Traveling Salesman Problem: The Efficiency of Simulated Annealing Applied to a Real Case Study

Eva Rodrigues, Cíntia Câmara, Maria Almeida
Department of Economics, Management, Industrial Engineering and Tourism
University of Aveiro, Portugal
egr@ua.pt , cintiacamara@ua.pt, beatrizamador@ua.pt

Pedro Nunes
TEMA / DEM
University of Aveiro, Portugal
pnunes@ua.pt

Ana Moura
GOVCOPP / DEGEIT
University of Aveiro, Portugal
ana.moura@ua.pt

Abstract

This paper deals with a traveling salesman problem that is performed daily by a Portuguese bakery company. The bakery delivers bread to multiple customers using only one vehicle and driver, leading to high costs and time consumption. The objective is to minimize total travel distance and optimize the distribution process to reduce costs. In this case, we have a typical Traveling Salesman Problem and in order to solve this problem, several solutions were first computed and compared, and then, these were used as initial solutions to a Simulated Annealing (SA) approach. The performance of the SA was tested for the real problem, with the actual company data and, an analysis of the SA behavior when started with different solutions was performed. The results obtained allowed the company to reduce its current route by more than 23%.

Keywords
Traveling Salesman Problem, Clarke and Wright Heuristic, Nearest Neighbor Heuristic, Simulated Annealing Metaheuristic

1. Introduction
Currently, globalization of markets contributes to an increasing competitiveness requiring organizations to continuously improve their performance. To this end, it is necessary to adopt an adequate logistics planning in order to reduce costs and achieve competitive advantage.

The transport sector is undoubtedly one of the most important and costly components of logistics activities, and it is therefore fundamental that companies have a well-designed and efficient distribution network. This leads to a strong and growing concern from several organizations in different sectors, to search for optimized routes that allow them to provide their services with the desired quality, in the shortest period of time and with the lowest cost possible, in order to maximize profits.

It is in this context that the Travelling Salesman Problem, the main topic of this article, arises. This is a Combinatorial Optimization problem whose objective consists in defining a route that has the shortest distance and/or shortest duration and, consequently, the lowest cost. According to Gilbert Laporte (Laporte 1992), in general, the methods used to solve this problem can be divided into exact and heuristic methods. The exact methods make it possible to obtain the optimal solution to the problem, however, as they have exponential complexity order, the computational effort for its resolution increases exponentially with the number of nodes to be visited. For this reason, researchers' attention is increasingly directed to heuristic methods. These, in turn, allow to obtain approximate solutions, i.e., they do not guarantee that a solution is optimal, nor do they indicate how close it is to the optimal solution, but they allow finding good solutions in a faster way for problems of large dimension. In addition to the exact and heuristic methods, it is also possible to resort to metaheuristics to solve optimization problems. These consist in an interactive approach that starts from initial solutions, many times previously obtained through heuristic methods, which aim to improve the initial solutions and, thus, get closer to the optimal solution.

This paper is organized and distributed in 6 sections, including this introduction which contains some theoretical notions, whose knowledge and internalization are relevant for the understanding of this study. Section 2, mentions several authors, as well as their scientific contributions which meet the subjects addressed in this article. In section 3, a brief reference is made to the origin and contextualization of the problem under analysis and the objective of this work is introduced. Section 4 describes the approach used, and presents the algorithms, namely the heuristic methods and the metaheuristic, which we will apply to obtain an improved solution. In section 5, all the results obtained are presented and analyzed. Finally, section 6 presents the conclusions resulting from the research and study carried out as well as the difficulties and limitations experienced during the analysis.

2. Literature Review

The Traveling Salesman Problem (TSP) is a well-known combinatorial optimization problem that seeks to find the shortest possible route through a set of cities and returns to the starting point. The problem is NP-hard and becomes increasingly difficult to solve as the number of cities increases. Therefore, researchers have developed various heuristics and metaheuristics to solve the TSP efficiently. In this section, we will discuss the application of heuristics and metaheuristics in solving the TSP problem, as well as summarize recent studies on this topic.

