Good Practice Proposal for the Implementation, Presentation, and Comparison of Metaheuristics for Solving Routing Problems

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Abstract

Researchers who investigate in any area related to computational algorithms (both defining new algorithms or improving existing ones) usually find large difficulties to test their work. Comparisons among different researches in this field are often a hard task, due to the ambiguity or lack of detail in the presentation of the work and its results. On many occasions, the replication of the work conducted by other researchers is required, which leads to a waste of time and a delay in the research advances. The authors of this study propose a procedure to introduce new techniques and their results in the field of routing problems. In this paper this procedure is detailed, and a set of good practices to follow are deeply described. It is noteworthy that this procedure can be applied to any combinatorial optimization problem. Anyway, the literature of this study is focused on routing problems. This field has been chosen because of its importance in real world, and its relevance in the actual literature.

Keywords: Metaheuristics, Routing Problems, Combinatorial Optimization, Traveling Salesman Problem, Good Practice Proposal.

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1. Introduction

Today, optimization problems receive much attention in artificial intelligence. There are various types of optimization, such as linear [1], continuous [2], numerical [3], or combinatorial optimization [4]. Usually, the resolution of problems arisen in these areas entails a great computational effort. Besides that, many optimization problems are applicable to real world situations. For these reasons, many different methods developed to be applied to these problems can be found in the literature.

In this way, route planning is one of the most studied fields in artificial intelligence. Problems arisen in this field are usually known as vehicle routing problems, which are a

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particular case of problems within combinatorial optimization subject. It is important to highlight that combinatorial optimization is the most suitable branch of optimization for facing routing problems, since the option of treating the variables as discrete ones permits a faithful adaptation. On the other hand, the use of another type of optimization, such as continuous optimization, which requires continuous variables, could lead to a less reliable adaptation.

In line with this, the comparison between different metaheuristics for solving routing problems is a complex task, since many factors must be taken into account. This fact creates a lot of controversy and can lead to much confusion and bad practices. Despite this, it is hard to find a methodology or procedure that helps researchers to describe and compare their metaheuristics in a reliable manner. In this way, the aim of this paper is to propose a procedure to facilitate an accurate comparison between different metaheuristics. It is noteworthy that these good practices are focused on routing problems. For this reason, the literature of this study is oriented to this kind of problems. This field has been chosen due to its importance in the real world, and its great relevance in the literature. Finally, we want to clarify that this study is an extension of the work presented in [5] for the International Joint Conference SOCO-CISIS-ICEUTE'14. In the present work several additional good practices are proposed, and the presented literature is updated. Additionally, some of the good practices proposed in [5] have been modified and supported with additional cites in order to facilitate their understanding.

As has been mentioned, until now, few methodologies and good practices have been proposed in the literature related with heuristics and metaheuristics. In [6], a small section about the evaluation of heuristics related to the Vehicle Routing Problem with Time Windows can be found. In this section, some advices to perform a fair comparison between different heuristics are described. The difference between this work and our proposal is that we have focused our attention in metaheuristics, instead of heuristics. Additionally, the bibliography of our paper covers a wider field, generalizing to all vehicle routing problems. The authors in [7] also mentioned the difficulty of finding standards in optimization research in terms of good laboratory practices. In this case, authors suggest a concrete set of recommendations that the community should adopt in order to enhance the replicability of studies. The difference between this valuable work and the present paper is that we have focused in one specific branch of optimization and a concrete family of problems. Furthermore, we have not only centered on good practices related to laboratory experiments. Besides that, we also propose some good practices to consider when implementing, and presenting, different techniques for comparison. In [8], some good research practices to follow in the development of novel metaheuristics are described. Finally, some articles can be found in the literature proposing methodologies to perform correct statistical tests. In [9], for example, a practical tutorial on the use of nonparametric statistical tests for comparing evolutionary and swarm intelligence algorithms is presented. In addition, in [10], a method for statistically compare different heuristics or metaheuristics is presented. The goal of that article is to propose a methodology to perform statistically correct and bias-free comparisons. In line with this, and being aware that this is not the sole objective of our paper (since we have addressed all the development-experimentation phase), a special mention to statistical tests is made in our paper.

