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Across Neighborhood Search algorithm: A comprehensive analysis

Adam P. Piotrowski

Institute of Geophysics, Polish Academy of Sciences, Ks. Janusza 64, 01-452 Warsaw, Poland

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ABSTRACT

Plenty of metaheuristics are proposed each year. Such methods are frequently based on various concepts, are described with use of different nomenclature and are compared on different benchmarks. As a result it is often hard for practitioners to evaluate how useful particular methods may be. In a number of critical papers the need for careful theoretical and empirical analysis of new metaheuristics has been addressed. The present study presents such an analysis of an Across Neighborhood Search algorithm (ANS), a simple and relatively new method proposed in 2016. Firstly, it is shown that ANS is mainly a simplified combination of a few Particle Swarm Optimization variants, not a fully novel approach. Secondly, it is shown that ANS is structurally biased, hence artificially samples some parts of the search space more frequently than the other parts. Thirdly, the difficulties with the choice of one of the ANS control parameters are discussed. Finally, ANS is empirically tested against 22 other metaheuristics proposed during the 1960–2015 period on CEC2011, CEC2014 and CEC2017 problems, showing moderate performance. Overall, ANS turned out to be better than older competitors, but poorer than the majority of methods proposed during the last 10 years.

1. Introduction

Among the very large number of metaheuristics that have been proposed relatively recently for solving numerical optimization problems, the Across Neighborhood Search (ANS) algorithm [47] may easily attract the attention of practitioners as a very simple and seemingly efficient alternative to the older methods. However, the abundance of proposed metaheuristics have already led to the publication of various critical papers [11,26,29,45] that aim at a more detailed investigation of such methods to find the similarities between them and the older approaches, and to assess their true efficiency and usefulness. In [38] one may even read (with what the author of the present paper agree to a large degree) that many "new" metaheuristics are "… not 'important contributions' at all, but rather marginal additions to the list of generally useless 'novel' metaphor-based methods that are best forgotten as quickly as possible". Fister et al. [15] go a step further, suggesting that creating pseudo-novel approaches by changing the nomenclature and 'inspiration' may lead to the emergence of pseudo-science. The present paper tries to answer the question: Is this the case for the ANS approach?

First, let us remind ourselves that according to the No Free Lunch theorems for optimization [46] the performance of all heuristic optimizers averaged over all problems is equal. However, the impact of No Free Lunch on the wide interest in metaheuristics seems to be limited, probably because most of "all problems", as defined in [46], cannot be of interest to anyone [19], and hence averaging over "all problems" is not useful.

E-mail address: adampp@igf.edu.pl

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But even putting No Free Lunch aside one may recall various papers that express case-specific or more general criticisms of metaheuristics. Some recent studies [11,26] point out that, although some rules of how to make a 'fair' empirical comparison among various heuristics have been suggested years ago, still frequently the competitions are organized in such a way that empirical evaluation of newly proposed algorithms leads to over-enthusiastic opinions on their performance. The unfair comparisons against older approaches have been revealed when proposing various Artificial Bee Colony variants [26], introducing Teaching-Learning based optimization [8] or the Flower Pollination Algorithm [11]. In [30] it was shown how much the final performance of metaheuristics depends on some details of the organization of the competition. Other research [21] shows that metaheuristics are frequently structurally biased, what means that they, without any reason justified by the fitness landscape, sample some parts of the search space more frequently than the others, what also affects their performance. Sörensen [38] pointed out that one of the most problematic issues with the novel metaheuristics is linked with their 'inspirations'. Various metaheuristics simply use different nomenclature, 'inspired' by the phenomenon they are based-on, what allows for the hiding of similarities between methods, and becomes a burden for the reader that may need a certain kind of vocabulary to read and understand papers that introduce such methods. In a few detailed studies it was indeed shown that specific, supposedly novel algorithms are de facto very similar to the older methods. In [45] the harmony search algorithm was shown to be just a special case of one of the well-known evolutionary strategies. According to [29] the black-hole based heuristic is a simplified variant of PSO with inertia weight [36]. In a recent review [34] a number of similarities between various metaheuristics based on physical processes and more classical older methods are very briefly sketched, leading to the opinion that many of them do not deserve to be called 'novel' approaches. Hence, studying theoretically the novelty, and verifying empirically the efficiency of recently proposed metaheuristics becomes a kind of a separate topic in the field, which aims at helping practitioners to choose the methods that indeed may be worth their attention. Such studies also help in better understanding and finding relations between already proposed methods. The present paper follows the ideas mentioned above and is devoted to in-depth theoretical and empirical analysis of the ANS algorithm [47], skipping its motivations and specific nomenclature.