The Nearest Neighbor (NN) algorithm is one of the simplest and widely used heuristics to solve the TSP problem. This algorithm starts with a random point and selects the closest unvisited city as the next destination. Several studies have shown that the NN algorithm performs well for small to medium-sized instances of the TSP (Dorigo et al.1991; Kizilateş et al. 2013). Other heuristics that have been used to solve the TSP include the Greedy algorithm (Liu et al., 2016), Clarke and Wright algorithm (Tantikorn and Ruengsak 2012; EK Hashi et al. 2015), and Christofides algorithm (Genova et al. 2017).

In order to achieve better solutions and in a reduced computational time, applying metaheuristics and hybrid algorithms has been increasing. Simulated annealing (SA) is one of the most popular metaheuristic algorithms used to solve the TSP problem (Geng X. et al.2011). SA is a stochastic optimization algorithm based on the physical process of annealing in metallurgy. The algorithm has been shown to be effective in finding high-quality solutions for the TSP, especially when combined with other algorithms. For example, Nunes et al. (2021) proposed a SA algorithm that uses the A-Star algorithm to create an initial solution and proposed a perturbation method to generate a higher diversity of solutions in order to find a set of quality solutions for the bicycle routing problem (BRP). Other metaheuristics that have been used to solve the TSP include Genetic Algorithm (GA) (Ding et al. 2019; Li and Li 2019), Tabu Search (TS) (Gao et al. 2022), Ant Colony Optimization (ACO) (Fei et al. 2022) and Particle Swarm Optimization (PSO) (Shahriari et al. 2020).

The TSP problem has numerous applications in various fields such as transportation, logistics, and communication. Ha et al. (2020) used the TSP to optimize the delivery route of a drone. The study used the GA technique to solve the TSP problem and showed delivery time could be reduced efficiently. Alhamdy et al. (2012) used the ants colony algorithm to optimize a route and compared this metaheuristic with tabu search, simulated annealing, and genetic algorithm. Another application of the TSP is in the field of molecular biology, where it can be used to solve the protein folding problem (Berman et al. 2000).

In conclusion, the use of heuristics and metaheuristics has significantly contributed to the optimization of the TSP in various fields. While each algorithm has its advantages and limitations, researchers have shown that the combination of multiple algorithms can achieve even better results. Therefore, the optimization of the TSP remains an active area of research with many opportunities for further study.

3. Case study presentation

The Estrela do Norte bakery, located in the north of Portugal, aims to deliver bread daily to 195 customers. Currently, the route taken by the bread distributor has a total distance of 86 063m and is covered at an average speed of approximately 22.65 km/h. The entire route takes 10h56mins, of which 3h48mins are spent driving and 7h8mins at stops. As can be seen, the average driving speed is relatively low, and this happens because the roads the route takes are relatively narrow and within small villages. Furthermore, the bread distributor is constantly stopping to make deliveries, which also highly influences the value of the average driving speed.

In addition to the above, it was found that the total route duration is quite long, and it was understood that this is mainly due to the total amount of time taken in stops. This value corresponds to a large part of the total duration of the route due to the high number of points that imply the stoppage of the bread distributor. In fact, if there are 195 distribution points which make the total stop time of 7h8min, the average stop time at each customer is 2.19 minutes. Thus, we conclude that the total stop time, when carefully analyzed, is not surprising since it includes not only the time of preparation and delivery of the bread bags (the service time) but also any necessary stops, such as lunch break.

Thus, in order to minimize the distance to be covered and to study the efficiency of the SA applied to this particular TSP, it was decided to apply the referred metaheuristic to five different initial solutions in order to understand, among the routes obtained, which is the best solution and which should be implemented.