The structure of this paper is as follows. In Section 2 the background that motivated this study is described. After that, in Section 3, the steps to follow in the implementation and presentation of metaheuristics are explained. In Section 4, how the results should be accurately presented is explained. This paper ends with the conclusions of the study, its utility, and our planned future work (Section 5).

2. Background

As has been mentioned in the introduction, route planning is a hot topic inside artificial intelligence. The different problems arisen in this field produce a huge amount of works annually in both international conferences [11, 12], and journals [13, 14, 15]. In addition, they inspire the edition of several technical reports [16], and scientific books [17, 18]. It is noteworthy that two of the most studied routing problems are the Traveling Salesman Problem (TSP) [19], and the Vehicle Routing Problem (VRP) [20], which are the focus of a great number of studies in the literature [21, 22].

The importance of routing problems can be justified in two ways: their inherent scientific interest, and the social interest they generate. On the one hand, most of the problems arising in this field have a great computational complexity. Being NP-Hard, the resolution of these problems is a major challenge for the scientific community. On the other hand, routing problems are usually designed to tackle real world situations related to logistics and transports. This is the reason because their efficient resolution entails a social and a business profit.

In line with this, several approaches can be found in the literature to address these problems efficiently. Arguably, the most successful techniques are the exact methods [23, 24], heuristics and metaheuristics. On the one hand, exact methods are search methods that track all the solution space to always find the optimal solution. These techniques are only valid for simple problems, or for relaxation of more complex problems. Otherwise, the execution times of these kind of methods are computationally inadmissible.

Furthermore, a heuristic is an optimization technique that solves a problem using specific information and knowledge of that problem. In this way, heuristics explore the space of feasible solutions intensifying the search in the most promising areas. This process is made with the intention of achieving good optimization results quickly. Generally, these techniques are used to solve well-known problems with simple formulations, such as standard TSP or the basic VRP, because of the difficulty of finding appropriate heuristics to real problems with complex objective functions and constraints.

Finally, a metaheuristic is an optimization technique that solves a specific problem using only general information and knowledge common to a wide variety of optimization problems with similar characteristics. Metaheuristics explore the solution space in order to achieve good optimization results with independence of the problem. For this reason, it is prudent to affirm that metaheuristics are more appropriate to solve real world problems with complex formulations, since they do not use any specific information of the problem in the exploration of the space of feasible solutions. Metaheuristics can be applied in a wide range of fields, such as transport [25, 26, 27, 28], medicine [29], or industry [30, 31]. Some of these algorithms are based on a single search, such as Simulated Annealing [32] and Tabu Search [33], and some others are based on a multiple search (population based algorithms), such as genetic algorithm (GA) [34, 35], ant colony optimization (ACO) [36], particle swarm optimization (PSO) [37, 38, 39], or imperialist methods [40]. Besides these, in the last years many new population techniques have been proposed, such as the Bat Algorithm (BA) [41, 42], the Gravitational Search Algorithm [43, 44] or Firefly Algorithm (FA) [45, 46]. Metaheuristics can also be classified in search based algorithms and constructive algorithms. Search based algorithms start from an initial complete solution or an initial set of complete solutions which are modified until reaching a final solution, while constructive algorithms start from a partial solution or a set of partial solutions which are built until reaching an final complete solution.

