Traveling Salesman Problem: a Prospective Review of Recent Research and New Results with Bio-Inspired Metaheuristics and Novelty Search

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Abstract The Traveling Salesman Problem (TSP) is one of the most studied problems in Computational Intelligence and Operations Research. Since its first formulation, a myriad of works has been published proposing different alternatives for it solving. Additionally, a plethora of advanced formulations have also been proposed by the related practitioners, trying to enhance the applicability of the basic TSP. This manuscript is firstly devoted to providing an informed overview on the TSP. For this reason, we first review the recent history of this research area, placing emphasis on milestone studies contributed in last years. Next, we aim at making a step forward in the field proposing an experimentation hybridizing three different reputed bio-inspired computational metaheuristics (namely, Particle Swarm Optimization, Firefly Algorithm and Bat Algorithm) and the Novelty Search mechanism. For assessing the quality of the implemented methods, 15 different datasets taken from the well-known TSPLIB have been used. We end this paper by sharing our envisioned status of the field, for which we identify opportunities and challenges which should stimulate research efforts in years to come.

Key words: Traveling Salesman Problem, Nature-inspired computation, Bio-inspired computation, Novelty Search, Combinatorial Optimization

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1 Introduction

In the current operations research and optimization communities, routing problems are one of the most studied paradigms. Two are the principal reasons that make this topic a paramount one in the field: their inherent practical nature and social interest, which allow routing problems to be applicable not only in leisure or tourism scenarios, but also in situations related to logistics and business; and their complexity, making such problems very difficult to optimally solve them even for medium-sized datasets. Arguably, the modeling and formulation of this kind of problems draws inspiration from real-world logistic and transportation situations, directly implying a social and/or business benefit in case of being properly solved. Furthermore, the efficient addressing of these problems usually supposes a tough challenge for the scientific community because of their NP-hard nature. This fact leads related researchers to the adoption of diverse artificial intelligence solvers, aiming at solving them in a computationally affordable fashion. The problem gets even more involved when bearing in mind the rich literature in regard to different formulations of variants. Among this wide variety of problems, the Traveling Salesman Problem (TSP, [1]) and the Vehicle Routing Problem (VRP, [2]) are widely recognized as the most studied ones. This study is focused in the first of these problems, the TSP.

In line with this, many optimization approaches have been proposed along the years for dealing with routing problem. Three are the most studied and well-established schemes: exact methods [3, 4], heuristics [5, 6], and metaheuristics. The present research is focused in the later ones, which have demonstrated a remarkable efficiency for properly solving routing problems, especially in the last decade. The most recognized methods in this category could be the Simulated Annealing (SA, [7]) and Tabu Search (TS, [8]) as local search-based solvers, and Ant Colony Optimization (ACO, [9, 10]), Particle Swarm Optimization (PSO, [11, 12]) and Genetic Algorithm (GA, [13, 14]) as population-based methods. In addition to these classical and recognized approaches, the design and implementation of new metaheuristics is a hot topic in the related operations research and optimization communities. As a result of this scientific trend, lots of successful solvers have been proposed in last years, such as the Bar Algorithm (BA, [15]), Firefly Algorithm (FA, [16]), Gravitational Search Algorithm (GSA, [17, 18]), or the Fireworks Algorithm Optimization (FAO, [19]), among many others.

The main contribution of this paper can be divided into three different points. First, we devote a comprehensive section for outlining the research made in recent years around the TSP problem, focusing our effort on its solving through the use of metaheuristic algorithms. Secondly, we take a step further over the state of the art on the elaborating on a new research direction: the hybridization of Novelty Search mechanism and bio-inspired computation algorithms for solving the TSP. The Novelty Search (NS, [20]) was proposed in 2008 as a way to enhance the exploratory ability of population-based algorithmic solvers. After showing its great performance applied to several optimization problems, we hypothesize its promising performance also for the TSP. To this end, we have developed different versions of well-known Swarm Intelligence methods, namely PSO, FA and BA, and we evaluate in this manuscript the performance of these metaheuristics embedding the NS mechanism on their basic scheme. We introduce along the paper the descriptions on how these methods have been modeled for tackling the problem at hand, and how the NS has been adapted for this discrete scenario. In order to assess the performance of each implemented solver, outcomes get over 15 instances are compared and discussed. Finally, an important additional contribution is our personal envisioned status of this field, which we present in the form of challenges and open opportunities that should addressed in the near future.

The rest of the paper is structured as follows: In Section 2 the TSP and some of its most important variants are described and mathematically formulated. Section 3 elaborates on the first contribution of the paper by analyzing the recent research done around the TSP. After that, in Section 4, the concepts behind NS are introduced, placing emphasis on how we have hybridized metaheuristic solvers with this mechanism. Considered heuristic solvers and their implementation details are described in Section 5. The experimental setup is detailed in Section 6, along with a discussion on the obtained results. Research opportunities for the area are highlighted in Section 7. Finally, Section 8 concludes the paper with a general outlook for the wide audience.

2 Problem Statement

In this paper, our experimentation with NS and the chosen bio-inspired optimization methods is done over the basic version of the TSP. As can be read in many scientific works, the canonical TSP can be represented as a complete graph $\mathcal{G} \doteq (\mathcal{V}, \mathcal{A})$, where $\mathcal{V} \doteq \{v_1, v_2, \ldots, v_N\}$ illustrates the group of vertex that represent the nodes of the graph, and $\mathcal{A} \doteq \{(v_i, v_j) : v_i, v_j \in \mathcal{V} \times \mathcal{V},\ i, j \in \{1, \ldots, N\} \times \{1, \ldots, N\}, i \neq j\}$ is the group of edges linking every pair of nodes in $\mathcal{V}$. Moreover, each edge (v_i, v_j) has an associated cost $c_{ij} \in \mathbb{R}^+$, denoting the traveling weight of this arc. Because of the symmetric nature of the basic TSP, it is assured that $c_{ij} = c_{ji}$, meaning that the cost of going from one v_i to another v_j is equal to the reverse trip (v_j, v_i).

