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Productivity Optimization by Optimal Allocation of Human Resources with Application in Real Case at the Wagons Maintenance of Iron Ore Rail Transport

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***Abstract*—*In the current industry the search for process optimization has been more and more constant, however many times this practice proves to be quite complex given the number of variables involved, an example of this is the case where from a heterogeneous group of workers want to define the best set of work pairs so that the collective productivity is as high as possible. In situations like this, the use of the metaheuristic genetic algorithm becomes quite attractive, since in the literature there are many examples of its use in the optimization of non-linear problems, with continuous and discrete characteristics of the control variables and with an exponential increase in the number possible solutions, in addition to the flexibility to incorporate the real problem constraints into the solution. In this context, this study codified a problem of real case for the definition of work teams in a mining wagon maintenance workshop. In the theoretical simulation stage, using historical team performance data, the genetic algorithm indicated a 22 percent better solution when compared to the random choice of work teams. Finally, the solution suggested by the genetic algorithm was implemented in the field, resulting in a performance increase of 7.9percent.*

I. INTRODUCTION

The constant need to increase competitiveness makes companies look for each once again optimize its processes and resources, among these, the rational use of labor can be highlighted, that is, properly distribute the people available to perform tasks on service fronts, so that the overall productivity of the process is maximized.

Human being by nature is a social being who by affinity criteria tends to form groups, thus the interpersonal relationship in the work environment is quite complex, involves many variables and among others can affect the indicator of productivity of an organization. That said, it is a current challenge for organizations to define the optimal allocation of personnel and guarantee the ideal working conditions, so that the highest possible profitability is obtained.

However, due to the high number of variables involved in the optimization 15 of the allocation of labor, the use of metaheuristic optimization techniques represents a very attractive alternative due to its robustness combined with results very close to the global optimum at a low computational cost. One of the most representative metaheuristic methods are genetic algorithms (GA), since they are based on the theory of natural evolution and genetics, have practical 20 application in the most different areas and stand out for their robustness and efficiency such as [1] and [2].

This work has as general objective to observe the dynamics of optimum allocation of human resources obtained by a traditional and recognized robust metaheuristic algorithm for problems with discrete characteristics, applied in a real scenario of a train wheel maintenance workshop that serves the mining market. This type of problem involves aspects of uncertainties in the algorithm's input data that attribute errors between the computational results and the field tests. This approach provides a perception of validation of the problem coding and attributes a potential of traditional optimization to the potential of less commonly used applications.

In a scenario of continuous search for process optimization and waste reduction in industries, it is extremely important, above all, to allocate resources available to perform tasks in the most appropriate way ([3]).

First of all, it is worth mentioning that in the routine of a railway maintenance area, decision making is a constant, some of them, due to the required agility added to the large number of variables involved, are not always taken in the best way, which can generate costs and inefficiencies in the production process ([4]).

On any freight railroad, one of the assets that most deserve attention by the maintenance team is its wagons, which show wear and tear mainly on its wheels due to wheel-rail contact. As a result, in addition to the wheels, the wagons also have a high maintenance demand on their bearings, these are positioned at the ends of the axles where the wheels are fixed and serve as a support point for the box of the wagon where the cargo is packed for transportation.

The set formed by an axle, two wheels and two bearings is called a wheeler, with each wagon having four of these in its structure. The workshop where this work was applied is responsible for maintaining the wheels of the iron ore wagons of a global mining company, whose fleet allocated to the railroad in question is close to 20 thousand wagons, thus totaling 80 thousand wheels.

Indeed, on the railroad to which this work refers, for operational reasons, when a car is identified with the need to change one or more wheels, it is not maneuvered alone for the maintenance shed, but within a fixed lot of 110 wagons called a homogeneous lot.

Thus, if you want to replace a single wheel of a wagon and considering that this activity takes 12 minutes, in fact it will not be just a wagon that will be stopped for maintenance for this time, but 110 wagons will be stopped for 12 minutes, waiting for a single asset to be maintained, that is, instead of 12 minutes of loss, there will be 1,320 minutes of available wagon time reduction.

In the case study approached monthly, the goal is to replace 4,500 defective wheels, knowing that each of these will require stopping a complete batch of 110 wagons, therefore, any reduction in the wheel change time has a potentialized gain due to the high quantity of impacted wagons, namely, for this monthly goal of changing wheelers, a reduction of 1 minute in the unit time of this activity would imply a gain of 495,000 minutes of available wagon time.

In this context, the present work is motivated to provide, through the use of the metaheuristic genetic algorithm, an optimized solution for the definition of workers pairs in a wagon maintenance workshop, more specifically maintenance of wheelsets, a problem that due to the many variables involved ends up making it is impossible to be optimized through simple human analysis.

II. INTELLIGENT SCHEDULING AND HUMAN RESOURCE MANAGEMENT OPTIMIZATION

The human factor has become an important competitive strategy in the nowadays industry, beside this, the fast change in workplace has demand new approaches to human resource management in order to optimize the workforce productivity and efficiency ([5]).

The article [6] describe in their work that most of companies has realized that with the increase of market competition only reduce its operation cost is not an advisable long-term strategy, so optimize process becomes more important than only reduce cost.

Workforce planning is a complex problem and its optimization is a NP-hard problem, so depending on its size, it could be impossible to be solved with exact or traditional numerical methods ([7]).

Manage the organization´s manpower and resources allow effective outcomes to be achieved, and nowadays with the use of technological devices it is possible to improve the virtual human resource management in order to keep track of staff performance and have the maximum outcome from the team using them minimum resources of the company ([8]).

Some industries have the human resource allocation management more important and complex than to others, for example the software industry, where usually multiskilled teams work in multiple projects, in this case optimization methods play an important role to minimize the total time needed in order to deliver a software, in the minimal cost and obeying the problem constraints ([9]).

The work of [9] presents an example of human resource optimization in software industry, where the focus was to combine Human Resource Allocation (HRA) and Staffing and Scheduling Software Project (SSSP) optimization.

SSSP problems are more complex to optimize than HRA problems, for the first one there is a general knowledge that meta-heuristic optimization is the best approach to adopt and the is very usual to use genetic algorithm ([10]).

The article [10] work divides workforce optimization in qualitative and quantitative models, the first one assumes a binary logic, where a worker has or not some skill, different from quantitative way, where for each worker each skill is quantified in a numeric range, so this allows that the workforce attributes be analyzed in a mathematical way.

The work [11] present in their work about different techniques of intelligent scheduling, one of the most efficient is the artificial intelligence approach, like as genetic algorithm, ant colony, fuzzy logic, etc.

It is possible to see some researches focused in improve human resource management using some methods based on fuzzy logic theories or heuristic optimization algorithms, as example of the work [5] that present an approach to provide a method to help managers to make decision in daily human resources management tasks.

III. METAHEURISTIC OPTIMIZATION

There is a lot of nature inspired metaheuristic methods to solve optimization problems, like as genetic algorithm and ant colony optimization, both proved to be very effective to this kind of use ([7]).

As [12] describe in their work, metaheuristic methods are very effective for complex optimization and can be used in general-purpose optimization problems from the real world.

The metaheuristic optimization methods offer good solutions in reasonable computational time, that is extremely important mainly for real-world problems which usually involve several variables and constraints that become the solution more complex ([13]).

One way to improve the performance of an optimization problem solution is to combine different metaheuristics techniques, what is called hybrid metaheuristic solution. This combination can be described as different metaheuristics methods applied sequentially at the same problem and at the end of process a better solution is obtained than in the case where only one method is applied ([14]). There are a lot of metaheuristic algorithms, for example Ant Colony Optimization, Genetic Algorithms, Particle Swarm Optimization, Simulated Annealing, Tabu Search, etc. These methods can be combined in the same problem in order to generate a hybrid algorithm that exploits the advantages and avoid the disadvantages of the multiple strategies combined ([14]).

The performance of mutation and crossover operator’s effects directly the genetic algorithm ([15]), The exploration ability in GA is one of the biggest advantages over traditional optimization methods, it allows GA to decrease the chances of trapping in local optima. ([16]).

The article [16] classify metaheuristic methods in three categories: evolutionary based, physics-based and swarm-based techniques, all of then inspired in animal behavior or physical phenomena.

The propose [17] show that meta-heuristic algorithms when compared with traditional methods, such as random optimization, perform much better in terms of the computational effort and the quality of the solution provided.

IV. APPLICATIONS OF GENETIC ALGORITHMS

The use of genetic algorithms in the optimization of processes is quite common and diverse, it is possible, for example, to use the technique in the optimization of the maintenance strategy of industrial equipment, obtaining the optimal periodicity for carrying out maintenance plans so that the equipment reliability is as high as possible with the minimum cost.

The article [18] presents a literature review about Flexible Job Shop Scheduling Problem (FJSSP) by approaches involving Genetic Algorithm (GA).

Another very common application of optimization through genetic algorithms is in the definition of work scales, which can be applied in the most diverse segments.

In addition to the use of genetic algorithms to define scales of team work, it is possible to find applications of GA for the formation of groups, as mentioned by the work of [19] where an GA was used to, from a heterogeneous group of students, suggest a combination of study groups for a distance learning platform, considering that the students allocated in each group had the least possible diversity in terms age, discipline, daily study time and study time.

The work of [20] used genetic algorithm in their work to optimize task scheduling in cloud computing environment and compared the results with several other methods in terms of total completion time, average response time, and quality of service parameters.

The work of [21] presents a metaheuristic optimization using genetic algorithm designed to provide an optimal cut-off grade in order to maximize the net present value in an operating mine process.

The work of [22] presents different metaheuristic methods being used to identify parameters of photovoltaic module, in this case were applied four methods: differential evolution, artificial bee swarm optimization, modified particle swarm optimization and artificial bee colony.

A genetic algorithm was used in the work of [23] to optimize the shape of a wind turbine. [24] presented in their job an optimization of generators' efficiency in a thermoelectrical process using genetic algorithm, where was seen that the output power and efficiency of these increased 51.9% and 5.4% when compared to case without optimization.

In some cases, a problem presents a multi-objective optimization and metaheuristic methods are also appropriate in situations like this, for example in the work of [15] where a multi-objective optimization was done using a hybrid metaheuristic algorithm to minimize operational and environmental costs in a waste collection operation.

V. WAGON MAINTENANCE

The maintenance scope of railway wagons is quite wide, due to the varied range of components that require maintenance, such as wheels, bearings, brake system, couplings and even the wagon's own superstructure.