As has been mention, many different metaheuristics can be found in the literature. These days, some of the most used ones are the population based techniques. Leaving aside the classical approaches, such as the GA or the ACO, some of the most popular methods in the current scientific community are the PSO, BA, harmony search (HS) [47], FA or flower pollination algorithm (FPA). Many studies can be found in the literature focused on these techniques. The PSO [37] is one of the most used swarm based technique, developed under the inspiration of the behavior of bird flocks, fish schools and human communities. It works with a population (called swarm) of candidate solutions (called particles), and the movements of every particle are guided by a parameter called velocity. Furthermore, BA is population technique, proposed by Yang in 2010 [41], which is based on the echolocation behavior of microbats, which can find their prey and discriminate different kinds of insects even in complete darkness. On the other hand, the HM [47] mimics the improvisation of music players, and it was conceptualized using the musical process of searching for a perfect state of harmony. Moreover, FA is a population technique first developed by Yang in 2008 [45], which is inspired on the flashing behavior of fireflies. This flashing behavior acts as a signal system to attract other fireflies. Finally, FPA is an evolutionary technique inspired by the pollination process of flowers [48]. These metaheuristics have been frequently used in recent years to solve routing problems [49, 50, 51, 52]. Since the main goal of this paper is not to describe deeply these techniques, we refer readers to any of the papers cited in this work to collect further information.

As has been pointed, on the one hand, heuristics are ad-hoc techniques which are focused on the resolution of one specific problem. Metaheuristics, however, can be applied to a wide variety of real problems whose complexity prevents developing appropriate heuristics. In this sense, the comparison among heuristics is simpler than the comparison among metaheuristics. No matter which the nature of heuristics is, or the parameters and features utilized, the best heuristic will be the one that obtains the best results in a reasonable time. Anyway, as can be seen in [6], the comparison of heuristics can also lead to problems if the results are not presented properly. On the other hand, the comparison between different metaheuristics is a complex process. Despite its importance, few papers related to this critical task can be found in the literature. As has been mentioned in the introduction, this lack of works has motivated the development of this study.

3. Good practices about the implementation and presentation of the metaheuristic

The set of good practices related to the implementation of metaheuristics is shown below:

- The problem constraints have to be detailed, classified in hard and soft constraints.

- A deep specification of the objective function must be made, which should include the soft constraints if necessary.
- In the presentation of the work, the type of metaheuristic being used must be precisely specified in the title or abstract of the paper, mentioning also heuristics, if used.
- The codification used to represent the solution has to be deeply described.
- The operators used in the implementation must be described in detail. If they have been developed by the author/authors of the study, they have to be clearly explained. On the other hand, whether the operators are not originally developed by the author, they have to be correspondingly referenced. Otherwise, the replicability of the displayed results is impossible.

The first step in the design of a technique for the resolution of routing problems is to define clearly the constraints and the objective function of the problem. Specifically, the objective function is an important issue related to the implementation of a technique. In problems like the TSP, this is not an issue, since the objective function is the distance of the route and the aim is to minimize it. For more complex problems, such as the Capacitated Vehicle Routing Problem (CVRP) [53] or Vehicle Routing Problem with Time Windows [54, 55], the function may vary depending on the objectives to be achieved. For the CVRP, for example, there are studies that prioritize the minimization of vehicles used [56], while others are focused on reducing the distance traveled [57]. For this reason, in order to avoid confusions, a good practice is to describe in detail the objective function.

Once the problem and its characteristics have already been introduced, it is important to present adequately the metaheuristic. One practice that should be avoided is the confusing denomination of the techniques. A typical example of this confusing naming can be to treat a technique as a metaheuristic, when the method uses heuristic operators in any of its steps. For this reason, the kind of algorithm which is being used must be precisely specified in the title or abstract of the paper.

When the problem and its objective function have been already defined, and the type of metaheuristic to develop is decided, the next step is to detail how it will be implemented and what kind of operators will be used. Although it seems simple, this fact could be controversial. As it is well-known, metaheuristics use different kinds of operators to modify and transform the available solutions, in order to improve them. Thereby, the first point to be considered is the following: to test the optimization ability of a metaheuristic to solve any routing problem, it is necessary to use neutral operators throughout the implementation, such as the well-known 2-opt operator [58], or Or-opt [59]. In other words, operators that use characteristics or information of the problem and optimize by themselves have to be avoided.