Thus, the principal optimization objective of the TSP pivots on the discovery of a route that visits each node once and only once (i.e. a Hamiltonian cycle in the graph G) minimizing the total cost of the whole route. This genetic problem can be mathematically formulated as

$$\underset{\mathbf{X}}{\text{minimize}} \quad f(\mathbf{X}) = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ i \neq j}}^{N} c_{ij} x_{ij} \tag{1a}$$

$$\text{subject to} \quad \sum\nolimits_{\substack{j=1 \\ i \neq j}}^{N} x_{ij} = 1, \quad \forall j \in \{1, \ldots, N\}, \tag{1b}$$

$$\sum\nolimits_{\substack{i=1 \\ i \neq j}}^{N} x_{ij} = 1, \quad \forall i \in \{1, \ldots, N\}, \tag{1c}$$

$$\sum\nolimits_{\substack{i \in \mathcal{S} \\ j \in \mathcal{S} \\ i \neq j}} x_{ij} \geq 1, \quad \forall \mathcal{S} \subset \mathcal{V}, \tag{1d}$$

where $\mathbf{X} \doteq [x_{ij}]$ is a $N \times N$ binary matrix whose entry $x_{ij} \in \{0, 1\}$ takes value 1 if edge (i, j) is used in the solution. Furthermore, the objective function is represented in Expression (1a) as the sum of costs associated to all the edges in the solution. Moreover, Expressions (1b) and (1c) depict that each vertex must be visited once and only once. Lastly, (1d) guaranties the absence of sub-tours, and forces that any subset of nodes S has to be abandoned at least one time. This restriction is needed to prevent the existence of sub-tours on the whole route.

Apart from this canonical formulation of the TSP, many different variants have been modeled along the years aiming at adapting and addressing different characteristics present in logistic and transportation world. We list here some of the most famous advanced variants of the TSP:

- *Asymmetric Traveling Salesman Problem* (ATSP, [21, 22]): The central characteristic of the TSP is that, although there may be arcs where c_{ij} = c_{ji}, in general $c_{ij} \neq c_{ji}$.
- *Multiple Traveling Salesman Problem* (M-TSP, [23, 24]): In the M-TSP, a set of m exact salesmen are available, which should visit a set of n cities starting and ending at the same city.
- *Traveling Salesman Problem with Time Windows* (TSPTW, [25, 26]): In this variant, the traveling salesman should visit each vertex respecting a time window fixed by each separated node.
- *Time-dependent Traveling Salesman Problem* (TDTSP, [27, 28]): The basic idea behind the TDTSP is that the cost of traveling between two different nodes is time dependent. In other words, travel times could significantly change over the day, for example, during $peak$ and $off-peak$ hours.
- *Generalized Traveling salesman Problem* (GTSP, [29, 30]): In the GTSP, the set of nodes is partitioned into different clusters. The main goal of this formulation is to find a minimum cost tour passing through exactly one node from each cluster.

Another interesting research activity can be detected around the named Rich Traveling Salesman Problems (R-TSP), also known as Multi-Attribute Traveling Salesman Problems [31]. This type of problems are specific cases of the TSP with complex formulations and multiple restrictions. The principal characteristic of a R-TSP problem is its complex formulation, which is composed by multiple constraints.

This feature directly leads to an increased complexity of resolution, which entails to a major scientific challenge at the same time. These problems are especially important in the current community because they model many real-world problems. Accordingly, the efficient solving of R-TSP can be useful in many valuable real-world applications. Some remarkable examples can be found in [32], [33] or [34].

As can be seen, the number of TSP variants proposed in the literature is overwhelming, making infeasible the listing of all the interesting and valuable formulation in this section. For this reason, we have outlined some of the most commonly used ones, with the intention of settling the idea that there is a vibrant scientific activity behind this problem.

3 Recent Advances in Traveling Salesman Problem

Since its formulation, the TSP has become one of the most employed benchmarking problems in performance analysis of discrete optimization algorithms. A plethora of methods have been applied to the TSP and its variants in last decades. We can highlight classical methods such as GAs [35, 36], TS [37, 38, 39] or SA [40, 41]. Besides this classical algorithms, more recent and effective approaches have been extensively used for solving the TSP, such as the ACO [42, 43], the PSO [44, 45] or the Variable Neighborhood Search (VNS) [46, 47]. In addition to these well-known methods, the TSP and its multiple derivations have been the focus of many benchmarking studies for measuring the quality of many recently proposed nature-inspired methods. Some examples are the FA [48], the CS [49], the ICA [50], the well reputed Artificial Bee Colony [51] or the Honey Bees Mating Optimization [52].

As can be seen, the TSP has been extensively used by operation research and computational intelligence researchers since its formulation for different purposes. The state of the art around this problem is such wide that, in this section, we will focus our attention on highlighting the research and advances conducted in the last few years. Being aware that the related literature is bigger than the represented in this systematic review, we refer interested readers to surveys such as [53, 3, 54, 55, 56].

3.1 Traveling Salesman Problem and Genetic Algorithms

Genetic Algorithm has been adopted by many authors of the current scientific community for being applied to the TSP and its variants. In [57], for example, we can find an interesting GA for solving the challenging large scale colored balanced TSP. In [58], Lo et al. explore the adaptation of the GA to the real-life oriented Multiple TSP. Additional common practice related to GA applied to TSP is the formulation of novel operators, as can be seen in [59], in which a new crossover operator is proposed. In [60] a so-called multi-parent crossover is formulated, which share some notions compared to that proposed in [61], called Edge Assembly Crossover. Additional valuable example of this practice can be found in [62], in which a multi-offspring genetic algorithm is proposed. Authors of that research claim that, in the basic version of GAs, the number of generated offsprings is the same as the number of parents. Thus, they explore the concept that, for the survival and diversity of the species, it should be desirable to generate a greater number of offsprings. In [63], Hussain et al. built an effective combination function called Modified Cycle Crossover Operator. In [64], authors present a new method to initialize the population of the GA on TSP, called greedy permuting method. Another initialization strategy is developed in [65], which rest its inspiration in the well-known k-mean algorithm. As can be easy checked, the literature around TSP and this successful method is abundant nowadays, being the subject of myriad of works year by year. Interested readers are referred to additional outstanding works such as [66], [67] or [68].