However, neglecting one or more of the aspects mentioned puts the railway's operational safety at risk, which can lead to major accidents with effects on the company's assets, the environment and even people.

5.1 Basic structure of a wagon

Among the various components of a railway operation, we highlight the rolling materials, which can be divided into the group of those that are pulled and those that are towed. However, among the tractors it is worth mentioning mainly the locomotives, responsible for tractioning the entire composition by the railroad, while in the group of towed vehicles, the wagons deserve special mention, which allow the packaging and adequate transport of the most varied loads by rail ([25] and [26]).

In Figure 1, a gondola wagon is shown, which is the most common type used for transporting iron ore and other minerals.

Fig. 1: Wagons. Source: [27]

Generally speaking, a wagon can be divided into four main elements, each of which has a defined function for the asset and can be subdivided into subcomponents, as shown in Figure 2.

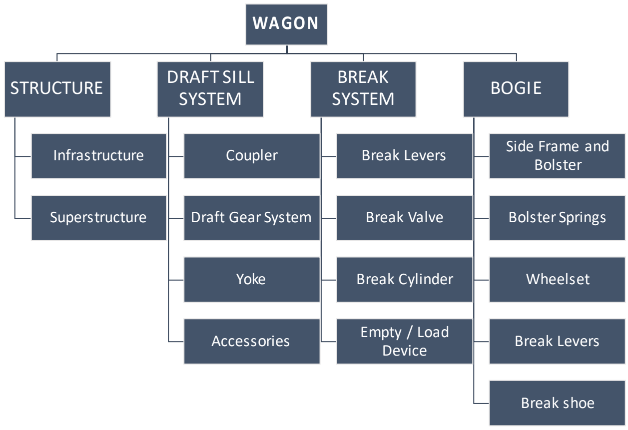

Fig. 2: Typical structure of a railway wagon.

The wagon's structure itself is divided into superstructure and infrastructure, since the first one corresponds to the box or platform of the wagon, responsible for the conditioning and security of the cargo to be transported, while the infrastructure is the support base of the superstructure.

The shock and traction set is responsible for ensuring the connection between the wagons, each of which has a hitch at its rear and another at the front in order to enable the series connection of several wagons.This set also plays an important role in absorbing the impacts of traction and compression between vehicles arising from the acceleration and braking dynamics of a train.

The brake system, on the other hand, performs the relevant function of controlling the speed of the train, this is done through a pneumatic system that, once combined with the brake gear and a set of shoes, allows the application of brake on the wheels of railway vehicles. Finally, the trick is responsible for distributing the weight of the wagon structure and the load to the rails through the wheels, in addition to inscribing the wagon in the curves and cushioning the impacts from the track and the rail wheel contact.

Each wagon has two tricks in its assembly, these can present different configurations as to some elements of their constitution, however the principle of operation is essentially the same. Figure 3 shows a very common trick used in railway cars.

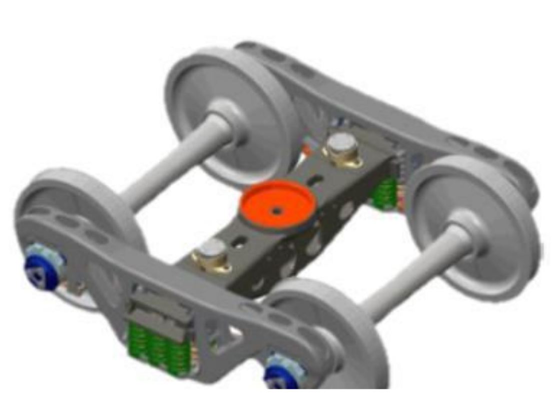

Fig. 3: Trick of a wagon. Source: [27]

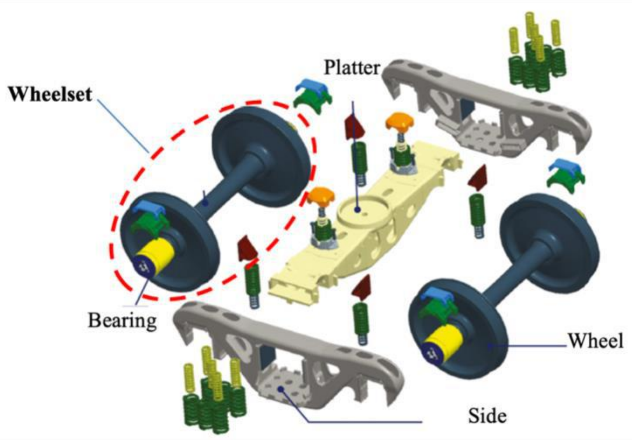

Fig. 4: Exploded view of a wagon trick. Source: [27]

As shown in Figure 4, the wagon wheels are in the trick, each pair of them is connected by an axle with two bearings at its ends, on which the right and left of the trick. This set formed by a shaft, two wheels and two bearings is called a wheel.

5.2 Aspects of wheelchair maintenance

Among the different components to be maintained in a wagon, one of the most important are its wheels, each of which, as previously mentioned, is formed by a set of two wheels connected by an axle with a bearing at each end. In this way, there are four wheelers per wagon, responsible for supporting the total load of the railway vehicle in addition to keeping it on the tracks.

As the wagon moves along the railroad, each wheel of the railroad wears out, 230 both in the wheel, due to the wheel-rail contact, and in the bearings, due to the friction that occurs in its internal parts, being in any railroad. Management of the maintenance of its fleet of wheelers is fundamental.

In this context of continuous deterioration of the wheels, as the wagons move along the railroad, the number of wheels to be maintained constantly changes, 235 thus, new wheels are added daily to the list of those in need of maintenance, in addition to replacing defective wheels. By others good in the maintenance shed.

Once the wheel is removed to maintain it is not discarded, but recovered, for this it is necessary to machine the wheels so that they acquire the proper profile again and have any defects in their bearing surface removed, and for cases of bearing defects, it is necessary to remove the old bearings and install new or maintained bearings.

The workshop where this work was developed is located in S˜ao Lu´ıs in Maranh˜ao and is responsible for replacing defective wheels with others in good condition.

As for the structure, the workshop in question has 5 railway lines for simultaneous change of wheels, operating 24 hours a day, every day of the year, which has provided about 4,500 wheels changed per month.

5.3 The wheel change process

To replace a wheel in the workshop where this work was developed, equipment called a false table is used, for this the wagon where the wheel to be replaced is located on this table, more specifically the wheel in question must be aligned with the center of the table base, then once this position is reached, two mechanics make a first intervention in order to release the wheel that will descend along with the base of the false table towards an underground gallery.

After the descent of the wheel to be maintained, the new wheel takes exactly the opposite path from the removed wheel, that is, the new wheel is raised through the false table from the underground gallery to the wagon trick, after that the two mechanics again intervene in the wagon and complete the wheel replacement.

The sequence of the steps for replacing a wheel is illustrated in Figure 5 where the steps for positioning the wagon, removing the wheel to be maintained and installing the new wheel are shown.

Each wheel change is made simultaneously by two mechanics, one acting on the right side and the other on the left side of the wagon, each of whom is responsible for a set of tasks until the new wheel is placed on the maintenance wagon.

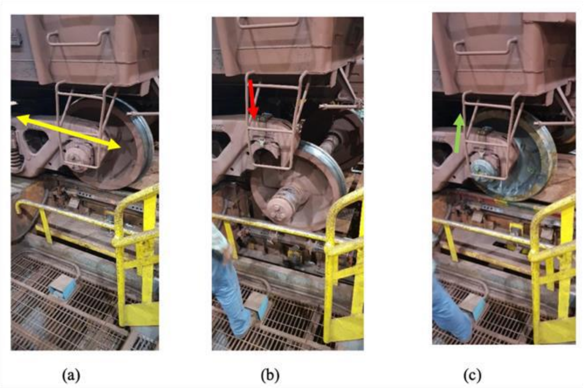

Fig. 5:Sequence of steps when changing wheels: positioning the wagon wheel on the table (a), removing the defective wheel (b) and installing the new wheel (c).

The estimated time for a pair of mechanics to change a wheel is 12 minutes, which is budgeted based on the ability to perform the task associated with the operational need to meet the ore transportation budget.

Each time this change is made, one of the mechanics of the pair registers the data of the maintenance they have just performed in a computerized system, using afor this purpose, with tablet the following information highlighted:

- Maintained car code
- Reason for changing the wheel
- Start time of the wheel change
- End time of changing the wheel
- Mechanics who changed the wheel
- Justification for carrying out maintenance above the expected time (if it exceeds 12 minutes)

5.4 Aspects of the problem complexity

Among the total of 120 possibilities of pairs, it is highlighted that in the formation of the set of 8 pairs, the same mechanic can only be present in a single pair, thus, the total possible scenarios of groups of 8 doubles formed from 16 mechanics can be calculated by the sequence below of products of combinations taken two by two:

$$Number\ of\ possible\ solutions = C_2^{16}.C_2^{14}.C_2^{12}.C_2^{10}.C_2^{8}.C_2^{6}.C_2^{4}.C_2^{2} \quad (1)$$

Looking at Equation 1, we can see a sequence of products of combinations taken two by two, which makes it possible to arrive at Equation 2, which generalizes the calculation of the total number of possible solutions for a problem of this type to an even number any M of mechanics.

$$Number\ of\ possible\ solutions = \prod_{i=0}^{i=(M-2)/2} C_2^{M-2i} \quad (2)$$

Once the expression of the combination contained in Equation 2 has been unfolded, Equation 3 is obtained, in which, due to the number of solutions possible for the problem to vary with the factorial of the number of mechanics M.

$$Number\ of\ possible\ solutions = \prod_{i=0}^{i=(M-2)/2} \frac{(M-2i)!}{2.(M-2i-2)!} \quad (3)$$

Knowing that the workshop where this work was developed has 16 mechanics in the morning shift, the number of options for groups of 8 pairs that can be formed with this team can be calculated using Equation 3, as shown below:

$$Num\ Options = \prod_{i=0}^{i=(M-2)/2} \frac{(M-2i)!}{2.(M-2i-2)!} = \prod_{i=0}^{i=(16-2)/2} \frac{(16-2i)!}{2.(16-2i-2)!} = \prod_{i=0}^{i=7} \frac{(16-2i)!}{2.(14-2i-2)!} = 81{,}729{,}648{,}000 \quad (4)$$

From the previous result it can be seen that the problem in question has 81,729,648,000 solution scenarios, that is, given a group of 16 mechanics, there are more than 80 billion possibilities of forming clusters of 8 double with them.