Due to its simplicity, invoked a number of times in the source paper [47], and freely available code (http://guohuawunudt.gotoip2.com/publications.html), the ANS algorithm is an attractive alternative both for practitioners that seek novel methods that could provide better solutions to their specific optimization problems and researchers that wish to use it as a competitor for their approach [31,35,49]. As a result, a more detailed insight is needed to find a relation between ANS and other metaheuristics, and to empirically verify how competitive ANS is. ANS attracted our attention for such an analysis due to five main reasons: 1. when readers skip some metaphors used in [47], a closer look at the equations governing the move of ANS individuals allows large similarities between ANS and some Particle Swarm Optimization (PSO) variants to be spotted; 2. in the source paper [47] ANS has not been tested on any widely used collection of benchmark problems, but on 18 simple, subjectively selected benchmarks; 3. in [47] the performance of ANS, introduced in 2016, has been compared almost solely against the performances of algorithms proposed five or more years earlier; 4. in the source paper [47], when testing ANS on the selected benchmarks one of its control parameters (called n) has been set by hand to a different value for each considered problem, and no rule for how to choose it for other problems has been given; 5. the MATLAB code of ANS available at web page http://guohuawunudt.gotoip2.com/publications.html, referred to in [47], differs in some details from the pseudocode shown in the publication [47].

The rest of this paper is organized as follows. In sections 2 the ANS algorithm is discussed. In Section 3 some variants of PSO are briefly reminded. Section 4 contains the theoretical discussion on the similarities between ANS and the selected PSO variants. Section 5 is devoted to the empirical comparison between ANS and over 20 other metaheuristics proposed between 1960 and 2015 (one year prior to the publication of ANS). It also includes the discussion on the sensitivity of ANS to some of its control parameters, the overview of the differences between the MATLAB code available from http://guohuawunudt.gotoip2.com/publications.html and the pseudocode given in the paper [47], as well as the analysis of the presence of structural bias in ANS, following the recent research on such unwelcome behavior in various other metaheuristics [21]. Finally, in Section 6 a general opinion regarding the novelty and efficiency of ANS is summarized, and the question to what extent the Sörensen's [38] and Fister et al. [15] comments, referred to in the first paragraph of this study, holds for ANS is answered.

2. Across Neighborhood Search

ANS [47], a newly introduced metaheuristic for numerical optimization problems, performs the search as follows. Assuming that one is interested in minimization, the goal may be defined as finding the global optimum solution $\mathbf{x}*$ such that

$$f(\mathbf{x}*) = \min_{\mathbf{x}\in\mathbf{\Omega}} f(\mathbf{x}) \tag{1}$$

where $f(\mathbf{x})$ is the real-valued function, $\mathbf{x}$ is a D-dimensional vector, $\mathbf{x} = \{x^1, \ldots, x^D\}$ with the domain $\Omega\subseteq\mathbf{R}^D$. ANS manages a population (or swarm, but we prefer the term population in this paper) of ps solution vectors (in [47] called also individuals, but let us use the term particles, as in PSO) $x^d{}_{i,g}$, where $i = 1,\ldots, ps$; $d = 1,\ldots,D$; and g is the generation counter. Here we do not use the notation and specific ANS nomenclature from [47], but stick to the more widely known PSO-based one. This changes nothing in the functioning of the ANS algorithm, but facilitates its understanding by the reader familiar with PSO.