3.2 Traveling Salesman Problem and Simulated Annealing

Despite being a classic method, SA is still the focus of many research around the TSP and its variants. In [69], for example, Ezugwu et al. proposed a hybrid metaheuristic for solving the TSP based in the SA and the recently proposed Symbiotic Organisms Search method. Zhang et al. presented in [70] the coined List-based SA, which main basis rests on a new mechanism for controlling the temperature parameter. The implemented method counts with a list of temperatures which maximum is used by Metropolis acceptance criterion to decide whether to accept a candidate solution. Furthermore, the temperature list is dynamically adapted according to solution space of the problem. In the short paper published in [71] an evolutionary SA is developed for the TSP and compared with additional metaheuristic such as the TS. An additional interesting research can be found in [72] in which the performance of the basic SA is improved through the use of a Greedy Search mechanism for properly dealing with the Large-Scale TSP. A very recent study can be found in [73], in which a SA is employed for increasing the population diversity of a Gene Expression Programming method, aiming to improve the ability of the search. Additional valuable related research can be found in papers such as [74], [75] and [76].

3.3 Traveling Salesman Problem and Tabu Search

Among the classic methods, probably the Tabu Search is the one that has suffered most the course of time. In past decades, TS was a successful method considered a cornerstone in the combinatorial optimization and TSP scientific community. Over the years, sophisticated methods laid aside the TS, being difficult today to find remarkable studies around the figure of the TS. Among these few studies, we can find as one of the most representative ones the research conducted in [77], in which a TS-SA hybrid solver is proposed for the symmetric TSP. One of the characteristics of this hybrid scheme is the development of a dynamic neighborhood structure, which principal goal is the enhancing of the search efficiency of the method, by means of the randomness reduction of the conventional 2-opt neighborhood. In [78], the TS is employed as part of a pool of metaheuristics for solving of the Open-Path Asymmetric Green TSP. The main objective of this multi-attribute TSP variant is to find a route between a fixed origin and destination, visiting a group of intermediate points exactly once, minimizing the CO_2 emitted by the car and the total distance traveled. An additional work can be analyzed in [79]. Among other aspects, authors of that study not only explore the efficiency of four different version of TS using different tabu mechanisms, but also the synergy between TS and ACO in a hybrid method.

3.4 Traveling Salesman Problem and Ant Colony Optimization

conversely to the TS, one of the most used methods in recent years in the TSP community is the ACO, as can be seen in works such as [80] or [81]. In the first of these works, the recently proposed multi-objective ACO is used for solving the multi-objective TSP under different configurations, using two, three and four objectives, and different numbers of ants and iterations. In the second research, a hybrid approach is presented which employs a PSO for optimizing the parameters that affect performance of the ACO algorithm. Additionally, a 3-opt heuristic is endowed to proposed method for improving local solutions. A similar solver is implemented in [82], called PACO-3Opt. This hybrid parallel and cooperative method, which counts with multiple colonies and a masterslave paradigm, employs also the 3-opt function for avoiding local minima. An additional well reputed research can be found in [83]. The principal value of this work is its application to the Dynamic TSP. For properly dealing with the unstable nature of this instance of the problem, authors endow the ACO with a local search operator (called unstring and string) which iteratively takes the best solution found by the algorithm and removes/inserts cities in such a way that improves the solution quality. The same dynamic formulation of the problem is also deemed in [84], implementing a variant of the ACO in combination with an Adaptive Large Neighborhood Search. Moreover, a note-worthy multi-objective version of the ACO is presented in [85] for solving the Bi-objective TSP. One of the essential characteristics of the proposed algorithm is the initialization of pheromone matrix with the prior knowledge of Physarum-inspired Mathematical Model. Additional interesting works focused on the ACO can be found in [86], [87], [88]. For readers interested on memetic or hybrid approaches, studies such as [89], [90] and [91] are highly recommended.

3.5 Traveling Salesman Problem and Particle Swarm Optimization

Since its introduction in 1995 by Eberhart and Kennedy, PSO has become the most used technique in the swarm intelligence field, and one of its main influential representatives. PSO was developed under the inspiration of the behavior of bird flocks, fish schools and human communities, and although it was not initially designed to be applied to discrete problems, several modifications have made it possible. Regarding the TSP, lots of papers have been devoted to its application in the last decade, highlighting contributions such as [92], [44] and [93]. Focusing our attention in the research conducted in the last recent years, we can highlight the work introduced in [94], in which a PSO in combination with a Metropolis Acceptance criterion is implemented. The fundamental reason of this merge is to enhance the PSO to escape from premature convergence, endowing the method with a sophisticated mechanism to decide whether to accept newly produced solutions. A highly interesting research was published in [95], in which a Probabilistic TSP is tackled through an adaptive multi-swarm PSO. In that adaptive PSO, random values are assigned in the initial phase of the search. After that, these parameters are dynamically optimized simultaneously with the optimization of the objective function of the problem. An additional improved PSO is proposed in [96] for solving the imprecise cost matrix TSP. Main modifications of the modeled PSO consist on adopting the swap sequence, swap operation and different velocity update rules. Another interesting example of enhanced PSOs can be found in [97], in which the multi-objective TSP is solved using the so-called Set-based Comprehensive Learning PSO. Further recently published works are [98], [99] or [100].