VI. CODING OF THE PROBLEM OF OPTIMAL PERSONNEL ALLOCATION IN THE MAINTENANCE OF WAGONS

Since this work used real field data, an extensive phase of field data collection and processing was initially necessary in order to provide the input information for the GA.

Considering the complexity of the database, in the initial stage of this work some assumptions and restrictions to the problem were assumed, such considerations will be addressed in the first part of this section and in the sequence the aspects of the coding and optimization of the problem will be detailed.

6.1 Preparation of the database

Given that each wheel change is registered in a maintenance system, it was possible through historical data to evaluate the performance of each mechanic by teaming up with different co-workers, that is, assuming a team of N mechanics, each of these being able to form N-1 doubles and each of these with their own average wheel change time.

Regarding the data of wheel changes used in this study, those that met the following specifications were considered:

- Made between January 1, 2018 and January 31, 2019

- Made between 7:00 am and 4:00 pm

- Made by exactly two mechanics

- Made by mechanics who after January 2019 were still on the shift from 7am to 4pm

Considering these criteria, 3,126 samples of wheel changes were part of the study, made by a total of 16 mechanics.

For the sample space of 16 mechanics, each possible solution of the problem will be formed by a grouping of 8 pairs, with a total of 120 different pairs possibilities (combination of 16 elements taken two by two).

From the historical data of the 3,126 wheel changes considered, of the 120 possibilities of workers pairs it was possible to obtain 96 average times of change, that is, so far there were 24 pairs whose mechanics had not worked together before to have their time sampled. For this group of pairs without a previous sample, the joint time of the pair was obtained from an approximation based on the individual times of each member of the pair.

Assuming A and B two mechanics who have never worked together and who are in the group of 24 pairs without sampling time, a weighted average between the average time of changing A's wheelset was considered as an estimate of the average wheel change time for double AB with other mechanics (excluding B), and the average time of changing B's wheel with other mechanics (excluding A), adding to this weighted average a constant of adjustment.

The weighting coefficients were obtained from the data of the 96 pairs that had their times already sampled, these were interpolated through the SOLVER tool in Excel in order to obtain an equation that allowed to calculate the time of a pair from the individual times of two mechanics, seeking to present a minimum error.

The following is a summary of the steps described in this session in Figure 6, which were followed to collect and prepare the database.

Once all the average wheel change times were obtained for the 120 possible workers pairs, the problem was modeled so that the genetic algorithm proposed an optimized combination of 8 mechanical pairs, so that the average change time of the wheels of this set was minimized.

6.2 Sequence of work adopted for optimization in the field

During the implementation of the AG, theratewere fixed crossover and the stopping criterion, but different parameters of population and mutation rate were considered in order to evaluate the performance of the GA in different configurations.

Each GA configuration was simulated 50 times and its results were compared with each other and also with respect to random choice and optimization, with the configuration that presented the best performance considered to be taken forward to the practical field-testing phase.

After the GA and its respective parameters were validated, it was moved to the field-testing phase, for which a smaller scope of mechanics was considered, since the 16 initially evaluated worked in two different provinces which would imply greater difficulty. to conduct the study simultaneously in two groups. Thus, we opted for the inspectorate that had more mechanics and that presented more sampled data from wheel changes, which would guarantee a greater consistency of the database to be considered.

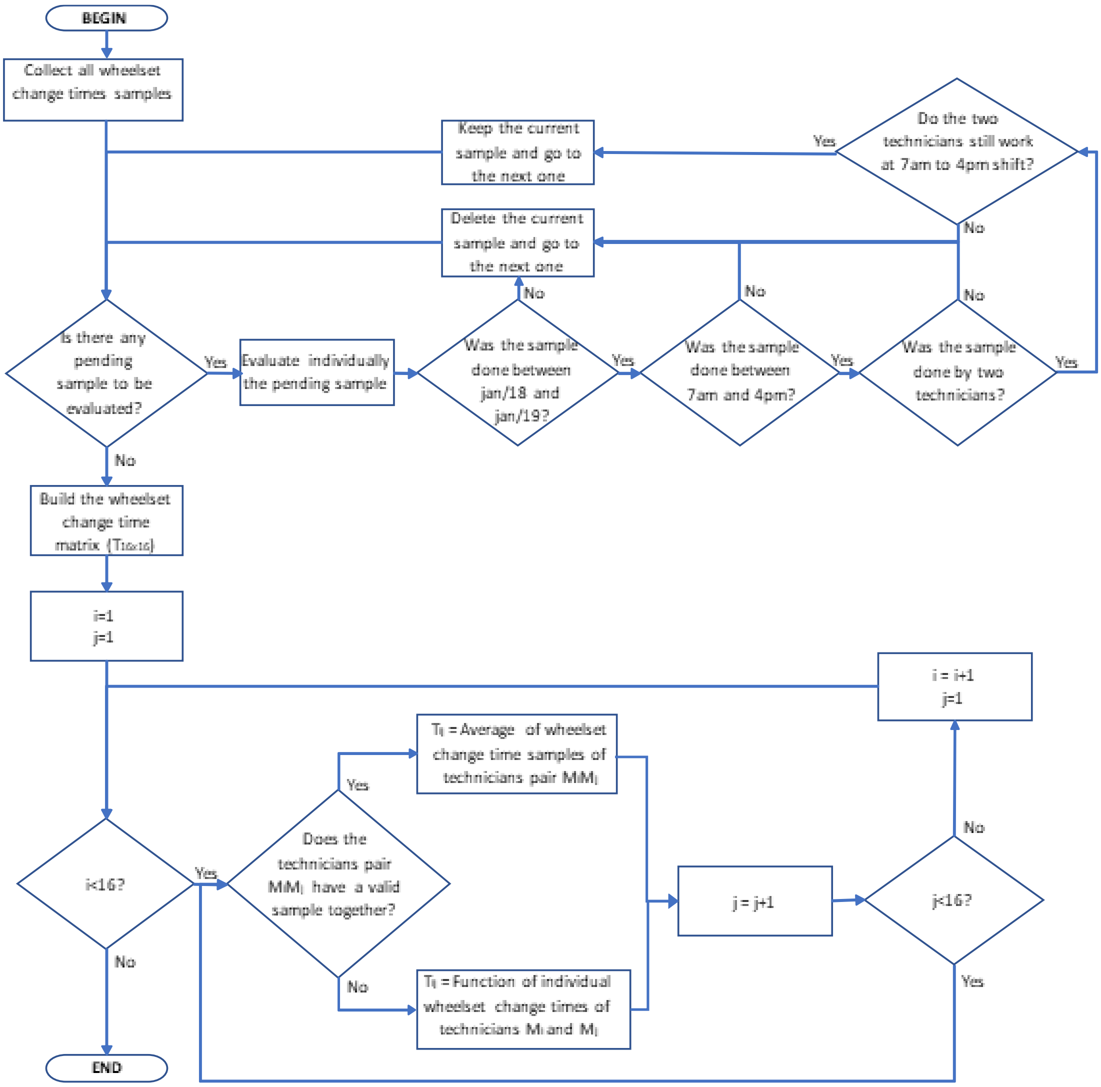

Fig. 6:Flow followed for collection and treatment of the database.

Thus, for the field testing phase the GA was run again considering now only the combination of mutation rate and population size that showed the best performance among the simulations made for the group of 16 mechanics. In this sense, considering from now on only the mechanics of the prioritized inspectorate, 10 mechanics were evaluated and, at the end of the optimization, were grouped into 5 workers pairs.

These 5 workers pairs proposed by the GA were implemented in practice,which caused a change in the scale of some employees and change in workers pairs 375 until then practiced, this new configuration being practiced for three months, between April and June 2019.

After three months of tests, it was then evaluated whether there was a reduction in the average time for changing wheels for this group of 10 mechanics, in addition to also comparing the average time for exchanges made by the called optimized pairs with those made by randomly formed pairs.

Figure 7 shows the flow of simulations and field tests, it can be seen that GA was tested with 6 different combinations of mutation rate and population size, with the best result being tested in the field within a control group.

To process the GA, a computer with a 2.10 GHz AMD processor, with 8 GB RAM and a Windows 10 64-bit operating system was used, being used in implementation of the Visual Basic programming language within the Excel environment.

