CMA–VNS2: An efficient hyper-heuristic algorithm for combinatorial black-box optimization

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1 Introduction

The CMA-VNS2 (Covariance Matrix Adaptation Variable Neighborhood Search, version 2016) solver is a hyper-heuristic entry for the second Combinatorial Black-Box Optimization Competition (CBBOC 2016[1]). A previous entry CMA-VNS [Xue and Shen, 2015] showed that a combination of the well-known CMA-ES (Covariance Matrix Adaptation Evolution Strategy) [Hansen et al., 2003] and an iterated VNS (variable neighborhood search) [Mladenović and Hansen, 1997] resulted in competitive results[2] for expensive combinatorial black-box optimization problems.

The *no free lunch* (NFL) theorems [Wolpert and Macready, 1997], however, find out that no algorithm can perform statistically better than any other algorithm on average, if no problem-specific information is considered (also known as the Black Box Optimization). Wolpert and Macready [1997] and Culberson [1998] proved the NFL theorems in different ways. Hence researchers developed at least two kinds of means to keep algorithms away from the pitfall of NFL theorems:

- To become a well-designed domain-specific (*ad-hoc*) algorithm [Burke et al., 2003]; and
- To detect and to take advantage of instance-specific, problem data set-specific, and/or domain-specific features promisingly, from case to case,

where most of the successful algorithms belong to the latter class [Poli and Graff, 2009]. The development of CMA-VNS2 fell in this last one as well.

2 Main Procedure

The searching behavior of CMA-VNS was a typical CMA-ES procedure followed by iterated tests of the VNS local search [Xue and Shen, 2015]. To enrich the library of searching strategies, CMA-VNS2 employs two new profiles as alternatives:

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[1]See http://web.mst.edu/~tauritzd/CBBOC/GECCO2016/.

[2]See http://web.mst.edu/~tauritzd/CBBOC/GECCO2015/.

P1 The profile P1 is exactly copied from CMA-VNS.

P2 The profile P2 is an intensification (or depth-emphasized) version of CMA-VNS. Particularly, the adaptive acceptance level [Kheiri et al., 2014] is maximized and the CMA-ES recommendations are minimized to suppress restarts of VNS; and the input solutions from *backbone* (common bits of *elite* sets) [Zhang and Looks, 2005] are considerably increased to pursue a promising start of VNS.

P3 The profile P3 is, in the opposite direction, a diversification of P2. P3 introduces a much larger *elite* set (and hence a smaller *backbone*) and extends the range of possible construction of neighborhood for VNS to skip attractions of local optima.

Three instance-specific features, i.e. the *dimension* (n), the *maximum evaluations* (m) and the *best objective value* (v), are available in the framework of CBBOC. CMA-VNS2 perceives the features for the selection of a search profile for each CBBOC instance.

A number of training instances were randomly generated from the CBBOC framework. Experiments were conducted on the instances to compare the average performances, regarding the mean best objective values, of the three profiles. Table 1 shows the best profile selection against different combinations of instance feature from experimental results. According to the results, P1 (CMA-VNS) was still competitive when *dimension* was huge enough. P2 (intensification) became the best profile for most of remaining instances. Whereas P3 (diversification) was helpful to escape from local optima for some cases, such as those with enough *evaluations* and small *dimensions*.

Table 1: Best profile selection of CMA-VNS2 on the training instances

Level of evaluations (m/n^2)	Dimension (n) $2^{5.5}$	2^{6}	$2^{6.5}$	2^{7}	$2^{7.5}$	2^{8}	$2^{8.5}$
High	P2† P3‡	P3	P3	P2	P2	P1	P1
Median	P2	P2	P2	P2† P3‡	P3	P1	P1
Low	P2	P2	P2	P2	P2	P1	P1

†: When v/n was lower than a threshold; ‡: Otherwise.

CMA-VNS2 adapted the profile selection strategy from above training results as the main procedure for the *no-training* track of CBBOC 2016. For the *training* track, an online comparison was conducted in the training phase at first, the profile selection could be overridden if the comparison showed a significant improvement over the preset profile.

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