The initialization process of a metaheuristic can be mentioned as an example of this fact. The most appropriate way to prove the optimization quality of a metaheuristic is to use a random initialization process, instead of using optimizing initialization functions to create individuals. If any heuristic initialization functions is used, the individuals will pass through an optimization process before the execution of the core of the metaheuristic. Therefore, it may not be known exactly what the capacity of optimization of a metaheuristic is when final results are obtained. In this case, it has to say that a heuristic has being implemented, because specific information of the problem is used. In line with this, the authors of the present paper want to clarify that a correct heuristic initialization process could be beneficial whether the objective of the study is to optimise a problem. In fact, functions like the Solomon's I1 [60], or the well-known Nearest Neighbor [61], have shown their efficiency multiple times in the literature. Nevertheless, as it has been mentioned, if the goal is to measure the optimization ability of a metaheuristic, the appropriate way is to use a random initialization process, avoiding this kind of heuristic operators.

Using now the combination operators as example (also known as crossover operators) and using the TSP as example, a heuristic operator would be the Very Greedy Crossover (VGX) [62]. The VGX is an operator for the TSP that uses the distances between cities to generate the children. It is logical to think that using this operator the GA will get good results for the TSP, as the VGX makes by itself a small optimization on the resulting individuals. If the objective is to implement a metaheuristic, operators like Order Crossover [63], Half Crossover [64], Order Based Crossover [65] or Modified Order Crossover [66] should be chosen as crossover function, since they are neutral operators. These functions, also known as Blind Crossover Operators, only care to meet the constraints of the problem and they do not use any kind of information related to the problem.

Regarding this matter, the next point to consider is introduced: comparisons between metaheuristic techniques with neutral operators and heuristic techniques with optimizing functions should be avoided. Otherwise, the comparison would be unreliable, because of the different nature of the techniques. For example, if our intention is to check the quality of the a crossover operator as the above mentioned VGX, the results obtained by this operator must be compared with the one obtained by other heuristic crossover function, such as the called Sequential Constructive Crossover (SCX) [67], or the well-known Heuristic Crossover [68]. Otherwise, if the performance of the VGX is compared with other neutral functions, as the OX, HX, OBX or MOX, the comparison is not going to be as fair as it should be.

Additionally, something important when developing any method, or operator, is the codification used to represent the partial, or complete solutions of the problem. The codification chosen has to be clearly described in any study. Depending on the representation used, some operators can be developed or not. Furthermore, if our intention is to compare some techniques, all of them need to follow the same encoding. This fact is extremely important if the operators utilized in the developed metaheuristics are developed by the authors of the study. The addition of this description clearly enhances the replicability of the operators and techniques. For this reason, omit the description of the encoding used can be considered as a bad practice.

Taking again the TSP as example, some representations have been used in the literature, each one with its own advantages and disadvantages. The most frequently utilized encoding is the path-representation, which codifies the solutions as permutations of numbers depicting the route [69]. Other commonly used representation are the Matrix [70], the Ordinal [71], the Binary [72] and the Adjacency one [71]. All these codifications have their own operators which cannot be used with other representations. This is the main reason because it is compulsory to describe the chosen codification.

Finally, it should be borne in mind that to make a completely reliable comparison between two metaheuristics, is mandatory the use the same operators and parameters for both, as long as possible. If it is not possible, operators used in both techniques must have similar characteristics. For this reason, the points explained above are of vital importance, both to make the results easily reusable in other studies, and to give credibility to a comparison performed in a work.