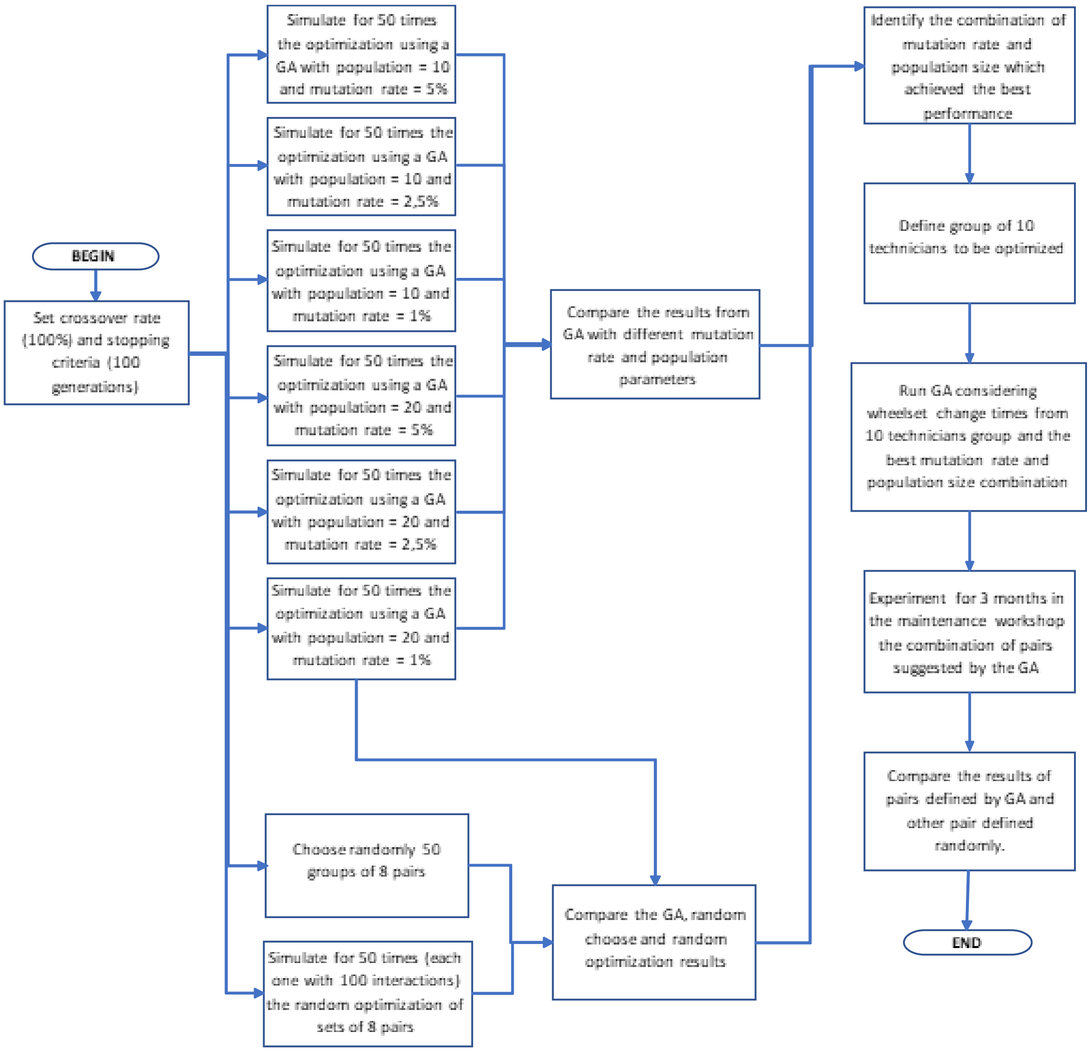

Fig. 7:Flow followed for simulations and field tests.

VII. TABULATION OF THE AVERAGE TIME OF CHANGE OF WHEELSET BY WORKER PAIR

The data of average time of change of wheelset by worker pair were structured in a matrix form, where the element T_{ij} represents the average time of change of wheelset formed by the pair mechanic i with mechanic j.

In this sense, it should be noted that in this time matrix the main diagonal of the same should not be considered valid, since a mechanic cannot pair with himself.

Another characteristic of the time matrix is that it is symmetrical, this is due to the fact that the average changeover time for the wheels of the mechanics pair AB is exactly equal to the time of the double BA, that is, the element T_{ij} of the matrix is exactly equal to the element T_{ji} , for any and i and j less than or equal to the total number of mechanics.

In the case of the problem in question, since there are 16 mechanics, the wheel change times table consists of a 16 x 16 matrix, where each element corresponds to the historical average of wheel changes made by two mechanics. A representative letter was assigned to each of the 16 mechanics, so the time 405 matrix looks as shown in Table 1.

To complete of Table 1, 240 data of average times of change of wheelsets were needed, which can be reduced by half given the symmetry of the table. However as seen previously, of the 120 required times 24 had never been sampled, that is, the mechanics of the pairs associated with the empty cells, in Table 1, until the time of data collection had never worked together before and therefore it was not possible to obtain their time. Despite the 24 missing times, another 96 were successfully obtained from historical data, so 80% of the data needed to use as an entry to the AG was available, which were then used to estimate the 20% that had no previous samples.

Table 1: Actual data on average wheel change times for 16 mechanics (min).

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
A	-	23.4	19.0	10.6	11.9	13.5	12.6	18.0	14.5	11.4	14.3	12, 7	11.9	13.0	16.1	12.6
B	23.4	-				11.7	21.7		20.6	15.0		15.0		19.5	17.2	12.6
C	19.0		-		14.9	14.8	18.0	11.7	17.3			10.4	12.8		13.2	11.0
D	10.6			-	12.0		11.5	12.4	11.2	13.0	23.5	10.8	12.8	11.8	17.2	12.3
E	11.9		14.9	12.0	-	12.5		16.3	15.9	21.7	21.5	15.5	15.8	11.8	14.3	12.3
F	13.5	11.7	14.8		12.5	-		33.0	13.6	11.3	15.3		13.0	10.4	12.4	10.8
G	12.6	21.7	18.0	11.5			-		12.0	10.7	16.3	11.3	12.9	10.9	25.6	12.9
H	18, 0		11.7	12.4	16.3			-					33.0 to 12.3	11.4		14.7
I	14.5	20.6	17.3	11.2	15.9	13.6			-		12.0 to 17.3	13 , 6		23.5		
J	11.4	15.0		13.0	21.7	11.3	10.7			-	12.9	12.1	11.5	14.0	26.0	14.0
K	14.3			23.5	21.5	15.3	16.3		17.3	12.9	-	13.0	12.2	14.0	14, 8	12.8
L	12.7	15.0	10.4	10.8	15.5		11.3		13.6	12.1	13.0	-	14.0	13.6	15.3	12.7
M	11.9		12 , 8	12.8	15.8	13.0	12.9	12.3		11.5	12.2	14.0	-	13.1	13.6	12.8
N	13.0	19.5		11.8	11.8	10 , 4	10.9	11.4	23.5	14.0	14.0	13.6	13.1	-	10.3	8.2
O	16.1	17.2	13.2	17.2	14.2	12.4	25 , 6			26.0	14.8	15.3	13.6	10.3	-	8.2
P	12.6	12.6	11.0	12.3	12.3	10.8	12.9	14.7		14.0	12 , 8	12,7	12,8	8,2	8,2	-

Among the 96 pairs with times already sampled in the evaluated history, 42 of these had at least 25 samples considered in determining their average wheel change time, so given their greater representativeness of data, these 42 pairs were considered to interpolate an equation that would allow estimate the average time for changing the wheel of a pair that had never worked together before, using the individual times of each mechanic when working with other partners.From the 42 times of the pairs whose values were obtained from more than 25 real samples each, an equation was simulated that considered the time of the 425 pair as being a weighted average between the time of the fastest mechanic in the pair and the slowest, adjusted by a correction constant, as shown in Equation 7.

$$Changeovertime = \alpha . SlowMechalnicalTime + \beta . FastMechalnicalTime + \gamma \tag{7}$$

After SOLVER processing, tool from Excel Microsoft Software, Equation 8 was reached, which when used as a comparison with the actual measured results 430 of the exchange times of the 42 pairs with more than 25 samples each, presented an average error of 7.8%. Thus, the 24 pairs that did not have previous samples had their average wheel change times estimated from Equation 8.

$$Changeovertime = -0.69 . SlowMechalnicalTime + 1.64 . FastMechalnicalTime - 0.07 \tag{8}$$

With the equation 8, it was possible to complete the remaining times in the matrix of average wheel change times, and then Table 2 was used as the input base for the genetic algorithm to be implemented. To provide the average wheel change times presented in Table 2 was used a huge electronic database with historical data of this task done by different mechanics, totalizing 21.856 samples, but considering that the main objective of this work was to implement in the real life the optimization suggested by GA, was necessary to discard 8.298 wheel change time samples that had the participation of workers who do not work anymore at the maintenance workshop.

Considering that there are some outliers in the 13.558 left samples after remove those done by past workers, a statistic treatment was necessary to remove these outliers, so in the end was used 12.037 samples statistically valid,8.

Table 2: Actual and estimated data for average wheel change times for 16 mechanics (min).

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
A	-	23,4	19,0	10,6	11,9	13,5	12,6	18,0	14,5	11,4	14,3	12,7	11,9	13,0	16,1	12,6
B	23,4	-	12,5	10,6	12,0	11,7	21,7	15,1	20,6	15,0	14,0	15,0	13,0	19,5	17,2	12,6
C	19,0	12,5	-	11,8	14,9	14,8	18,0	11,7	17,3	13,5	13,1	10,4	12,8	13,6	13,2	11,0
D	10,6	10,6	11,8	-	12,0	12,1	11,5	12,4	11,2	13,0	23,5	10,8	12,8	11,8	17,2	12,3
E	11,9	12,0	14,9	12,0	-	12,5	13,3	16,3	15,9	21,7	21,5	15,5	15,8	11,8	14,3	12,3
F	13,5	11,7	14,8	12,1	12,5	-	12,9	33,0	13,6	11,3	15,3	12,7	13,0	10,4	12,4	10,8
G	12,6	21,7	18,0	11,5	13,3	12,9	-	12,1	12,0	10,7	16,3	11,3	12,9	10,9	25,6	12,9
H	18,0	15,1	11,7	12,4	16,3	33,0	12,1	-	15,8	12,0	13,7	12,5	12,3	11,4	13,4	14,7
I	14,5	20,6	17,3	11,2	15,9	13,6	12,0	15,8	-	12,0	17,3	13,6	12,7	23,5	13,4	11,5
J	11,4	15,0	13,5	13,0	21,7	11,3	10,7	12,0	12,0	-	12,9	12,1	11,5	14,0	26,0	14,0
K	14,3	14,0	13,1	23,5	21,5	15,3	16,3	13,7	17,3	12,9	-	13,0	12,2	14,0	14,8	12,8
L	12,7	15,0	10,4	10,8	15,5	12,7	11,3	12,5	13,6	12,1	13,0	-	14,0	13,6	15,3	12,7
M	11,9	13,0	12,8	12,8	15,8	13,0	12,9	12,3	12,7	11,5	12,2	14,0	-	13,1	13,6	12,8
N	13,0	19,5	13,6	11,8	11,8	10,4	10,9	11,4	23,5	14,0	14,0	13,6	13,1	-	10,3	8,2
O	16,1	17,2	13,2	17,2	14,3	12,4	25,6	13,4	13,4	26,0	14,8	15,3	13,6	10,3	-	8,2
P	12,6	12,6	11,0	12,3	12,3	10,8	12,9	14,7	11,5	14,0	12,8	12,7	12,8	8,2	8,2	-

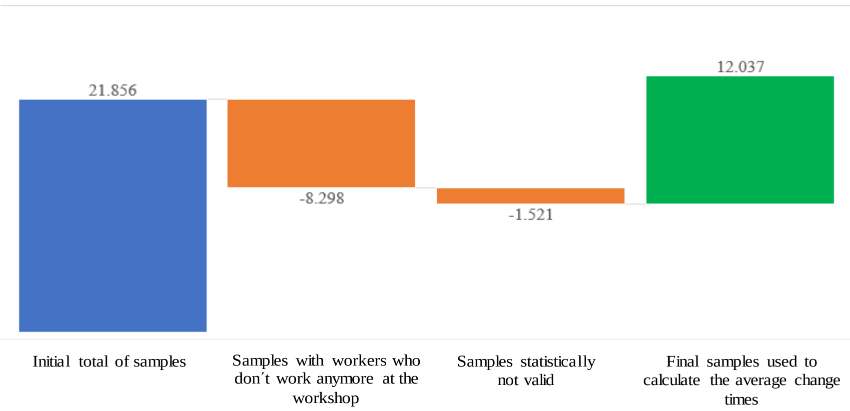

Fig. 8:Quantitative sample data of workers used.