4. Methodology and approach presentation

For the development of this paper and in order to obtain the necessary information, one of the authors traveled the current route with the bread distributor and, this way it was possible to collect numerous data, namely:

- The location of each stop point;
- The stopping time at each of the points;
- The average driving speed;
- The total driving time;
- Total stopping time;
- The total journey time;
- The current route used by the bread distributor.

In order to enable the study and analysis of this data, it was first necessary to determine a distance matrix that included all the distances between the 196 points/costumers. To this end, having the coordinates of each of the 196 costumers, the Google Matrix API (Google's program which provides distances and travel times for a matrix of origins and destinations) was used in all the distances and the 196 x 196 distance matrix obtained. It is important to mention that the matrix initially obtained was not a symmetrical matrix, however, knowing the conditions of the roads to be travelled (no one-way roads) and realizing that the few asymmetric points did not present a significant difference in values, it was decided to undervalue these small disparities and transformed this matrix into a symmetrical matrix.

After obtaining the distance matrix, the TSP was solved in order to find the shortest distance route and, consequently, the shortest duration and the lowest cost, which allows visiting all customers passing only once through each of them.

Initially, to solve the TSP, we tested the possibility of using an exact method and, as for a symmetric TSP $(\boldsymbol{d_{ij}})$= $(\boldsymbol{d_{ji}})$, there are $\frac{(\boldsymbol{n-1})!}{\boldsymbol{2}}$ possible solutions (Moura, 2022) it was concluded that it would be very complex and, mainly, very time consuming to obtain a solution through this method for the 196 costumers, since $\frac{(\boldsymbol{196-1})!}{\boldsymbol{2}} = \boldsymbol{2,54 \times 10^{365}}$ possible solutions would have to be analyzed, taking a very high computational time.

After concluding that the exact method would not be a feasible approach, the metaheuristic SA was applied. SA is a heuristic optimization algorithm that is inspired by the physical process of annealing in metals. It was introduced by S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi in their 1983 paper "Optimization by Simulated Annealing" (Kirkpatrick et al., 1983). SA randomly changes the current solution and accepts the change based on a probability distribution controlled by the temperature parameter. As the temperature decreases, the algorithm becomes more selective and only accepts better solutions. SA can find the global optimum of a non-convex and multimodal objective function, but it can be slow and requires tuning of the temperature and cooling schedule parameters.

One of the decisions to be made when applying SA is the initial solution. Since the key point of this algorithm is to allow hill climbing, one of the ways to verify not only the convergence time, but also the quality of the solutions found, is running the algorithm with different initial solutions. So, to apply the SA to the TSP and to study its efficiency when different initial solutions are used, the following methodology was adopted (Figure 1):