4. Good practices for result publication

Having described the characteristics of a metaheuristic, it is appropriate to show the results it can get. This is a very important step, since according to the form that the results are presented their replicability can increase, and other researchers can use them to compare their techniques. This is a crucial issue for the relevance and impact of any study. These are the set of good practices related to the showing of results:

- As long as the problem allows, the experimentation have to be performed with instances obtained in a benchmark. Obviously, the more instances are tested, the richer the study. Each used instance must be referenced, with its name and the benchmark it belongs to.
- It is vital to show the execution times, accompanied by their time unit and an explanation of the characteristics of the computer on which the tests were carried out.
- Apart of showing the runtime, to make a fair comparison between different techniques presented in different studies, it is highly recommended to show the convergence behavior of each technique used in the experimentation.
- The more data displayed, the richer work. Thus, comparisons made with the metaheuristic will be more reliable. For every instance, this information should include at least the number of executions carried out, and, both for objective function and runtime, best and worst results, the average and the standard deviation.
- For a fair and rigorous comparison it is necessary to perform an appropriate statistical analysis with the obtained results.
- If possible, it is completely advisable to share the source code of the implemented algorithms with the scientific community.

First of all, the best way to check and measure the quality of any technique is to apply it to several instances of the problem in study. Arguably, the best option is to perform an experimentation using one of the numerous benchmarks that can be found in the literature. These benchmarks are composed of instances of a specific problem, which can be used to validate any developed technique [73]. Many of these instances have a known optimal solution. In this way, the effectiveness and efficiency of a metaheuristic can be measure by comparing its results with those offered by benchmarks. Taking into account this fact, it is much easier to contrast the quality of a technique if its results are compared with the ones obtained by other techniques that have used the same benchmark. Therefore, one good practice to perform a fair comparison is to apply different techniques to the same instances, and compare the obtained results. Focusing on routing problems, there are a lot of benchmarks for a large number of problems, such as TSPLIB [74] or VRPWeb (*http://neo.lcc.uma.es/vrp*). In line with this, it should be noted that the use of new instances and benchmarks is necessary when the addressed problem is new for the scientific community. Anyway, as far as possible, the use unknown instances has to be avoided. Hence, as a conclusion, we strongly encourage the use of a benchmark for the fair comparison of techniques.

In line with this, something to note in any study is the decimal precision used in the results of the employed instances. This fact is especially important in works like [75], or [76], where new benchmarks for vehicle routing problems are presented. Additionally, these two papers are correct examples of how a new benchmark has to be presented. Typically, in classical benchmarks as TSPLIB, Christofides/Eilon [77] or Golden et al. large-scale benchmark for the VRP [78], the travel costs are rounded in order to work with integers. In other works, as in [79], distances are treated as real numbers. Although this fact seems to be a trivial practice, the lack of specification may lead to a confusion, as can be proved in our previously published works [73] and [80].

When we want to show results, one important point is the runtime. In this way, it should be avoided to show the results without showing the execution times. This is especially crucial if all the developed techniques have been implemented in the same computer. Although it may be logical, it also must be specified in which unit the runtime is displayed, i.e., seconds, minutes, etc. Apart from showing in detail the runtimes of the technique, it is also important to note the characteristics of the computer used for the tests.

Although the runtime is helpful for comparing two techniques shown in the same study, the use of another parameter is more reasonable for the comparison between techniques developed in different works. This fact is given because it could be not fair to compare the runtime of different algorithms if they have been run in different computers. It is logical that the more powerful the computer, the less time needed to execute a metaheuristic.

Thus, a good measure to compare techniques is showing their convergence bahavior. The convergence is a parameter that measures the trend of a method to stabilize after time, and it is used to analyze the behavior of a technique over the execution. In general, it can be said that one technique has converged if its current state is very common to its ancestor, and its successor.

The convergence behavior of one method can be measured in diverse ways. Anyway, this parameter is usually calculated using two main approaches. The first one is the number of iterations needed to obtain the resulting solution. This value will vary depending on the technique being used. For example, for a Tabu Search or Simulated Annealing, this value will be the number of iterations performed to reach the solution. For a GA, it could be the number of generations executed. Some examples of works using this approach can be [81], [82] and [83]. On the other hand, the second way to calculate this parameter is the number of objective function evaluations needed to reach the final solution of the problem. In this case, this value will be calculated in the same way for almost every technique.