VIII. COMPUTATIONAL CALCULATIONS AND ANALYSIS OF RESULTS

The GA modeling was conceived through order-based representation, thus each chromosome was composed by a sequence of 16 letters, so that each letter represented a different mechanic, with each two sequential letters representing a worker pair. In summary, a chromosome of the problem in question corresponds to a grouping of 8 pairs and its objective function is the result of the average changeover times for these 8 pairs, whose times are shown in Table 2. An example is given in Table 3 viable chromosome for the problem at hand.

Table 3: Example of a viable chromosome for the problem.

	Par 1		Par 2		Par 3		Par 4		Par 5		Par 6		Par 7		Par 8		Average Time Chromosome (min)
	C	K	G	L	F	D	J	B	H	O	E	M	I	N	A	P	14,6
Double Time (min)	13,1		11,3		12,1		15,0		13,4		15,8		23,5		12,6		

To test the performance of GA against different input parameters, it was evaluated by varying the population size (10 and 20 individuals) and the mutation rate (1%, 2.5% and 5%), thus totaling 6 different combinations, defining for all the same stopping criterion that was the limitation in 100 generations.

The crossover rate was 100% and the method of choosing individuals to cross was linear standardization, a method very similar to the roulette wheel, with the only difference that the probabilities of each chromosome draw depend not only on the original aptitude of the individuals, but rather of the relative position of each one of them before the list of all the chromosomes of the population when ordered in descending order by criterion of aptitude. The performance evaluation of each chromosome was done through the fitness function shown in Equation 9, where N is the number of individuals in the population, and i is the chromosome index in the population in decreasing order of the objective function. It is usual to adopt 1 ≤ Max ≤ 2 and Max+Min = 2, so in this work was set Min = 0.5 and Max = 1.5.

The Max and Min parameters defines the selection pression, the bigger the difference between Max and Min the bigger the selection pressure will be, this way the GA search will strongly favor the best individuals found so far, in opposite, low selection pressures favor a little bit more chromosomes with low fitness, but at the same time allow the GA to explore unknow search areas.

$$Fitness = Min + (Max - Min).\frac{Ni}{N-1} \qquad (9)$$

From the fitness presented in Equation 6 it was possible to potentiate the 475 performance differences between chromosomes, since if they were evaluated directly by the original objective function, which is the average of the wheel change times of the 8 pairs of the chromosome, there would be a greater risk of individuals with good and bad performances presenting very close chances of being drawn for crossover.

With this change in fitness, a more effective criterion was obtained in prioritizing the best chromosomes, which reduced the chance of GA losing efficiency due to ineffective draws. Table 4 shows an example of this for a hypothetical population.

Table 4: Example of assessment in fitness chromosome a hypothetical population.

Individuals composed by pairs of workers																Function Objective	% of draw	i	*Fitness*	% of draw
K	H	N	C	E	F	B	I	A	O	L	G	P	D	J	M	13.94	9.9%	7	0, 8	8.3%
E	B	L	O	H	C	A	K	M	D	I	G	P	N	F	J	12.20	11.3%	1	1.5	15.0%
K	J	D	P	N	B	C	I	G	L	M	A	E	F	H	O	13.87	10.0%	5	1.1	10.6%
H	N	E	I	B	M	L	O	A	P	D	C	F	J	G	K	13.45	10.3%	4	1.2	11.7%
O	L	J	H	M	K	C	I	P	A	N	E	G	D	B	F	13.05	10.6%	3	1.3	12.8%
F	O	J	I	C	G	D	M	H	N	A	B	L	P	K	E	15.53	8.9%	9	0.6	6.1%
C	N	B	L	H	A	D	G	P	M	F	I	O	J	E	K	16.51	8.4%	10	0.5	5.0%
H	C	M	P	E	I	B	J	G	L	O	D	N	K	F	A	13.92	9.9%	6	0.9	9.4%
L	M	H	J	D	O	A	E	N	K	B	G	P	C	I	F	14.42	9.6%	8	0.7	7.2%
N	A	C	D	H	L	M	F	G	E	J	I	K	B	P	O	12.22	11.1%	2	1.4	13.9%

The precision gain that can be achieved with the adjustment fitness, this finding is clear from the comparison between the worst and the best individual in the population, with average wheel change times of 16.51 and 12.20 minutes respectively. If your objective function values were considered for selection for crossover, the worst individual would have an 8.4% chance of being drawn and the best would have 11.3%, whereas considering the use of fitness these percentages change to 5.0 % and 15.0%.

From the above observation, it can be seen that the use of Equation 6 as fitness allows to better evidence the extremes between the best and worst chromosomes, which for the genetic algorithm is of great value since the tendency of the best individuals to be drawn will be greater, there will soon be a greater chance that the best genes will perpetuate over the generations.

After the stage of linear standardization, the drawing of individuals took place using the roulette method, where each chromosome of the population was represented by a slice of an imaginary roulette, the size of this slice being proportional to the fitness of each chromosome. After all the slices of theroulette were delimited, a random number was generated simulating a spin of the roulette, which in turn had a fixed hand indicating the slice drawn, thus the greater the fitness, the greater the slice of this chromosome and the greater your chance to be drawn.

As it is a problem of combinatorial and non-numerical optimization, the operator crossover to be chosen for this AG cannot just copy part of the genetic material of two parents and join in a child, given that there is a risk of some genes repeating.

For cases like this, the operator crossover must take into account the relative position of each gene within the chromosome and not just the absolute position, that is, just saying that a particular gene is located in position 4 of the chromosome would not make much sense, this information would only have value coming together with the specification of the genes present in adjacent positions 3 and 5.

Therefore, once two chromosomes of the population were drawn, the crossover operator used was the OX crossover (order crossover), its basic operation can be summarized following the steps below:

- Step 1: Randomly draw two cut points on the chromosome.

- Step 2: With two chromosomes (C_1 and C_2) copyto the child chromosome (C_3 the genes of C_1) that are between the two cut points previously drawn.

- Step 3: From the position after the second cut point, copy to C3 the C_2genes that are not yet present between the two cut points of the child chromosome.

- Step 4: If you reach the end of the child chromosome without having all the positions filled, continue filling it from the beginning of it following the same logic as the previous step.

Table 5 e 6 illustrates the steps described above, through which it is possible to see that the crossover OX is very suitable for this type of problem, since it does not allow having two identical genes within the same chromosome after crossing.

As for the mutation, it occurred so that it did not generate inconsistent individuals, as for example when there are two identical letters on the same chromosome, which would mean that the same mechanic would be allocated to two workers pairs at the same time. Thus, the mutation was based on a random draw of two positions on the chromosome, after which the genes in these positions inverted and gave rise to a new chromosome, as shown in Table 7.

In addition, in order not to lose the best individual of each generation, elitism was adopted, thus the algorithm was designed to always take the best individual of the current generation to the next generation.

For the purpose of validating the algorithm, each of the 6 combinations of population size (10 and 20 individuals) and mutation rate (1%, 2.5% and 5%) was simulated 50 times and the distribution of these 50 times average change of wheels obtained after optimization via GA was compared with 50 average times generated from the random choice of a group of 8 pairs of mechanics.

The performance of the proposed genetic algorithm was also compared with a random optimization, having been verified generation by generation the evolution of the optimization for both methods.

After the simulations, a comparative performance analysis was performed between each of the 6 combinations of population size and mutation rate scenarios, with the best performance being adopted for the field tests.

Table 5: sequence CrossoverOX.

STEPS	CHROMOSOME																	OBSERVATION
1	C_1	K	H	N	C	E	F	B	I	A	O	L	G	P	D	J	M	Parent chromosome C_1: the cutoff points between genes 2 and 3 and 13 and 14 were drawn.
1	C_2	E	B	L	O	H	C	A	K	M	D	I	G	P	N	F	J	Parent chromosome C_2: the genes marked in red are already contained between the Ccutoff points$_1$.
-	C_3																	Child chromosome$_3$ still empty.
2	C_3			N	C	E	F	B	I	A	O	L	G	P				The genes between positions 3 and 13 of C_1 are copied to the same positions in C_3.
3	C_3			N	C	E	F	B	I	A	O	L	G	P	J			As N and F of C_2 already appear in C_3 between the cut points, take the Jgene from C_{22} and copy it to the position after the second cut point in C_3.
3	C_3			N	C	E	F	B	I	A	O	L	G	P	J	H		As J is the last gene in C_2, one must search from the beginning of C_2 which gene it does not yet appear in C_3, in this case it is the H gene, which must then be copied to the next empty position of C_3.
3	C_3			N	C	E	F	B	I	A	O	L	G	P	J	H	K	After H in C_2 the next gene that does not yet appear in C_3 is K, so it must be placed in the position after H in C_3.

Table 6: sequence CrossoverOX - Continued.

Step	Chromosome																	Observation
4	C_3	M		N	C	E	F	B	I	A	O	L	G	P	J	H	K	As we reached the end of C_3 but there are still empty positions at the beginning of the chromosome, we must follow the logic of copying the Cgenes$_2$ that have not yet appeared in C_3 only considering from the first position of C_3.
4	C_3	M	D	N	C	E	F	B	I	A	O	L	G	P	J	H	K	Finally, the *crossover is completed* by copying the D of C_2 to the last position of C_3 that was empty.

Table 7: Chromosome mutation for optimization based in order.

E	B	L	O	H	C	A	K	M	D	I	G	P	N	F	J		Original chromosome before mutation.
E	B	L	O	H	C	A	K	M	D	I	G	P	N	F	J		Positions 5 and 12 drawn for mutation.
E	B	L	O	G	C	A	K	M	D	I	H	P	N	F	J		Chromosome after mutation.

IX. DESCRIPTION AND ANALYSIS OF THE RESULTS IN A REAL CASE

After compiling the 3,126 real samples of wheel changes made in the field, it was possible to elaborate the average wheel change times matrix for the 120 pairs possible to be formed with a team of 16 mechanics, as presented previously in Table 2, this being the reference used as a basis for assessing the skills of chromosomes.