3.6 Traveling Salesman Problem and Bat Algorithm

Focusing our attention in recently proposed nature-inspired methods, and starting with the well-known BA, we can find an interesting recent study in [101], in which a hybrid approach is proposed in combination with genetic operators crossover and mutation, and using the 2-opt and 3-opt operators as local search mechanisms for improving searching performance and speed up the convergence. Another interesting approach is proposed in [102], which principal contribution is the velocity scheme used, represented as the number of permutations needed for a bat to reach the best candidate of the swarm. A similar alternative was presented in [103], which employs Nearest Neighbor tour construction heuristic for initialize the population and the 2-opt edge-exchange algorithm for the local search step of the method. Among all these papers, we should highlight the research proposed in [104], not only considered as the first adaptation of the BA to the TSP and asymmetric TSP problems, but also being the most cited one. Several aspects make this study interesting, such as the use of the well-known Hamming Distance as distance function or its *inclination* mechanism, allowing the method to modify the solution space scheme along the running.

3.7 Traveling Salesman Problem and Firefly Algorithm

If we turn our attention to the FA, we can highlight the research recently proposed in [105]. Authors of this study clearly inspired in the previously cited [101], endowing to the adapted FA both crossover and mutation mechanisms, and employing both 3-opt and 2-opt function for enhancing the convergence and search performance of the method. An additional hybrid scheme is also proposed in [106], in which a FA is combined with a GA. Authors of that work redefine the distance of firefly algorithm by introducing swap operator and swap sequence to avoid algorithm easily falling into local optimums. A more elaborated study is presented in [107], which is focused in the solving of the Multiple TSP, being this a generalization of the TSP in which more than one salesman is allowed to be used in the solution. In [108], a swap-based FA is developed, which bases its movement strategy on the widely employed swap function. Furthermore, authors of this paper integrate their FA with Nearest-Neighborhood initialization, reset strategy and Fixed Radius Near Neighbor 2-opt operator. Two further interesting and valuable studies are presented in [109] and [110], The former one has the particularity of adopting the dynamic mechanism based on neighborhood search algorithm, while the second one is combined with $k - opt$ algorithm. Additional recent papers focused on the FA application can be found in [111], [112] and [113].

3.8 Traveling Salesman Problem and Cuckoo Search

Regarding the CS, arguably, the most valuable research published recently is the one published by Ouaarab et al. in [49], which is considered by the community as the first application of the CS to the TSP. This paper has serve as inspiration for subsequent research, such as [114]. In that paper a Random-Key CS is proposed, which develops a simplified random-key encoding scheme to pass from a continuous space to a combinatorial space. Especially interesting in the work proposed in [115], in which a subpopulation-based parallel CS on OpenMP (Open Multi-Processing) is implemented for solving the TSP. Lin et al. developed a so-called Genotype-Phenotype CS in [116], which essential contribution is the representation scheme used for building the solutions. Furthermore, the CS has been present in combination with other methods, such as the studies shown in [117] and [118], in which the CS is implemented combined with an ACO. Another example of this trend can be found in [119], which hybridizes a CS with the Metropolis Acceptance Criterion of SA algorithm, in order to allow accepting inferior solutions with certain probability.

3.9 Traveling Salesman Problem and Artificial Bee Colony

Since its inception in 2007 by Karaboga and Basturk, the Artificial Bee Colony (ABC, [120]) has also been adapted for solving combinatorial optimization problems such as the TSP. In recent years, specifically, it has been the focused scope of some valuable studies within the TSP community. Very recent is the research proposed by one the designers of the technique, Karaboga, along with Gorkemli in [121], in which new improved versions of the discrete ABC are introduced for solving the symmetric TSP. Very recent is also the work that can be found in [122], in which a hyperheuristic method called Modified Choice Function is implemented for properly regulating the choosing of the of the neighbourhood search operators used by the onlooker and employed bees. An additional valuable study was presented in [123], introducing a hybrid ABC algorithm which adopts the threshold acceptance criterion method as accepting mechanism. Especially valuable is the work introduce by Venkatesh and Singh in [124], in which the challenging Generalized Covering TSP is tackled. To do that, authors developed an ABC with dynamic degrees of perturbations, where the degree to which a solution is modified for generating new bees is reduced along the execution. Singh also participated in the conduction of the work presented in [125] along Pandiri, in which a hyper-heuristic based ABC is designed for facing a k-Interconnected Multi-Depot TSP. Further remarkable studies can be found in [126], [127] or [128].

3.10 Traveling Salesman Problem and Imperialist Competitive Algorithm

ICA is a multi-population metaheuristic introduced in 2007 which finds its inspiration in the concept of imperialism, dividing the whole population in independent empires which fight to each other aiming at conquering the weakest colonies of the rest of the empire [129]. The solver has also been prolific in the TSP community, being used in many reputed studies published recently. We can find in [50] the first adaptation of this sophisticated method, which has served as main inspiration for many authors and works such as [130]. In [131], an improved version of the ICA was presented for dealing with the generalized TSP. Authors of that work improved the basic version of the ICA with some mechanisms such as is a novel encoding scheme, assimilation policy procedure, destruction/construction operators and imperialist development plans. Furthermore, Taguchi Method is employed for properly configure some of the most crucial parameters of the algorithm. Chen et al. proposed in [132] an hybrid method combining the ICA with a policy-learning function. The central idea behind this hybridization is to permit weak colonies to generate increasingly promising offsprings by learning the policies of strong individuals. A brief adaptation of the ICA can also be found also in [133], as part of a pool of metaheuristics for solving the TSP and the ATSP. Interested readers on this specific metaheuristic are referred to the following works: [134], [135] and [136].

3.11 Traveling Salesman Problem and other Nature-inspired Metaheuristics

Regarding the nature-inspired community, the proposal of the PSO and ACO two decades before decisively influenced in the creation of a surfeit of methods, which clearly inherit their essential philosophy. For the design and proposal of these novel approaches, many different inspirational sources have been considered, such as 1) the behavioral patterns of animals such as buffaloes or whales, 2) social and political behaviors as hierarchical societies, or 3) physical processes such as optics systems, electromagnetic theory or gravitational dynamics.

