376
kroA200	Euclidean	29368	308280	148116	88264
USGS	Haversin (Km)	-	24031	11707	7851

Table 4: Results for modified GRASP (GRASP*) - Test II

It is possible to notice that between the values of $p = 50\%$ and $p = 75\%$ there is a large drop in the distance for the 4 benchmark databases. Taking the GRASP* with $p = 75\%$ as reference (the smallest values), there is a gap ranging from 48% to approximately 68% compared to GRASP* with $p = 50\%$ and values from 160% to 258 % comparing with GRASP. The reduction in the cost of responding to the problem in question (with the USGS database) of approximately 49% between the two GRASP* options is noteworthy. However, for an optimal response, neither proposal obtained a better value than CW. The normal GRASP presented very high values, however, due to the complexity of the problem and a low number of interactions (100 executions).
With the experiments demonstrated, it is possible to analyze the positive impact that the new proposals can present for the problem of minimum paths for trucks operating in open pit mines:

- The methodology of analysis contemplates geographic locations, allowing an analysis linked to the positioning coming from mine GPS (Global Positioning System) information , as in de Silva et al. [1996].
- With the NN* it was possible to diagnose a saving of 16% in the minimum path proposed in relation to NN for the visitation of all the mines.
- GRASP* (with $p = 75\%$) represents a metaheuristic capable of presenting a solution to the real problem of visiting open pit mines with approximately 70% economy (in Km) with only 100 executions compared to original GRASP.
- Savings of time of operation and maintenance of trucks, in addition to the expense with fuel were implicitly obtained.

These savings will impact on the activity that, as already commented, corresponds to 60% of the investment mining in open pit mines.

6. Conclusion

With the results shown, it can be confirmed that a small randomness properly inserted in an algorithm already consolidated in the literature, can present promising results. Just as a certain index of control over a complete randomness can also offer gains.
Taking the NN* and GRASP* in comparison, considering the question of randomness, this question worked in opposite ways for the two. While the NN* benefited from the introduction of randomness (as shown in Table 2, where it gained in some comparisons and presented satisfactory answers to both the problem and the benchmark bases), GRASP* benefited from the control over the random question (the best results were presented with a higher probability p of the nearest neighbour being chosen).The computational cost that can be attributed to the search for a better solution, due to the number of executions, may or may not be feasible for the problem analysis process, varying in the types of problems addressed.
For the problem of open pit mine, taking the territory in question, the NN* presented a viable solution, with a simple implementation and a reasonable computational cost. On the other hand, GRASP* presents an acceptable response, although it has minimal local evidence. This solution

can enable savings during the process of servicing mines trucks, reducing the paths traveled, consequently collaborating with issues of fuel, truck wear and maintenance demands.

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