Using the proposed modeling, where each chromosome was formed by a sequence of 16 letters in which each represented a mechanic, the optimization code was written using a genetic algorithm that initially adopted rate crossover of 100%, mutation rate 1%, population of 20 chromosomes and stopping criteria for reaching the hundredth generation.

The optimization code was simulated 50 times with the average computational processing time for each simulation being 12 minutes and 58 seconds. In each of the 50 simulations, the average solution optimized by the genetic algorithm was calculated for each generation, resulting in Figure 9.

Calculating the average of the optimized value upon reaching the hundredth generation of each of the 50 simulations, an optimized average time was obtained for the set of 8 pairs of 11.1 minutes, with the lowest value found in the simulations being 11 minutes, which illustrates the effectiveness of the convergence of the implemented GA.

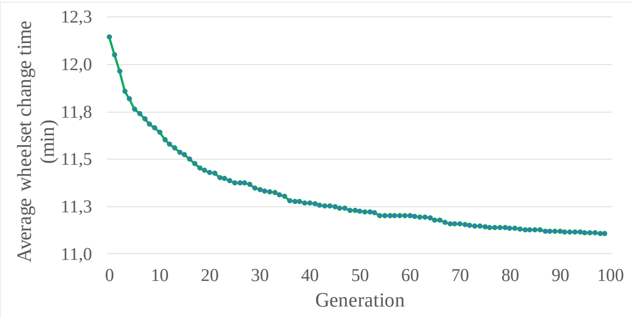

Fig. 9:Evolution of GA in 100 generations (Population = 20 and Mutation rate = 1%).

9.1 Comparison of optimization via AG versus random choice

In order to compare the quality of the choice of working pairs through optimization via genetic algorithm versus the choice of pairs at random, the results obtained by the 50 simulations of the GA were compared with 50 random choices of clusters of 8 workers pairs, resulting in the data distributions shown in Figure 10.

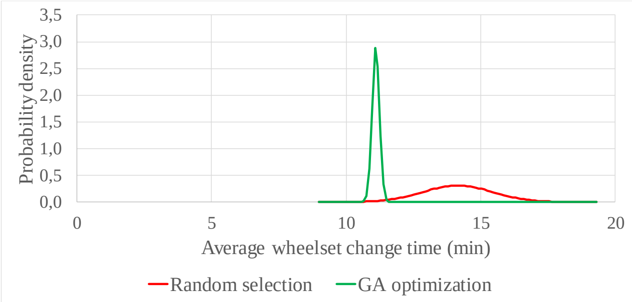

Fig. 10:Distribution of 50 average times for changing wheels obtained via GA versus random choice.

For the 50 results obtained through the genetic algorithm, an average time was found of 11.1 minutes with a standard deviation of 0.14 minutes, while for the 50 results obtained by random choice the average was 14.2 minutes and the standard deviation 1.29 minutes, both with normal distribution characteristics.

Through this simulation, it can be seen that the optimization via genetic algorithm is able to enhance the performance of the work team, since compared to the random choice of workers pairs, which is the method commonly adopted in practice, the GA presented a reduction 22% of the average wheel change time and a 89% reduction in standard deviation.

9.2 Comparison of optimization via GA versus random optimization

In addition to comparing the set of 50 samples of average exchange times obtained through the genetic algorithm with another 50 samples obtained from the random choice of workers pairs, it was also considered to simulate 50 random optimization cycles to compare with GA's performance over generations.

The random optimization consisted of choosing randomly and sequentially 100 samples from groups of 8 pairs, being then calculated for each set of 8 pairs the average time of change of associated wheel. The average optimized time for each iteration is given by the lowest average time found so far, so in the hundredth iteration the optimized time will be the shortest average time found over the 100 samples generated at random.

50 random simulations were run and the average time optimized for each iteration was compared with the 50 simulations of the genetic algorithm, with the result of the comparison shown in Figure 11.

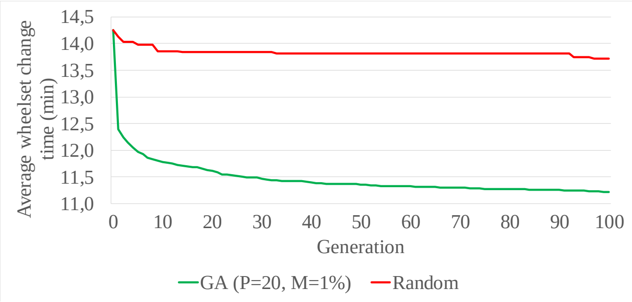

Fig. 11:Comparison of performance between random optimization and optimization via GA (P = population and M = mutation rate).

The average of the 50 simulations of random optimization was 13.7 minutes, while through the GA an average of 11.1 minutes was obtained, that is, the optimization via GA was 19% more efficient than random optimization.

In addition to the superiority in the final value that the optimization found,it is clearly seen in Figure 11 how much the genetic algorithm proved to be faster than the random optimization, it showed stagnation in a good part over the 100 iterations, given that between the generations 10 and 90 practically the average time optimized randomly did not vary, while the GA value was consistently reduced.

9.3 Analysis of sensitivity of the parameters of the GA

In order to test the sensitivity of the parameters adopted in the genetic algorithm and also to confirm that the parameters used until then with a mutation rate of 1% and a population of 20 individuals were in fact assertive choices, simulations of optimization through the same GA changing only these parameters in order to compare their performance.

Two population size options (10 and 20 individuals) and 3 mutation rate options (1%, 2.5% and 5%) were considered, thus totaling 6 possible combinations on Tables 8 and 9.

For each combination of parameters, 50 optimization simulations were performedand in each simulation the same stopping criterion was used, which was reaching the hundredth generation of individuals.

The averages of the values optimized for each generation for each of the possible parameter combinations are shown in Figure 12, from which it is observed that the 3 simulations that considered a population of 10 individuals had a worse performance than the 3 simulations with population of 20 individuals, with the average 11.3 minutes and 11.1 minutes, respectively.

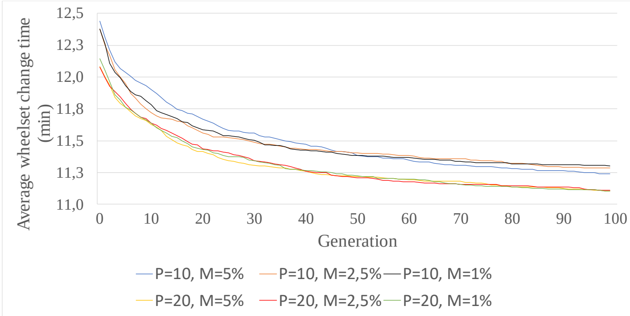

Fig. 12:Comparison of AG for different population parameters (P) and mutation rate (M).

It is important to say that each curve in the figure 12 was obtained from an average of 50 simulations of GA optimization, that totalized 3.760 min of simulation time, with the following main statistics results.

Observing the simulations with a population size equal to 20, it was seen that even changing the mutation rate between 1%, 2.5% and 5% there was no significant difference between them over the generations, however considering the same mutation rates for the case of the population being 10 individuals, there was a greater variation in GA performance, especially in the first 50 generations.

From the results obtained, it was seen that the definition of the mutation rate at 1% with a population of 20 individuals, which were the parameters used until then, constitute an acceptable configuration to run the constructed genetic algorithm, and these are the parameters to be used. considered for field implementation.

Table 8: Summary of simulations with variation in population size and mutation rate with stop criteria in 100 generations.

	Total number of simulations	Total simulation time (min)		Optimized Wheel Change Time (min)	Simulation Time (min)
S1 - P=10, M=5%	50	596.7	Average	**11.2**	11.9
			Standard Deviation	0.19	1.0
			Maximum	11.8	12.5
			Minimum	11.0	8.9
S2 - P=10, M=2,5%	50	634.7	Average	**11.3**	12.7
			Standard Deviation	0.20	0.7
			Maximum	11.7	13.1
			Minimum	11.0	10.0
S3 - P=10, M=1%	50	561.4	Average	**11.3**	11,2
			Standard Deviation	0.24	1.2
			Maximum	11.9	14.2
			Minimum	11.0	8.0

Table 9: Continue - Summary of simulations with variation in population size and mutation rate with stop criteria in 100 generations.

	Total number of simulations	Total simulation time (min)		Optimized Wheel Change Time (min)	Simulation Time (min)
S4 - P=20, M=5%	50	623.8	Average	11.1	12.5
			Standard Deviation	0.10	0.7
			Maximum	11.4	13.4
			Minimum	11,0	9.5
S5 - P=20, M=2,5%	50	725.4	Average	11.1	14.5
			Standard Deviation	0.12	2.2
			Maximum	11.4	17.9
			Minimum	11.0	9.6
S6 - P=20, M=1%	50	648.1	Average	11.1	13.0
			Standard Deviation	0.14	1.1
			Maximum	11.4	15.7
			Minimum	11.0	9.7
TOTAL	300	3790.0			

9.4 Verification in the field

The entire optimization process was based on real data on the time of change of wheelsets, provided that they met some criteria as previously discussed, so at the end of the optimization, the algorithm indicated a combination of workers pairs that based on the data historical, supposedly together they would be able 645 to present an average time of change of wheels optimized for the workshop in point.

At this point, with the indication of the optimized group of workers pairs, the strategy to assess the real gain arising from the optimization was based on the indication of the genetic algorithm to maintain fixed workers pairs, in order to make the greatest number of wheel changes using the pairs indicated by the algorithm. After this redefinition of the pairs, the average time for changing the workshop was followed by three months, then the average time for changing the wheels before and after implementing the optimization of the pairs was compared.

From 16 mechanics considered in the problem, 10 of them belonged to the same province and 6 belonged to another, thus, in practice, the algorithm could indicate a pair formed by two mechanics from two different provinces, which is to be avoided because this way - there were two inspectors for the same work team.

The inspectorate with 6 people, in addition to making wheel changes, was also responsible for other maintenance services, while the one with 10 mechanics was exclusively responsible for changing wheels, for this reason the latter team had the highest percentage of wheels changed in the workshop.

As shown in Table 2, considering 16 mechanics, there are 120 possible pairs to be formed, however in the problem in question 24 of these pairs had not worked together in the last 13 months so that they could have their time sampled, in which case the Equation 1 as a way to estimate the time of the pair and thus enable the necessary data to run the optimization code.

