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Since CEC 2005 competition on real-parameter optimisation: a decade of research, progress and comparative analysis's weakness

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Abstract Real-parameter optimisation is a prolific research line with hundreds of publications per year. There exists an impressive number of alternatives in both algorithm families and enhancements over their respective original proposals. In this work, we analyse if this growth in the number of publications is correlated with a real progress in the field. We have selected five approaches from one of the most significant journals in the field and compared them with the winner of the competition celebrated within the IEEE Congress on Evolutionary Computation 2005. We observe that not only these methods are unable to get the good results of the winner of the competition, published several years before, but that they often avoid this type of comparison. Instead, they usually compare with other approaches from the same family. We conclude that the comparison with the state-of-the-art of the field should be mandatory to promote a real progress and to prevent that the area becomes obfuscated for outsiders.

Keywords Real-parameter optimisation · Evolutionary algorithms · Nature-inspired algorithms · IEEE CEC 2005 · State-of-the-art · Comparison weaknesses

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1 Introduction

Real-parameter optimisation consists in finding the assignment for a set of real-valued decision variables that produces the best solution for a given problem. Usually, this kind of problems is also referred as global optimisation or continuous optimisation in the literature. Without loss of generality, the goal is to find the values of a parameter vector $\mathbf{x} = \{x_1, \ldots, x_D\}$ that minimises a given function $f(\mathbf{x})$ and satisfies some constraints:

$$\min_{\mathbf{x}\in S} f(\mathbf{x}), \tag{1}$$

$$x_i \in [a_i, b_i], \quad i = 1, \ldots, D \tag{2}$$

where S is the set of possible values for $\mathbf{x}$, commonly known as the *search space* and constraints (2) define the domains of the variables. Also, it is not uncommon to tackle problems with constraints (Coello 2002) but, in the context analysed in this work, they are rarely considered.

Different methods have been proposed for real-parameter optimisation according to the properties of these functions: continuity, dimensionality, differentiability, smoothness, modality… In the 1950s, computers ability to execute operations very fast promoted the conception of simulated optimisation (Box 1957; Bremermann 1962; Fogel 2000;

Friedberg 1958), and soon, the first evolutionary computation methods appeared: *evolutionary programming* (EP) (Fogel 1962; Fogel et al. 1966), *genetic algorithms* (GAs) (Goldberg 1989; Herrera et al. 2003; Holland 1962, 1975) and *evolution strategies* (ESs) (Schwefel 1981; Rechenberg 1965; Schwefel 1968, 1975).

Since then, we have witnessed the birth of a large number of strategies for simulated real-parameter optimisation, the biologically inspired ones acquiring some special relevance (Xiong et al. 2015). Evolutionary algorithms simulate biological evolution; solutions are individuals that mutate and reproduce to generate new candidate ones; the fittest ones survive whereas those unfit perish. Particle swarm optimisation (PSO) (Kennedy and Eberhart 1995) imitates birds flocking or fishes schooling when searching food or escaping predators: the members of the swarm wander through the area trying to optimise some utility measures, such as their own comfort, and they consider their neighbours' movements with the expectation of increasing their probability of success. Ant colony optimisation (ACO) (Dorigo et al. 1996; Dorigo and Stützle 2004) takes its inspiration from the foraging behaviour of ants; they explore an area by random displacements and at the same time, they deposit a substance on the floor, which is evaluated by the other ants; as time passes by, pheromone tracks emerge, connecting the food and the anthill. Harmony search (HS) (Geem et al. 2001) mimics the improvisation process of jazz musicians. HS was later shown to be a special case of ES (Weyland 2010). Artificial bee colony (ABC) (Karaboga and Basturk 2007) simulates honey bee swarms exploiting food sources. Bacterial foraging optimisation (BFO) (Passino 2002) is inspired by the social foraging behaviour of *Escherichia coli*. And the list continues with many other examples, such as leapfrog optimisation (Snyman 1982), or shark smell optimisation (Abedinia et al. 2014). As non-biologically inspired and firmly settled down methods, it is worth citing differential evolution (DE) (Storn and Price 1997) and scatter search (Glover 1977), among others.

Many of the published works in the field have developed experiments with particular function sets and specific running conditions, which complicates, or even prevents, the comparison between two or more proposals. In 1996, a concrete benchmark, with both real-parameter and travelling salesman problems, was proposed to carry out a coordinated competition (Bersini et al. 1996). Unfortunately, it was not widely adopted. Not until 2005 was the first widely consolidated benchmark on real-parameter optimisation proposed, for the competition within the *IEEE Congress on Evolutionary Computation* (CEC) (Garcia et al. 2009; Liao et al. 2014; Suganthan et al. 2005).

The clear winner of the CEC 2005 competition was IPOP-CMAES (Auger and Hansen 2005a), named G-CMAES in some publications and during the conference, as recognised in Garcia et al. (2009); Hansen (2005). This algorithm is an evolution strategy with covariance matrix adaptation and increasing population size. The CEC 2005 competition became an important milestone in the field, because since then, researchers have had a standard framework and a point of reference at their disposal, IPOP-CMAES (apart from the respective winners of subsequent competitions, such as BIPOP-CMAES (Hansen 2009) for the Black-Box Optimisation Benchmarking 2009, among others), for the venture of designing better algorithms and contributing to the real-parameter optimisation field.