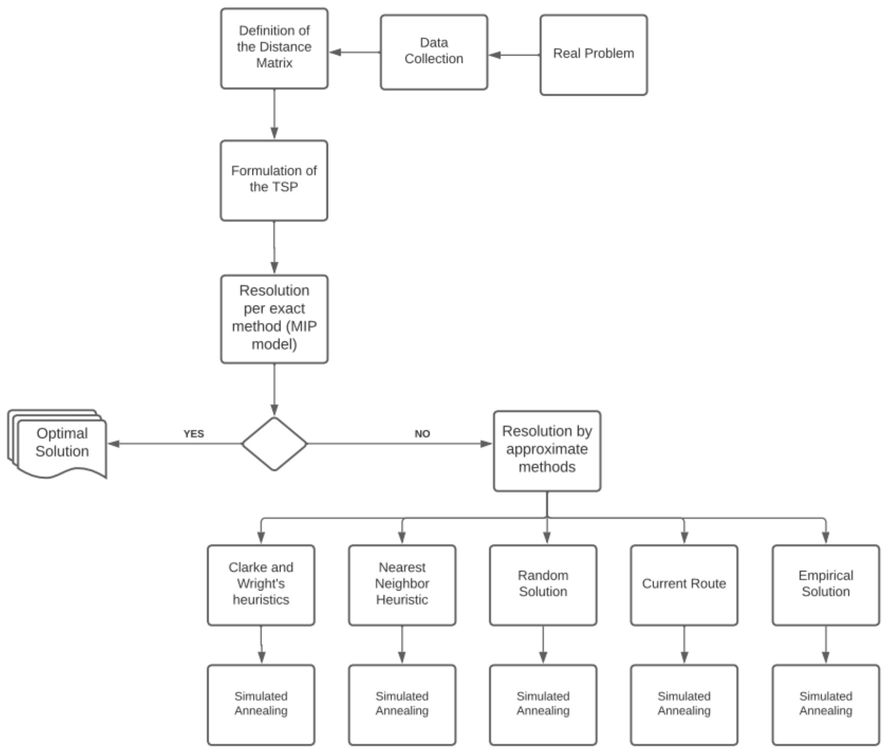

Figure 1. Flowchart of the adopted methodology

The various initial solutions were obtained using different ways, as shown in figure 1. The first two were obtained using the well-known algorithms Clarke and Wright's and the Nearest Neighbor. Another three solutions were used:

- a random solution;
- the route currently travelled by the bread distributor;
- an empirical route.

This last one, the empirical route, was obtained from the solution found by the NN algorithm, by making small changes in the order in which some customers were visited. This approach was enabled by the fact that when plotting the NN solution on a map, there were obvious changes that allowed an improvement of the solution.

Therefore, the following initial solutions were used:

- Currently traveled (CT);
- Clarke and Wright (CW);
- Nearest Neighbor (NN);
- Random Route (RR);
- Nearest Neighbor empirically improved (NN-EI);

5. Simulated annealing approach

We based the SA approach on Nunes et al. (2021) work. First, we will present how the various initial solutions to the real problem were obtained, and then we will use the SA to improve the initial solution of the real TSP. Since this metaheuristic starts from a previously built initial solution, we then intend to verify the influence each initial solution has in terms of convergence and objective function values. Also allowing to verify its relevance in terms of obtaining the various local optimums.In this section the procedure used to obtain the different initial solutions is explained (section 5.1), and then the SA implementation and related results and behavior with each of initial solutions (section 5.2).

5.1. Initial Solutions

As previously mentioned, to be able to apply the SA and to evaluate its behavior when using different initials solutions, the following initial solutions were computed:

- CT - Initial solution that corresponds to the currently traveled route;
- CW - Initial solution obtained through Clarke and Wright's heuristic method;
- NN - Initial solution obtained through the heuristic method of Nearest Neighbor;
- RR - Initial solution obtained in a random way;
- NN-EI - Initial solution obtained empirically from analyzing the route resulting from the application of the Nearest Neighbor, having knowledge of the road already traveled.

To begin with and since the goal is to minimize the distance of the route currently traveled by the bread distributor, the current road was defined as an initial solution for the subsequent application of the SA. This route has been traveled for more than 15 years and presents approximately 86 063 m, as shown in table 1. Then, considering all the 195 costumers, both Clarke and Wright's heuristics and the Nearest Neighbor heuristic were applied. The Clarke and Wright heuristic is widely applied to the vehicle routing problem, it is also applied to the TSP. This heuristic starts from an initial node and determines the cost of inserting that node into all the others. Then a list is drawn up with routes from that node to every other client and the respective costs are calculated. The list is sorted in a decreasing cost order, with the best solution corresponding to the minimum total cost. The first node in the ordered list is then always chosen and inserted in the route. In contrast, the NN is a greedy heuristic which starts from the city of origin, and at each step, adds not yet visited cities, whose distance to the last city entered in the route, is as short as possible. These two algorithms were implemented with Python and the results obtained are presented in table 1.