In practice, each province formed its work teams using its own mechanics, that is, although it was not forbidden, it was not common to mix the mechanics of one province with those of the other, except when necessary due to some operational issue, such as the lack of a mechanic, which usually occurs due to vacation, training, illness, legal leave, lunch break, etc.

It is noteworthy that the more pairs without real samples of their wheel change time, the more times it will be necessary to use Equation 1 to estimate this value and the greater the chance of error in this interpolation, consequently the greater the chance of inaccuracy in the result of the optimization algorithm.

Considering only the inspectorate formed by 10 mechanics, there is the possibility of forming 45 pairs, and for the problem in question, only 3 of these pairs had no past samples of wheel changes and only in these cases would it be necessary to use Equation 1, which would reduce exposure to error due to this approximation.

It is known that the genetic algorithm originally considered 16 mechanics, based on these data, several simulations were made that showed a potential gain in the average time for changing the wheels if the combination of workers pairs pointed out by him was adopted, but for practical proof it was seen that working simultaneously with 16 mechanics would make the field test more complex due to the issues previously exposed, so it was decided to do the field tests considering the inspectorate composed of 10 mechanics as a control group.

Once only the group of 10 mechanics was adopted, Table 10 of times was obtained to be considered by the genetic algorithm as input data for the evaluation of the optimized combination of workers pairs.

Table 10: Matrix of average wheel change times for the inspection of 10 mechanics (min).

	A	B	D	G	J	K	L	M	N	O
A	-	23.4	10.6	12.6	11.4	14.3	12.7	11 , 9	13.0	16.1
B	23.4	-	10.6	21.7	15.0	14.0	15.0	13.0	19.5	17.2
D	10.6	10.6	-	11.5	13, 0	23.5	10.8	12.8	11.8	17.2
G	12.6	21.7	11.5	-	10.7	16.3	11.3	12.9	10.9	25.6
J	11.4	15 , 0	13.0	10.7	-	12.9	12.1	11.5	14.0	26.0
K	14.3	14.0	23.5	16.3	12.9	-	13.0	12.2	14.0	14.8
L	12.7	15.0	10.8	11.3	12.1	13.0	-	14.0	13.6	15.3
M	11.9	13.0	12.8	12.9	11.5	12, 2	14.0	-	13.1	13.6
N	13.0	19.5	11.8	10.9	14.0	14.0	13.6	13.1	-	10.3
O	16.1	17.2	17.2	25.6	26.0	14.8	15.3	13.6	10.3	-

From the times indicated in Table 6, the genetic algorithm was run again,considering the parameters of mutation rate of 1%,rate crossover of 100%, population of 20 individuals and stopping criteria reaching 100 generations. After running the optimization via GA considering the times in Table 10, an indication of 5 pairs of work was obtained, which became the desired combination of work team, since making the wheel changes through these pairs is expected to 700 have an average time for changing the wheel better than considering the random formation of the pairs.

It is worth mentioning that within the group of 10 mechanics considered for the field tests, there were people who worked at different scales, so even though all of them were working the morning shift, every day part of the 10 people were off duty while others were working.

The fact that the scale provides that two mechanics working on different scales there are days when when one is working the other will be off, has a direct impact on field tests since among the 5 pairs suggested by the AG there were pairs that currently worked on different scales, there would soon be days that it would be impossible for them to work together in the workshop.

The work schedule hitherto practiced in the workshop consisted of a cycle of four days of work followed by a day off, followed by another four days of work followed by two days off. Altogether there were six different scales, all running in this sequence, just differing by the lag between them, so every day there was one or two scales off, which meant that on specific days some mechanics were not simultaneously in the workshop, Table 11 shows the workshop scales, it shows for example that on days 5 and 6 a mechanic working on scale 1 and another on scale 2 will not be together in the workshop, because the first will be off on the first day while the second will be off on the second day.

Table 11: Practical work scales in the workshop (T = working day, F = day off).

Scale / Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Scale 1	T	T	T	T	F	T	T	T	T	F	F	T	T	T	T	F	T	T
Scale 2	F	T	T	T	T	F	T	T	T	T	F	F	T	T	T	T	F	T
Scale 3	F	F	T	T	T	T	F	T	T	T	T	F	F	T	T	T	T	F
Scale 4	T	F	F	T	T	T	T	F	T	T	T	T	F	F	T	T	T	T
Scale 5	T	T	F	F	T	T	T	T	F	T	T	T	T	F	F	T	T	T
Scale 6	T	T	T	F	F	T	T	T	T	F	T	T	T	T	F	F	T	T

However, after the indication of the optimized pairs, the two mechanics that made up each of the five pairs of work indicated by the genetic algorithm were placed on the same scale of work, so that for example, in the combination of pairs, mechanic A was the ideal pair for mechanic B, both working on the same scale, so that in most cases they could change wheels together.

Even defining fixed work pairs and adjusting the scales to facilitate the formation of these work groups in practice, it was not possible to guarantee that all wheel changes were always carried out by the optimized pairs, since during the working day there is a need to do rotation of the team for lunch in addition to medical absenteeism, holidays and other absences of personnel that may occur.

With the 5 pairs indicated by the GA as an optimized combination of work group, the suitability of the workers pairs was disclosed to the team and the inspector of the area was instructed to do his utmost to maintain this combination. In order to remember the new workers pairs, it was fixed in the workshop notice board which pairs should be adopted from that moment.

For comparison purposes before and after the implementation of the optimized workers pairs, we observed the history of the last 9 months before the optimization and another 3 months after the change, thus totaling a performance analysis in a window of 1 year.

In this 12-month period, 10,835 wheeler changes were accounted for, of which 7,228 exchanges were carried out by the inspectorate composed of 10 mechanics who were prioritized for field tests, that is, approximately 67% of the workshop’s production in the approached shift was fulfilled. precisely by the chosen control group.

The standardization of working pairs based on the indication made by the genetic algorithm became effective as of April 1, 2019, and continued until June 30 of the same year, in this period the maximum effort was made to keep the mechanics of each working together one of the 5 workers pairs appointed by the AG, because if the formation of the wheel change pairs remained essentially random, it would be impossible to associate any gain in productivity with the implementation of the pairs signaled by the GA.

Considering the inspectorate formed by the 10 mechanics, 7,228 wheel changes were carried out between 1 July 2018 and 30 June 2019, with the average wheel change times shown in Figure 13.

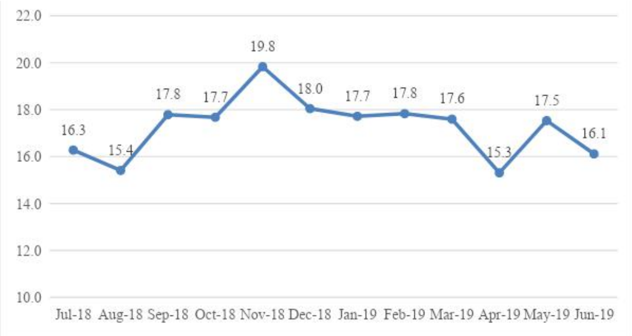

Fig. 13:History of the average wheel change time of the control group (min).

It can be observed that although the months of April and June 2019 have shown excellent results, with average wheel change times of 15.3 and 16.1 minutes, respectively, the month of May fell short expectations, presenting 17.5 minutes, a better value, but very close to the level that had been occurring before the optimization.

The disagreeable result in the month of May 2019 can be understood through operational factors that may have compromised the performance in that specific month, in this case, there were huge impacts due to the lack of new wheels to be installed, since several times in the month May after the mechanic removed a bad wheel from the wagon, instead of having the new wheel readily installed in place of the one just removed, given the lack of new wheels, the same wheel was removed for the process of recovery and after the whole cycle of maintenance of the wheel it returned to the wagon, which considerably affected the average time of changing wheels.

In addition to any operational impacts not directly associated with the performance of the work teams, as occurred in May 2019 with the impact due to the lack of wheels, there are other variables that can also affect the average changeover time, such as failure of industrial equipment and lack of manpower, however, historically the problem of lack of wheels has been the most representative of all.

In order to reduce the seasonality of possible operational problems that may compromise the average time for changing wheels, the same period of 12 months was analyzed, however in quarterly windows, the result being shown in Figure 14.

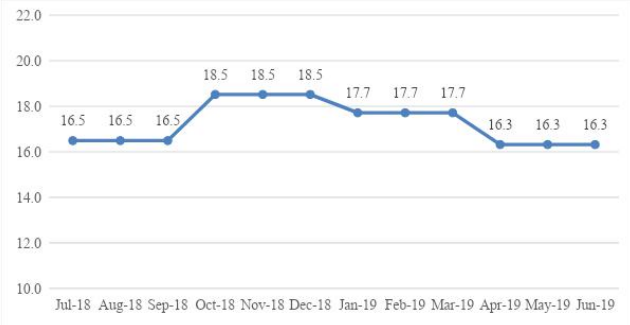

Fig. 14:Average time of wheel change grouped by quarter (min).

In the quarter between April and June 2019, the period in which optimization was tested in practice, the best average wheel change time in the last 4 quarters was obtained, and compared with the quarter between January and March 2019, there was a reduction of 17.7 to an average of 16.3 minutes, which represents an improvement of 7.9% between the first and second quarter of 2019.

Since there is a practical understanding that the impact due to lack of wheelhas been the biggest problem in the workshop and that this directly affects the average time of changing the wheel, even though it has no direct relationship with the performance of the work team, it was decided to take ning the month- to-month impact of this lack of wheelset and purging this effect from the average switching times, so that it would be possible to have a more adjusted and more consistent result with the performance aspects of the work teams. Raising the impact due to the lack of wheels, we arrived at Table 12 through which it is possible to see that in May 2019 there was the greatest impact on the changeover time due to the lack of a new wheel to replace the one removed from the wagon, being that in this month the average time of the control group was 17.5 minutes, of which 4.4 minutes were of impact due to the duo having to wait for the arrival of the new wheel, thus, purging this effect, the average change time of adjusted itinerary for the month of May 2019 would be 13.1 minutes.