For this reason, in the current community a countless number of methods of this kind can be found. Along this section, some of the most successful metaheuristic solvers in the TSP community have been reviewed. In any case, we are perfectly aware that the whole community is composed by a plethora of additional methods, usually less used than the ones outlined here. Furthermore, despite the comprehensive nature of this section, we are also conscious about the difficulty of congregating all the related works published. For this reason, we have only considered these ones that are strictly related with the TSP community, and which have been published in recognized scientific databases.

In any case, a reader may think of certain methods that deserve mention, or even a whole section. Seeking the completeness of this study, in the last part of this section we show a table summarizing additional methods that have been used in recent years for solving the TSP. In this Table 1 we depict the name of the method, its main inspiration and some related works.

4 Novelty Search

The main objective of the NS is to enhance the diversity capacity of a populations-based metaheuristic. To do that, this mechanism finds novel solutions in the behavioral space instead of the search space. Usually, candidates that comprise a population tend to congregate in the same region of the solution space. Conversely, this tendency does not happen in the behavioral space, which is structured employing the Euclidean distance. In this way, we can measure numerically the novelty of a candidate $\mathbf{x}$ using the following formula:

$$\rho(\mathbf{c}) = \frac{1}{k}\sum_{i=1}^{k} d(\mathbf{c}, \boldsymbol{\mu}_i), \tag{2}$$

Name	Inspiration	Refs.
Flower Pollination Algorithm [137]	Pollination process of flowers	[138] [139]
Harmony Search [140]	Mimicking the improvisation of music players	[141] [142]
Fireworks Algorithm [19]	Fireworks explosion and location of sparks	[143] [144]
African Buffalo Optimization [145]	The organizational ability of African buffaloes	[146] [147]
Brain Storm Optimization [148]	Human brainstorming process	[149] [150]
Golden Ball Metaheuristic [151]	Teams and players organization in soccer world	[152] [153]
Penguins Search Optimization [154]	Collaborative hunting strategy of penguins	[155] [156]
Honey Bees Mating Optimization [157]	Honey-bees mating process	[158, 52]
Whale Optimization Algorithm [159]	Social behavior of humpback whales	[160]
Water Cycle Algorithm [161]	Natural surface runoff of water	[133]
Swallow Swarm Optimization [162]	Reproduce the behavior of swallow swarms	[163]
Black Hole Algorithm [164]	Black hole phenomenon in the open space	[165]
Hydrological Cycle Algorithm [166]	Movement of water drops in natural cycle	[167]
Dragonfly Algorithm [168]	swarming behaviors of dragonflies	[169]
Pigeon-inspired optimization [170]	Homing characteristics of pigeons	[171]

Table 1 Summary of additional nature-inspired methods and their application to the TSP

where $d(\cdot,\cdot)$ represents the Euclidean distance. Additionally, k is the number of neighbor solutions chosen from the subset of neighbors candidates selected from the subset of neighbors $\mathcal{N} = \{\mu_1, \mu_2, \ldots, \mu_k\} \subseteq \mathcal{P}$ (i.e. the neighborhood size). This last parameter is problem-dependent which should to be established empirically. Additionally, the selection of individuals is conducted using the distance metric, which is also depends on the problem.

It is important to highlight that despite NS has demonstrate a great efficiency in many works published up to now [172, 173, 174, 175], the strategy for properly adapting this mechanism to a problem is still weakly defined, and it is subject to the problem at hand [176].

In the research that we are presenting in this paper, NS has been applied in the same way for the three implemented bio-inspired metaheuristics. Something crucial when implementing NS is the modeling of a proper distance metric. In this study, the function selected in the Hamming Distance $D_H(\cdot,\cdot)$, which is detailed in the following section. Additionally, a subset $\mathcal{B}$ is considered, in which all the discarded and replaced candidates are inserted every generation. This way, the size of $\mathcal{B}$ is the same as the main population of the solver.

Conceptually, the subset $\mathcal{B}$ is comprised by the solutions which are potentially *novel*, and prone to be re-introduced in the main population. Thus, when an evolved candidate $\mathbf{c}_i$ is better than the individual which is going to replace, it is directly inserted into the principal population, while the replaced solution is introduced in $\mathcal{B}$. On the other hand, if the trial candidate is not better than its preceding version, the former is inserted into $\mathcal{B}$. Additionally, once the t-th generation comes to its end, if r_{NS} (a value drawn from a normal probability distribution) is lower than the parameter $NS_P \in [0.0, 1.0]$, the NS mechanism is conducted. In this research, we have set $NS_P = 0.25$ after a comprehensive empirical analysis.

It is also noteworthy that there is not a specific scientific consensus about the proper number of solutions that should be re-introduced in the main population throughout NS, and how they should replace the existing individuals. In this regard, researchers advocate to adapt these criteria depending on the problem at hand. In this specific work, we have set the number of reinserted candidates to 8. These solutions replace the worst individuals in terms of fitness of the main population. Moreover, these candidates are selected from $\mathcal{B}$ based on their distance regarding the whole swarm. Thus, the 8 solutions having a greater diversity with respect to the population are those chosen for reinsertion.

Lastly, the main contribution that we propose in our implemented NS procedure consist on a novel neighborhood changing procedure. Specifically, every time a candidate $\mathbf{c}$ is inserted in $\mathcal{B}$, its movement function $\Psi(\cdot,\cdot)$ is modified. Hence, when a candidate is re-introduced in the principal population, it can explore the solution space using different strategies. This simple mechanism enhances both the diversity of the swarm and the exploratory capacity of the algorithm.

5 Proposed Bio-inspired Methods

We propose in this work the combination of three different bio-inspired metaheuristic methods and the NS mechanism. Before specifying the details of each solver, we introduce here some crucial aspects for properly understanding the research conducted. These aspects are related to solution representation and the metrics used for measuring the different between different candidates.