Regarding the RR route, it was generated from a random function using Python. This means that this initial solution was not determined based on objective function, it was determined by choosing a random path, without any limitation. The total distance of this route is 868 314 meters as can be seen in table 1.

Taking into account the best of the initial solutions obtained so far, which correspond to the solution obtained through the Nearest Neighbor heuristic, and based on the knowledge about the route taken by the bread distributor, it was believed that this initial solution could be improved. This can be justified, due to the greedy nature of the Nearest Neighbor heuristic. This algorithm sometimes tends to take the traveler in a direction that, in that interaction, is the closest costumer, but in global terms this choice would not be the best, because it leads to a longer or less efficient track. Thus, after an evaluation, the route was empirically improved, and a total distance of 73 009 m was obtained.

In table 1, apart from the computational times, the objective functions are presented, that is, the total distances of the routes initially obtained that will be considered as initial solutions for the application of the SA.

Table 1. Objective function and computational times of initial solutions

	RR	CT	CW	NN	NN-EI
Objective function (in meters)	868 314	86 063	89 671	77 452	73 009
Computational time (in seconds)	0,016398	-	0,264151	0,222795	-

Analyzing the results, it is clear that the RR solution is the one that presents the highest objective function value, which is not surprising, since it is generated randomly and the total number of nodes to visit is high.

Regarding the results obtained by the heuristic methods, it can be concluded that the best solution was the route obtained through the NN heuristic since it tends to create shorter and more direct routes, compared to the Clarke in Wright heuristic, which becomes advantageous in scenarios whose points are close to each other.

Finally, considering all the initial solutions, we conclude that the one that presents a significantly better value when compared to the other initial solutions is the solution obtained empirically. This can be justified by the fact that it started from a good initial solution (NN solution), and an improvement was made, even if empirically.

In addition to the above, and analyzing Table 1, the solution obtained by CW (89 671) is worse than those obtained by CS (86 063) meters. This proves that, in real problems, heuristic methods are useful and can be an aid to decision-making.

5.2 Simulated Annealing approach

As mentioned before, the SA is used to solve the real problem, and the perturbation used consists in swapping two points from a solution, randomly. One of the advantages of this metaheuristic is the convergence guarantee. However, although convergence is guaranteed, it can be very slow, since the guarantee arises when the cooling scheme is such that it causes the temperature to decrease very slowly. With this in mind and to implement the SA, several decisions have to be made:

- Initial solution;
- Initial temperature;
- Cooling scheme;
- Length of plateau;
- Neighborhood structure (size and maximum distance between two points to do the permutation);
- Stop criterion.

The first decision is already explained above since the initial solution will be one of the previously presented solutions (section 5.1). The initial temperature, the length of plateau and the neighborhood structure were refined several times, using a grid search approach, to obtain the best possible results and to ensure that the metaheuristic converged (Figure 2, 3, 4, 5 and 6). Note that the neighborhood structure encompasses 2 different parameters, its size, i.e., the maximum number of new solutions that are generated in each iteration of the algorithm, and the maximum distance between two points that are swapped during the perturbation. Both these parameters were tuned through an iterative search. The stop criterion is based on a maximum number of iterations which is defined by the way the convergence was enabled.

Finally, the cooling scheme consists in linearly decreasing the initial temperature, which is done based on the initial temperature, the total number of iterations, and on the decreasing temperature step, which was also a parameter tuned by an iterative process.
Thus, the results obtained after implementing the metaheuristic and after refining the parameters are specified in table 2 below

Table 2. SA solutions

Initial Solution	RR	CT	CW	NN	NN-EI
Objective function (m) of the initial solution	868 314	86 063	89 671	77 452	73 009
Objective Function (m) after applying SA	124 396	73 335	76 864	74 170	65 345
Percentage variation (%)	85,67	14,79	14,28	4,24	10,50
Computational Time (s)	2017,4574	137,8364	749,1761	6,8716	971,82

The convergence of the SA for each of the initial solutions is shown in Figures 2-6 below. Analyzing the solutions obtained and the convergence graphs, it is clear that the application of the SA significantly improved the objective function when applied with all the initial solutions, as expected. The percentage variation of the objective function improvement is quite different among the solutions, ranging from 4.24% to 85.67%. Furthermore, it can be seen (Table 2) that the computational time required to achieve a solution varies significantly for each of the initial solutions, varying from a few seconds to almost 34 minutes.