Table 12: History of impacts on wheel change time due to lack of available wheel between July 2018 and June 2019.

	jul	ago	sep	oct	nov	dez	jan	fev	mar	abr	may	jun
Total wheelsets changes made by control group	453	857	498	437	385	665	500	690	504	800	733	706
Exchanges made by nonoptimized dual control group	431	817	493	429	371	633	462	676	465	224	187	268
Exchanges made the optimized dual control group	22	40	5	8	14	32	38	14	39	576	546	438
Average time of purging NO optimized double impact by wheelset (min)	14,9	14,1	15,0	14,4	15,4	16,8	17,0	16,9	14,8	14,8	13,1	12,7
Average time of the optimized pairs purging impact per wheel (min)	10,7	11,6	11,6	12,5	19,3	12,2	13,7	17,9	14,2	14,4	13,1	12,3

Figure 15 shows the history of the average wheel change time for the control group purging the impacts due to lack of wheel, in which the effect of optimization is more clearly perceived in the months of April, May and June 2019, where we see a reduction in average time, with 14.7 minutes in the month before the optimization and at the end of the third month running with the optimized fixed pairs, we reached the time of 12.4 minutes. minutes, which represents a reduction of 2.3 minutes per wheel change or 15.6%.

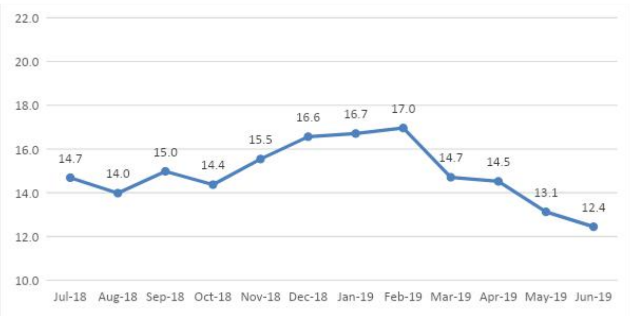

Fig. 15:History of the average wheel change time excluding the impact of unavailability of new wheels (min).

It is known that as of April 2019 there was a greater search for the maintenance of fixed workers pairs, the definition of these pairs being obtained from the indication of the genetic algorithm, whereas before this month the definition of workers pairs was done in an essentially random way.

Although there has been a greater repetition of the so-called optimized pairs since April 2019, it is worth clarifying that it was not possible to guarantee that all exchanges in this period were carried out exclusively by these pairs, however when compared with the period before April, the percentage of exchanges made by the pairs considered to be optimized was much higher, as can be seen in Table 13.

Table 13: History of the rate of exchange of wheelsets made by optimized pairs between July 2018 and June 2019.

	jul	ago	sep	oct	nov	dec	jan	fev	mar	abr	may	jun
Wheels changed	453	857	498	437	385	665	500	690	504	800	733	706
Wheels changed for non-optimized pairs	431	817	493	429	371	633	462	676	465	224	187	268
Routes exchanged for optimized pairs	22	40	5	8	14	32	38	14	39	576	546	438
% of exchanges made for optimized pairs	5%	5%	1%	2%	4%	5%	8%	2%	8%	72%	74%	62%

From Table 13 shows that in the three months before field tests, on average, only 6% of wheel changes months of the month were made by the so-called optimized pairs, while from April 2019, after running the optimization algorithm, readjusting the work schedules and disclosing to the team the optimized pairs that should be followed, was reached in the period of field assessment an average of 69% of the exchanges made by the control group being performed by the optimized pairs.

Through this evaluation, it is possible to make the connection between the percentage of exchanges made by the optimized pairs and the average time of change of wheels of the control group. For the first quarter of 2019, we had 16.1 minutes as an average time for changing wheels, purging the effect of lack of wheels, and in this same period only 6% of the exchanges sampled belonged to so-called optimized pairs, whereas in the test phase of field, which took place in the second quarter of 2019, obtained an average change time of 13.3 minutes, excluding impacts from lack of wheels and 69% of exchanges made with optimized pairs in the same period, that is, an increase of 63 percentage points in the rate of exchanges made by optimized pairs resulted in a reduction of 17.4% in the average wheel change time.

In order to evaluate the average changeover times of wheelsets month by month, analyzing in this case separately the exchanges made by the pairsappointed by the GA with those said to be not optimized whose formation took place at random, the data in Table 14 was obtained.

Excluding the losses associated with waiting per wheel, it is observed in Table 14 that in the 12-month period in question in only 2 of them the average time of the optimized pairs was worse than the average time of the randomlyformed pairs (times highlighted in red), which represents an assertiveness rate regarding the greater efficiency of the pairs proposed by the GA of 83% of the months in this observation window.

Table 14: History of the average times for changing wheelsets made by optimized and non-optimized between July 2018 and June 2019.

	jul	ago	sep	oct	nov	dez	jan	fev	mar	abr	may	jun
Total wheelsets changes made by control group	453	857	498	437	385	665	500	690	504	800	733	706
Exchanges made by nonoptimized dual control group	431	817	493	429	371	633	462	676	465	224	187	268
Exchanges made the optimized dual control group	22	40	5	8	14	32	38	14	39	576	546	438
Average time of purging NO optimized double impact by wheelset (min)	14,9	14,1	15,0	14,4	15,4	16,8	17,0	16,9	14,8	14,8	13,1	12,7
Average time of the optimized pairs purging impact per wheel (min)	10,7	11,6	11,6	12,5	19,3	12,2	13,7	17,9	14,2	14,4	13,1	12,3

In order to give more representation to the sample, still continuing in Table 14, if only the months in which the optimized pairs made at least 20 exchangesin the month were considered, of the 12 months there would be 8 left, in which in all of them the average exchange time of optimized pairs races were better than when compared to the average time of non-optimized pairs, which reinforces the quality of the indication of the five pairs indicated by the genetic algorithm. Considering the first and second quarter of 2019, there was a reductionfrom 17.7 to 16.3 minutes in the average wheel change time, that is, the wheel change was 1.4 minutes faster after the implementation of the optimization, even considering the impacts due to lack of wheels. This value, despite appearing to be small, in addition to the large number of wheel changes made and the high cost of leaving a wagon stopped, is estimated to have a high potential for financial gain.

In the workshop in question to change a wheel it is necessary to stop a complete batch of 110 wagons and not just the wagon with the defective wheel to be replaced, thus, it is estimated that every 1 hour of a batch of 110 wagons stopped the company stops earning approximately R$ 13,000.00 and knowing that in the second quarter of 2019 there were 2,239 wheel changes made by the control group, at an average time 1.4 minutes less than the first quarter of the same year, this means that there were a 52.2 h reduction in the unavailability of 110 wagon lots, which meant that the company stopped losing R$ 679,163.33 with wagons stopped in maintenance between April and June 2019.

As of July 2019 it was no longer it is possible to collect new performance data from the control group since from that date there has been a shift in the work shift on the part of the company, which caused a total redistribution of the work teams and the duplication references were lost the optimized ones, however according to the 3 months of practical tests of the optimization of the distribution of the workers pairs via genetic algorithm, the improvement in the average performance of the control group was noticeable.

X. CONCLUSION

A practical application of optimization was presented, where based on historical performance data from a maintenance team, combined with the use of the metaheuristic genetic algorithm, it was possible to arrive at an optimized solution for the distribution of work teams, so that the average performance of the team as a whole was maximized.

After 50 simulations of GA with 1% mutation rate, population of 20 individuals and 100-generation stop criterion, an optimized mean time of 11.1 minutes was obtained, which was 19% better than when compared to the mean time from 50 simulations of random optimization.

When observing the consistency of the GA, we noticed that after 50 simulations, the optimized average times produced by the GA showed an average of 11.1 minutes and a standard deviation of 0.14 minutes, which shows improvement when compared to the average of 14.2 minutes and standard deviation of 1.29 minutes produced from the random generation of 50 clusters of 8 pairs of work each, thus the average time for changing the wheels of the solution proposed by the AG was 22% better than when compared with the choice randomization of teams.

In fact, it was found that the problem modeling, GA coding and its population parameters, mutation rate and stopping criteria proved to be robust enough to deliver an optimized solution within an acceptable computational time for the complexity of the problem. addressed, whose number of possible solutions exceeded 81 billion alternatives.

In the field test stage, it was seen that comparing the average time of changing wheels in the quarter after the implementation of the optimization with the quarter before the field test phase, a reduction of 7.9% was noticed, reducing this time from 17.7 to 16.3 minutes, which represents an estimated financial gain of R$ 112,300.00 per month in the case study company.

In the individual evaluation month by month within the quarter in which the optimization was implemented, it was observed that in the second month (May / 19) there was a sharp increase in the average time for changing wheels, this peak being explained by the impact of the lack of wheels new ones in the wheelyard.

In order to compare the collective performance of the team before and after the proposed optimization, disregarding impacts caused by aspects outside the direct scope of the mechanics, the average wheel change times were recalculated, purging the impact of changes that took longer than anticipated by delay in waiting for the new wheelset to be installed in the wagon, in this case, in a more pronounced way, the gain achieved with the optimization was also observed, and after three months working with the teams in an optimized way, an average time of 12.4 minute wheel change, which represents a 15.6% reduction compared to the 14.7 minute time that was practiced in the month immediately prior to the optimization implementation.

The reduction in the average wheel change time between April and June 2019 could be associated with the implementation of the improvement proposed by the genetic algorithm, since it was seen that in the optimization evaluation quarter, an average of 69% of the changes were made by the five pairs suggested by the GA, an index that in the quarter prior to the improvement was only 6%.

From the evaluation of the average time for changing wheels, purging any impacts due to the lack of new wheels, seeing a quarter before and one after the implementation of the optimization, it was found that an increase of 63 percentage points in the proportion of wheel changes made by Optimized doubles caused a 17.4% reduction in the average time for changing wheels in the quarter, which was reduced from 16.1 to 13.3 minutes.

Also evaluating the average time of changing wheels, purging the effect of impacts due to lack of wheels, we observed that in a window of 12 months, in 10 of them the average time of exchanges made by so-called optimized pairs was less than the average time of the wheels. exchanges made by non-optimized pairs, which represents an assertiveness rate of 83% for the indication made by the genetic algorithm.

Although the field tests were carried out for an inspectorate of 10 people in a single shift of the workshop in question, since the maintenance data are recorded in a computerized system by all the teams at all times, there is a glimpse of great opportunity for future work the development of software capable of interpreting field data as it is inserted in the computerized system and from this information, using the same programming logic developed in this work, it is possible to indicate an optimized combination of work teams for the current condition of the workshop, thus expanding the gain found in this experiment to all shifts and all processes of the workshop where this work was developed.

In addition, it will be possible to evaluate in subsequent works the performance of this problem from metaheuristic algorithms most recently presented in the literature and that have documentary satisfactory performance for problems of a discrete nature.

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