Besides this, to provide richness and replicability to a study, it is highly recommended to display a complete set of results, showing important data as the mean, the best result or the standard deviation. As it is mentioned in [6], where several tips to compare heuristics are introduced, display only the best results of a heuristic, as is often done in the literature, may create a false picture of the quality of the technique. This statement may be also applicable to metaheuristics. In this way, display only the best results in a comparison of techniques is considered a bad practice. Therefore, the average result based on multiple executions is considered the best basis for the comparison.

Once the results have been presented, and in order to perform a fair and rigorous analysis of the results, an appropriate statistical test is required. Some studies in the literature can be found describing some guidelines to conduct a correct analysis. One of these studies is the presented by Derrac [9]. There are several different methods to conduct a proper analysis. Some of these methods are the Friedman's Test [84], the Holm's Test [85], or the Wilcoxon Test [86]. These are examples of non-parametrical tests, and they have been used frequently in the literature [87, 88, 89]. Additionally, some parametrical tests can also be used, such as the Student's t-test [90, 91] or Normal z-test. Anyway, these two tests are only applicable if we assume that the developed algorithms results follow a normal distribution. In this regard, several studies and tools can be found in the literature in order to check the normality of any technique and distribution [92, 93, 94].

Finally, one additional good practice that would help the replication and the use of new proposed techniques is the sharing of the source code to the scientific community. In this regard, the availability of the implementation as well as the extended data of the results supposes a contribution to the scientific community. In this way, results can be analyzed in detail, and novel techniques can be compared objectively. Furthermore, this good practice enhances the modification and improvement of the existing techniques and the incorporation of new methods to commercial optimization softwares. This is particularly important because most real-world systems for optimizing vehicle routes are custom made and lack the latest findings published in the literature. This fact is reflected in a recent survey of road-based goods transport applications [95].

5. Conclusions and further work

Routing problems and metaheuristics for their resolution are subject of a large number of studies annually. Every year, many novel techniques or modifications of existing ones are developed by researchers. For this reason, comparisons between techniques are widely used in many studies, since they are appropriate to check the quality of new proposed techniques. Despite this, it is hard to find any specific methodology or procedure that helps researchers to compare different techniques in the field of routing problems, either within the same or different works. This has led to the existence of studies and works that have been carried out bad practices, both in describing techniques such as present or compare results. This is what prompted us to do this work, in which a procedure of good practice to facilitate the comparison between metaheuristics oriented to solve routing problems has been defined. With this procedure, researchers will be able to make comparisons easily and reliably.

Showing examples of the application of these good practices would increase the extension of this paper considerably. Moreover, it is beyond the scope of this theoretical work. For this reason, and understanding that it could be useful for the reader, we recommend the reading of [52] and [96] to see two examples of the application of these good practices.

Regarding the possible future work, one of our proposals is to modify the different benchmarks in the literature, so that not only the best results have to be shown for each instance. The details of the technique that has been used to achieve the best result should also be shown, mentioning the runtimes, iterations needed and details of implementation. This would facilitate the comparison between techniques and the replicability of the results.

Additionally, we are aware that many other good practices can be added to the list presented in this work. These additional good practices can be as important as the ones described in this paper. Anyway, the ones detailed here are recommended for any rigorous and objective study.

In [73] we defined a methodological proposal in the showing of results in benchmarks to eliminate ambiguities in the comparison of VRP solving techniques. Now, in this paper, we extend that proposal introducing a procedure of good practice to present metaheuristics and their results properly, with the aim of facilitating the comparisons between different techniques. As future work, we plan to perform a methodology to help the researchers to realize proper, detailed and objective analysis of the studies made. In this way, we aim to facilitate the comprehension of the results and its capacity to be replicated and discussed. In addition, we want to extend our study to other fields and problems inside the optimization and soft computing, where several interesting papers are published annually [97, 98].

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