When solving the TSP, the way in which the routes are encoded can follow diverse strategies. In this work, the frequently referenced path encoding has been used. Thus, each individual is represented as a permutation of numbers depicting the sequential order in which the nodes are visited. For instance, in a given 10-node dataset, a possible solution could be encoded as $\mathbf{x} = [8, 9, 1, 4, 3, 5, 2, 6, 7, 0]$, meaning that node 8 is visited first, followed by nodes 9, 1 and so forth. Each candidate adopts this approach. Additionally, the objective function employs is the total cost of a complete path give in Expression (1a).

Probably, the most crucial issue when adapting the PSO, FA, and BA to a discrete problem such as the TSP is to design the functions resembling how candidates move around the solution space, while guaranteeing their efficient contribution to the search problem under study. For conducting these movements, three well-known movement operators have been used depending on the distance between individuals:

- *Insertion:* this is one of the most frequently used functions for solving combinatorial optimization problems of different nature. Specifically, it selects and extracts one randomly chosen node from the route. Afterwards, this node is re-inserted again in the route in a randomly selected position.

- *Swapping function*: This well-known function is also widely employed in lots of research studies [177]. In this case, two nodes of a solution are selected randomly, and they swap their position.
- *2opt:* This operator first proposed in [178] has been extensively applied in different kinds of routing problems such as the TSP [179, 180]. The main design principle behind this operator is to randomly eliminate two arcs within the existing route, in order to create two new arcs, avoiding the generation of sub-tours.

At this point, it is interesting to clarify that $Insertion$ has been considered as main operator for all metaheuristic methods; $Swapping$, and $2opt$, however, compose the pool of functions that NS considers for the reinsertion of candidates.

Finally, for assessing the distance between two different individuals (routes), the well-known Hamming Distance $D_H(\cdot,\cdot)$ has been adopted. This function is calculated as the number of non-corresponding elements in the sequence of both individuals, e.g. if the following vectors represent two feasible routes:

$$\mathbf{x}^p = [8, 9, 1, 4, 3, 5, 2, 6, 7, 0],$$
$$\mathbf{x}^{p'} = [8, 7, 1, 4, 3, 5, 0, 6, 2, 9],$$

their Hamming Distance $D_H(\mathbf{x}^p, \mathbf{x}^{p'})$ would be equal to 4. Once the distance between the two individuals has been computed, the movement is performed. We now introduce the metaheuristic algorithms under consideration:

5.1 Bat Algorithm (BA)

The BA was proposed by Yang in 2010 [15], and it is based on the echolocation behavior of microbats, which can find their prey and discriminate different kinds of insects even in complete darkness. As can be read in several surveys [181, 182], this method has been extensively adapted for dealing with very diverse optimization fields and problems. The fact that many studies can be found in the literature purely focused on BA confirms that it attracts a lot of interest from the community [183, 184, 185, 186].

The Bat Algorithm was first proposed for solving continuous optimization problems [15]. Thus, a discrete adaptation must be conducted for properly accommodating its scheme to the combinatorial nature of the problem tackled in this study. In the literature, several adaptations of this kind can be found [187, 188]. First, each bat in the populations represents a feasible solution of the TSP. Moreover, both loudness A_i and pulse emissions r_i concepts have been modeled analogously to the naïve BA. In order to simplify the approach, no frequency parameter has been considered. Besides that, velocity v_i has been deemed adopting the Hamming Distance as its similarity function as v_p^t = rand$[1, D_H(\mathbf{c}_p, \mathbf{c}^{best})]$. In other words, the velocity v_i of the p-th bat in the population at generation t is a random number, which follows a discrete uniform distribution between 1 and the Hamming Distance between $\mathbf{c}_p$ and the best bat of the swarm $\mathbf{c}^{best}$

With all this, $\mathbf{c}_p$ moves towards $\mathbf{c}^{best}$ at generation t as:

$$\mathbf{c}_p(t+1) = \Psi\left(\mathbf{c}_p(t), \min\left\{V, v_p^t\right\}\right) \tag{3}$$

where $\Psi(\mathbf{c}, Z) \in \{Insertion, Swapping, 2opt\}$ is the movement operator, parametrized by the times Z this function is applied onto $\mathbf{c}$. After Z trials, the best considered movement is chosen as output.

5.2 *Firefly Algorithm (FA)*

The first version of the FA was developed by Xin-She Yang in 2008 [189, 16], and it was based on the idealized behavior of the flashing characteristics of fireflies. As we have pointed for the BA, the FA has been the focus of many recent comprehensive surveys [190, 191, 192, 193, 194]. Furthermore, it has been recently applied in many different problems and knowledge fields [195, 196, 197, 198].

Because the canonical FA was conceived for dealing with continuous optimization problem, some modifications have also been done for its proper adaptation. Thus, as in the previously described BA, each firefly of the swarm represents a possible solution for the TSP. Moreover, light absorption has been considered, which is an essential concept for adjusting fireflies' attractiveness. For the movement of the fireflies around the solution space the same logic shown in Expression (3) has been followed. Finally, for measuring the similarity between two individuals, the $D_H(\cdot,\cdot)$ has also been used.

5.3 *Particle Swarm Optimization (PSO)*

PSO is one of the most used swarm intelligence metaheuristics, and it has been adapted to both continuous [199] and discrete problems [200, 201] in very recent years. Works such as [202] have inspired us for the discrete PSO developed in this research. Also in this adaptation each individual of the population (particles) represents a feasible solution for the faced problem, while the calculation of the velocity $v_i^{(t)}$ and movement functions have been considered as for the previously described solvers. Furthermore, movement criterion represented in Expression (3) has also been deemed for driving the movement of particles. Lastly, $D_H(\cdot,\cdot)$ has also been taken as distance function.