It is possible to conclude that the solution obtained using the RR was the one that has the most significant improvement. This 85.67% improvement, despite corresponding to a reduction of 743 918 m, required a considerable computational time, 33 minutes. When the SA uses the CT, the improvement is of, approximately, 11.87%, which corresponds to a reduction of 12 738 meters. This in turn, only required about 2 minutes and 17 8364 seconds of computational time.

On the other hand, when the SA uses the CW, an improvement of 14.28% was obtained, which corresponds to a reduction of 12 807 m, while the improvement resulting from the SA with NN is 4.24%, representing a reduction of 3 282 m compared to the current route. Regarding to the computational times, the SA with CW (12 minutes) is much higher when compared to the computational time required by the solution obtained by SA with NN (less than 7 seconds). Analyzing the SA with IS, we conclude that a reduction of 7 664 m was achieved, which corresponds to a 10% improvement and required almost 17 minutes of computational time, a relatively high value. In order to choose the best route to be implemented it is necessary to consider the values of the objective function (Table 2).

Analyzing the values, of the objective function presented in Table 2, we can state that the worst route corresponds to 124 396 m achieved with SA with RR, a much higher solution than the route currently traveled by the bread distributor (CS). It is also possible to see that the routes obtained with SA with NN and CW present similar values for the objective function: 74 170 and 76 864 meters, respectively. In addition to the above, it is also possible to conclude that the best values were obtained by SA with CT and NN-EI: 73 335 meters and 65 345 meters, respectively. Which is curious because both solutions were computed using empirical knowledge. This proves that for many problems, in particular real problems, heuristic methods are useful as an aid to decision-making.

Figures 2-6 show the convergence of the SA approach when using different initial solutions. For the RR, the objective function is improved considerably during the process; however, since the initial random solution was poor, the algorithm takes a long time to converge, since it needs a lot more iterations. Furthermore, the solution converges to a much longer route, compared to the initial solution adopted by the company, which is not interesting. The SA with the CT, CW, and NN-EI, as initial solutions have similar behavior, i.e., converge to a better solution with a similar number of steps. However, with different initial solutions, the approach converges to different local minimum, highlighting the importance of obtaining a good initial solution before applying the SA. On the other hand, the NN solution took a very short time to converge to the best solution found, which occurs because it is already a good solution, and it is near to a local optimum, from which the SA is not able to improve anymore.