6 Experimentation and Results

The performance of the three developed solvers has been gauged through 15 contrasted TSP datasets, all of them drawn from the famous TSPLIB repository [203]. The size of the considered datasets is between 30 and 124 nodes. Taking as inspiration the good practices proposed in [204], similar functions and parameters have been considered in all solvers, aiming at obtaining fair and rigorous insights. Additionally, 20 independent runs have been executed for each (*dataset*, *technique*) combination. Thus, we provide statistically reliable findings on the performance of each method. The population size has been established to 50 individuals for each method. In FA, the value of the light absorption coefficient is configured as $\gamma = 0.95$, whereas for BA $\alpha = \beta = 0.98$, $A_i^0 = 1.0$ (*loudness*) and $r_i^0 = 0.1$ (*rate*).

In the following Table 2 the outcomes obtained by each method are shown. For properly understanding the influence of NS in each metaheuristic scheme, we shown not only the outcomes of each method using this mechanism (represented with the subscript $_{NS}$, but also the results of the basic versions. Average (Avg) and standard deviation (Std) are provided for each (*problem*, *technique*) combination. Moreover, we also included in the table the mean generation number t_{conv} for which the best solution was met for every technique and problem instance. We represent this value in hundreds. Furthermore, we depict in bold the best outcome obtained for each metaheuristic, in order to facilitate the visual analysis of the influence of the NS. All the tests conducted in this work have been performed on an Intel Core i7-7600U, and Java has been used as the programming language.

Additionally, and being aware that the comparison between the selected schemes PSO, FA and BA is not the focus of this study, a statistical test has been carried out with the obtained results for the sake of completeness. To do that, and following the guidelines in [205], the Friedman's non-parametric test for multiple comparison has been conducted, which allows to check if there are significant differences in the results obtained by all reported methods. Thus, in the last row of Table 2, we have displayed the mean ranking returned by this nonparametric test for each of the compared algorithms and scenarios (the lower the rank, the better the performance). Additionally, the Friedman statistic obtained is 35.914. The confidence interval has been set in 99%, being 9.236 the critical point in a χ^2 distribution with 5 degrees of freedom. Since $35.914 > 5.991$, it can be concluded that there are significant differences among the results.

Several conclusions can be drawn from the results obtained through this preliminary experimentation. First of all, it can be seen how the employment of the NS mechanism highly favors the obtaining of better results in all the three deemed metaheuristic schemes. In the case of the PSO, the NS improves the average quality of the outcomes in 13 out of 15 instances. For the FA, this improvement appears in all the 15 datasets. Finally, the BA reaches better solutions in 14 out of 15 cases. These findings support the hypothesis that the NS procedure enhances the exploratory capacity of the three considered bio-inspired metaheuristics thanks to the diversification it injects in the population.

Instance		PSO			PSO_{NS}			FA			FA_{NS}			BA			BA_{NS}		
Name	Optima	Avg	Std	t_{conv}	Avg	Std	t_{conv}	Avg	Std	t_{conv}	Avg	Std	t_{conv}	Avg	Std	t_{conv}	Avg	Std	t_{conv}
Oliver30	420	**420.3**	0.47	0.21	420.4	0.49	0.10	421.0	0.80	0.04	**420.4**	0.58	0.03	421.2	1.69	0.18	**420.2**	0.43	0.11
Eilon50	425	435.4	4.49	0.80	**432.2**	3.89	0.40	**439.3**	2.91	0.14	439.4	2.33	0.11	436.0	5.33	0.71	**432.0**	3.88	0.38
Eil51	426	437.1	4.10	0.78	**434.5**	5.51	0.39	442.5	3.08	0.15	**440.0**	2.22	0.14	437.1	4.85	0.76	**433.5**	2.61	0.35
Berlin52	7542	**7667.3**	89.00	1.07	7699.8	148.69	0.49	7678.1	51.64	0.29	**7593.2**	25.98	0.16	7711.4	118.35	1.05	**7620.5**	100.98	0.49
St70	675	693.6	7.55	1.86	**689.8**	10.09	1.30	702.7	3.92	0.32	**697.3**	3.40	0.26	696.7	8.53	1.97	**688.4**	4.53	1.05
Eilon75	535	565.1	5.04	1.96	**549.4**	7.37	1.25	572.6	2.53	0.38	**569.2**	2.99	0.27	564.3	6.39	2.08	**555.2**	6.85	1.27
Eil76	538	565.2	7.34	2.47	**557.4**	7.87	1.24	572.4	3.27	0.42	**568.7**	2.79	0.23	565.4	7.68	2.28	**557.8**	7.87	1.05
KroA100	21282	22335.0	372.26	8.00	**21907.6**	495.90	5.03	22586.1	77.63	1.14	**22429.9**	77.35	0.47	22528.1	524.92	7.62	**21740.0**	246.23	5.27
KroB100	22140	23457.0	412.72	6.34	**22743.8**	259.96	5.70	23653.9	172.21	1.05	**23346.2**	147.47	0.58	23393.3	374.39	7.64	**22795.2**	343.61	5.04
KroC100	20749	22064.4	430.82	7.50	**21368.8**	347.78	5.74	22197.0	117.20	0.97	**21900.3**	117.55	0.46	22135.8	286.75	7.56	**21347.7**	430.22	5.10
KroD100	21294	22684.9	292.39	6.86	**21866.2**	338.32	5.45	22634.3	104.09	1.19	**22312.3**	85.21	0.48	22561.2	373.45	7.84	**22040.2**	514.55	4.81
KroE100	22068	23362.7	537.66	7.03	**22586.2**	286.88	5.35	23453.4	126.53	1.18	**23248.9**	112.23	0.45	23550.5	384.86	6.50	**22649.8**	393.95	5.76
Eil101	629	673.8	7.47	5.11	**635.0**	6.84	3.97	670.2	4.21	1.00	**662.3**	3.10	0.58	670.5	11.41	5.84	**654.6**	4.99	3.85
Pr107	44303	46592.5	563.92	9.25	**45746.3**	1056.43	5.86	46336.4	224.35	1.35	**45941.3**	90.77	0.42	46727.4	897.94	10.80	**45709.8**	981.18	6.47
Pr124	59030	64150.5	1635.70	14.85	**60387.7**	898.76	11.12	64505.9	332.04	1.43	**62552.8**	204.86	0.84	64436.7	1985.18	14.84	**60554.1**	1179.60	11.39
		FRIEDMAN'S NON-PARAMETRIC TEST																	
Rank		4.0333			2.1			4.5333			4			4.7			**1.8333**		

Table 2 Obtained optimization results using BA, FA and PSO for TSP in combination with the NS mechanism.