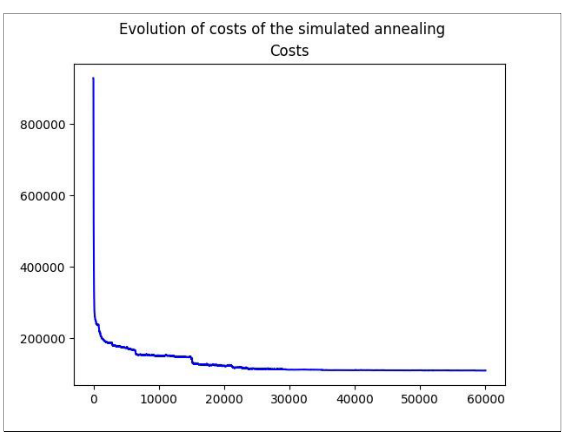

Figure 2. Convergence graph of SA With RR

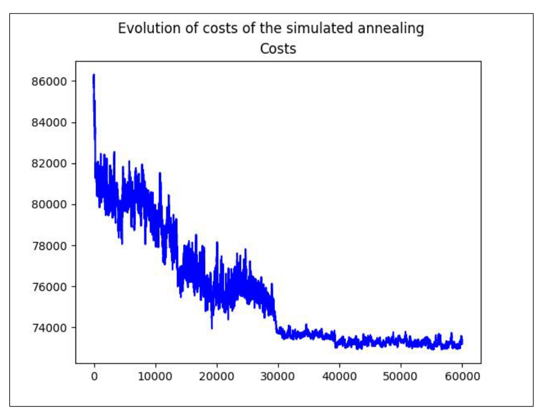

Figure 3. Convergence graph of SA with CT

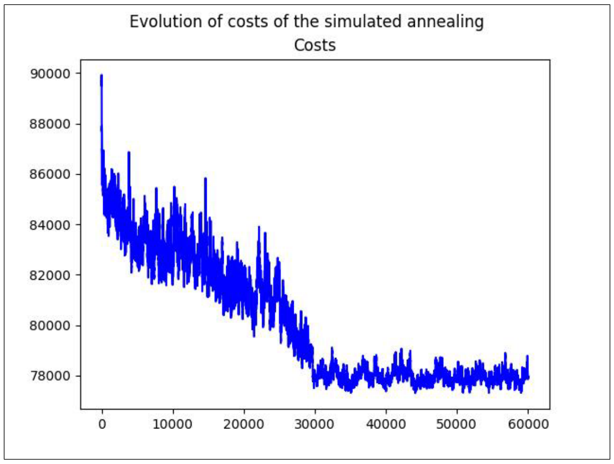

Figure 4. Convergence graph of SA with CW

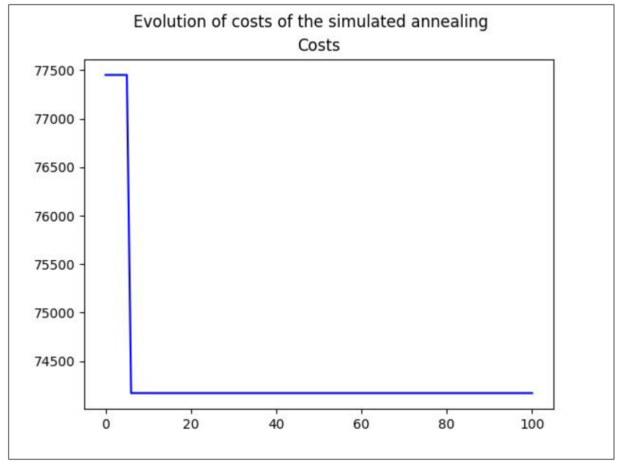

Figure 5. Convergence graph of SA with NN

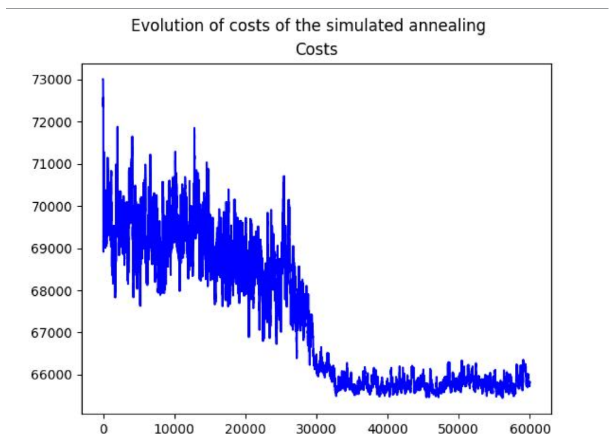

Figure 6. Convergence graph of SA with NN-EI

Finally, it should be noted that the best solution is achieved when the SA starts with the NN-EI solution, with 65.345 meters. Furthermore, comparing this solution with the route currently traveled by the bread distributor, it was possible to see that there is an improvement of 23%, since there is a reduction of 20.718 meters to the route. Thus, if we consider the currently average speed used by the bread distributor, 22.65 km/h, we see that this saving is equivalent to about an hour of work, so this should be the route to implement from now on.