Equally interesting is the phenomenon that can be observed regarding the convergence behavior. In such a case, it can be seen how the introduction of the NS mechanism in the metaheuristic scheme supposes also an improvement on the convergence, reaching the final solution in a lower number of generations, and lower computation effort. Along with the improvement of the results, this feature supposes a huge advantage for the NS procedure.

As final reflection, and being something easily observable through the results obtained by the Friedman's non-parametric test, we can highlight that the methods using NS are the ones that reached better outcomes. In this sense, BA_{NS} has emerged as the best alternative, followed by PSO_{NS} and FA_{NS}. Likewise, BA_{NS} is the solver that presents the best convergence behavior among the six implemented techniques. In any case, and it has been mentioned before, the comparison between the different metaheuristics fall outside the scope of this experimentation.

7 Research Opportunities and Open Challenges

In light of the literature overview made in Section 3, and the novel experimentation conducted exploring the synergies between bio-inspired computation and NS, it is unquestionable that the TSP is a topic that still attracts a remarkable attention from the related community, being the scope of abundant research material. The current state of the computation and the multiple resources in hands of practitioners open the opportunity of facing new challenges in the field. In this context, we foresee promising research directions along diverse axis, among which we pause at the following ones.

- As has been outlined in Section 3, an ample collection of classical and sophisticated solvers have been proposed in both past and recent literature for efficiently solving the TSP and its variants. One of the main challenges that the community should face urgently is to standstill the elaboration of additional novel methods. Despite the existence of a wide variety of well-reputed methods, part of the community continues scrutinizing the natural world seeking to formulate new metaheuristics mimicking some new biological phenomena. Some recent examples con be found in recent studies such as [206], [207] and [208]. These novel methods do not only not offer a step forward for the community, but also augment the skepticism of critical researchers. These practitioners are continuously questioning the need of new methods, which apparently are very similar to previously published ones. Conversely to this trend, the whole community should pull in the same direction, trying to adapt the existing methods to more complex formulations of the TSP, and explore the different synergies that can arise between different approaches or mechanisms.

- Related to the previous challenge, currently, the TSP is still conceived by the community as a benchmarking or an academic problem, with a very limited applicability to real-world problems. Trying to deal with this stigma, practitioners on the field should work on the formulation of richer and highly complex formulations of the TSP, aiming to adapt the problem to real logistic and transportation problems. This research trend, which is currently receiving some attention from researchers, has led to the coining of the term *rich* or *multi-attribute* TSP. As has been pointed in Section 2, these problems are grasping the interest of the scientific community for their closer match to realistic situations. Despite this growing activity, the research behind these specific formulations is still not remarkable. This fact is, in part, because part of the community is working in the branch mentioned in the previous challenge. Thus, through this paper, we call for a profound reflection around not only the formulation of new complex formulations of the TSP, but also the exploration of new ways for their solving, such as hybridized and memetic metaheuristics.
- Finally, we highly encourage the related researchers for considering the tackling of TSP instances of large size. Many of the studies that can be found in the current literature deal with controlled problem dataset of small-medium size (in terms of number of nodes). The experimental part of this study is also an example of this tendency. Notwithstanding, real-world problems are prone to have a higher magnitude, supposing a challenge for both researchers and their proposed solvers. In fact, large scale instances not only hinder the efficiency of many of the often-used methods, but they also suppose a compromise for the convergence of the solvers. In this context, the consideration of new optimization approaches, such as the ones referred as *large-scale global optimization* techniques can unchain unprecedented benefits for this field. Some methods that can be considered for being applied are the SHADEILS [209] or Multiple Offspring Sampling [210]. Additional interesting research trend related to computational efficiency can be found in the area of cooperative co-evolutionary algorithms [211]. Lastly, an additional promising alternative could be the design and implementation of self-adaptive solvers [212].

8 Conclusions

This manuscript has focused on the well-known Traveling Salesman Problem. In the first part of this work, we have briefly introduced this famous problem, along with some of its most valuable variants. After that, we have made a systematic overview of the recent history of this problem, describing some of the most remarkable studies published in the last years. To do that, our attention has gravitated around both classical (SA, TS, GA...) and sophisticated (BA, ICA, FA) metaheuristic solvers. After this literature review, we have presented an experimental study focused on the hybridization of the Novelty Search mechanism and three different bio-inspired computation schemes: Particle Swarm Optimization, Firefly Algorithm and Bat Algorithm. The performance of the implemented solvers has been tested over a benchmark comprised by 15 well-known datasets. Main conclusions drawn from this first study support the hypothesis that NS is a promising mechanism for being considered in the TSP solving, proving that this procedure helps metaheuristics to improve the quality of their reached results.

After these preliminary tests, we have concluded our research by sharing our envisioned future of the related community. To do that, we have pinpointed several inspiring opportunities and their related challenges, which should gather most of the research efforts made in the coming years. Among our detected future lines, we advocate the facing of bigger and more applicable datasets, using alternative methods not yet deeply explored, or synergistic hybridization of solvers proposed by the related experts along the years. Arguably, we foresee an exciting and still prolific future for the TSP community, adding new alluring nodes to visit in this endless path that the TSP research is.

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