6. Summary and conclusions

This paper presents an efficient approach to solve a Travelling Salesman Problem by applying the Simulated Annealing metaheuristic. The main objective sought was to reduce the route currently taken by the bread distributor of a Portuguese bakery and, for this, several initial solutions were computed to be considered as an initial solution for the SA. To determine these initial solutions, several methods were used, including Clarke and Wright's heuristic and the Nearest Neighbor heuristic.

The results obtained allowed us to conclude that, in fact, by applying Simulated Annealing it is possible to improve the current route made by the distributor. It was also possible to conclude that the best solution is achieved when the SA uses the NN-EI initial solution. Thus, it is suggested that this route should be implemented since it’s shorter and reduces distribution time and associated costs.

The proposed goal was achieved: the total distance to be covered for the distribution of bread to 195 customers is reduced in more or less 20 km, which corresponds to more than 23% of the initial route’s length.

Moreover, this study provides relevant information about the behavior of Simulated Annealing in different scenarios that can be useful for future research about the application of this metaheuristic to the Travelling Salesman Problem and other combinatorial optimization applications. Thus, as a suggestion for future research, we propose the application of other metaheuristics as well as the use of other methods to obtain initial solutions.

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Eva Rodrigues is a Master's student in Industrial Engineering and Management at the University of Aveiro. She has a keen interest in research and is actively pursuing topics related to optimization and problem-solving techniques. Eva's academic achievements include an award from the Grace Academy 2021 for her research on the impact of the COVID-19 pandemic on the wine industry. Currently, she is participating in the Erasmus + program at the University of Brescia in Italy, where she is furthering her studies in industrial engineering and management.

Cíntia Câmara is a Master's student in Industrial Engineering and Management at the University of Aveiro. Currently, under the Erasmus+ program, she is at Valladolid University in Spain, where she is deepening her studies in engineering and industrial management in an international context. At the academic level she has the Grace Academy 2021 award where he conducted a study on the impact of the COVID-19 pandemic on the wine industry. Her main areas of interest are logistics, operational research, operations management and Lean Manufacturing.

Maria Almeida is a Master's student in Industrial Engineering and Management at the University of Aveiro whose main areas of interest are logistics and data analysis. Moved by the desire to learn and improve, she is a person who is always seeking new and different experiences and opportunities which challenge her while adding value to her professional and personal path. That's the reason why she was a member of a Junior Enterprise during her academic path and that's why she is also currently studying at the University of Linköping in Sweden through Erasmus + program.

Pedro Nunes is a PhD student in the Department of Mechanical Engineering, at University of Aveiro, Portugal. He concluded his MSc in Mechanical Engineering at the same institution, in 2018. He was a research fellow between 2018-2020 at TEMA (Centre for Mechanical Technology and Automation), when he published articles in international conferences and journals in the context of bike routing, multi-objective routing, and sensorization of soft mobility vehicles. The main objective of his PhD is the development of flexible and customizable predictive maintenance solutions. In this scope, he has publications on international conferences and journals in the fields of Industry 4.0, smart manufacturing, logics and advanced research technologies.

Ana Moura is an Assistant Professor in the Department of Economics, Management, Industrial Engineering and Tourism of the University of Aveiro. She is a Researcher in GOVCOPP and a researcher collaborator with the Institute of Systems Engineering and Computers of Coimbra (INESC-Coimbra). She received her PhD from the Faculty of Engineering of the University of Porto in 2005. Her primary area of interest is the application of Decision Support Systems and Optimization Methodologies to industrial problems and organizations, in general. The main application areas have been in logistics and distribution, more precisely in: Vehicle Routing Problems and Three-dimensional Packing Problems. More recently, her research interest is in the application of operations research methodologies to production systems.