In this work, we analyse the progress made ten years after the CEC 2005 competition. In particular, we examine the published literature of real-parameter optimisation from three points of view: the number of publications, the generation of better algorithms, and the comparison relationships among the proposals. Our results show that the literature contains published works that do not improve upon IPOP-CMAES, at least under the empirical framework defined in the CEC 2005 competition; but more importantly, they avoid this comparison. In particular, we observe the emergence of communities that compare new proposals with methods from the same community, and rarely consider approaches from other communities (as initial evolutionary models did with regard to other existing methods, such as mathematical programming, simplex, or pattern search, among others). We conclude that, avoiding the comparison with the state-of-the-art, at that time, is not a good practice, because the real progress is not clear and the knowledge of the field becomes uncertain. We shall emphasise that we do not intend to define the performance criteria and conditions for which new proposals should be accepted for publication. Instead, we advocate that:

- A comparison with the state-of-the-art methods is always necessary;
- A standard comparison methodology is advisable, reference point of the research community (functions and running conditions); and
- Authors must specify the advantages that new proposals incorporate over state-of-the-art models. We understand the creative and subjective aspects of this part of the work. Some proposals might clearly outperform the best methods, some others might get better results in a certain set of problems of particular interest, some might just be new nature metaphors brought to simulation without a clear performance advantage over the state-of-the-art, but at least being operationally original in the way they address the problem (Sörensen 2015)… On the contrary, we frankly discourage publishing the ith improvement of a model, for which

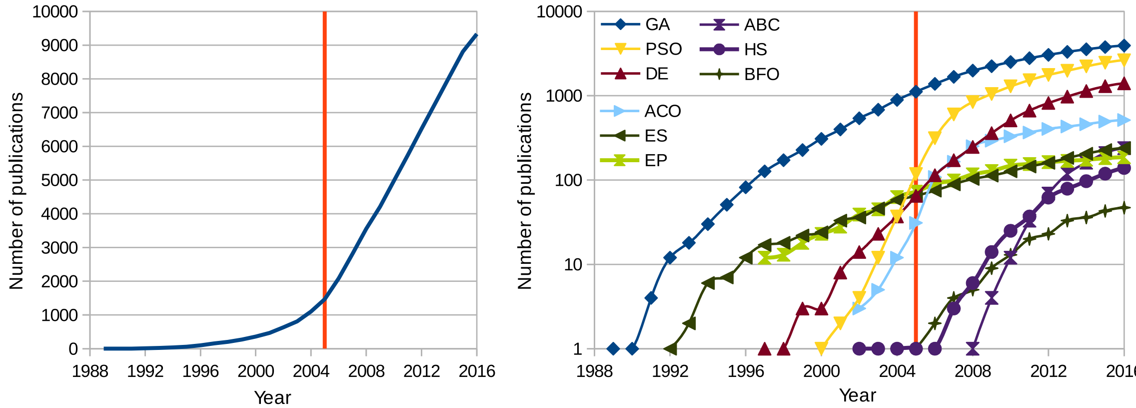

Fig. 1 Cumulative number of publications of evolutionary algorithms and nature-inspired algorithms for real-parameter optimisation of some of the most important metaheuristic families. *Left* all the families together; *Right* separated by family in logarithmic scale. Year 2005 is marked with a *vertical line*. (Results updated on October 6th, 2016)

its authors can not specify its benefits over the best approaches.

The rest of the work is structured as follows. Section 2 studies the number of publications in real-parameter optimisation from some of the most prominent metaheuristic families. Section 3 briefly describes the different proposed benchmarks for carrying out studies in real-coding optimisation. Section 4 analyses some relevant publications in the field in terms of the progress made and the comparisons carried out with previous publications. Section 5 evaluates the case with a publication 10 years after the CEC 2005 competition. The discussion is given in Sect. 6, and conclusions in Sect. 7.

2 Research on real-parameter optimisation: a snapshot

In the last decades, we have witnessed a significant increment in the number of publications of real-parameter optimisation methods. These publications can be categorised into one of the following groups:

- *Enhancement of an existing metaheuristic* Works in this group aim to improve the performance of a given metaheuristic, adapting some of their parameters and/or decisions, or introducing specialised components.
- *A new biologically inspired approach* A process in nature is analysed, simulated and adapted for real-parameter optimisation. This way, a notorious variety of sources of inspiration establishes the foundations of new algorithms each year. These new biologically inspired models often promote subsequent works in the previous group.
- *Applications to specific real-parameter problems* Proposals in previous groups are sometimes applied to address specific problems, such as THz quantitative analysis (Li 2015). We shall mention that in some cases, they include specific improvements that might be analysed as cases of the first group.
- *Others* Finally, other works do not fit well in the groups above because they are theoretical studies of previously approaches or adaptations to discrete combinatorial problems, among others.

Figure 1 shows the cumulative number of publications of some of the most important metaheuristic families, all together on the left and separated on the right, for real-parameter optimisation. These results were obtained from Scopus using queries of the form:

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("real-parameter optimisation" OR
"global optimisation"
OR "continuous optimisation") AND
("<family name>").
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Though these queries inevitably retrieve false positive documents, the results show the following significant trends:

- The number of publications of evolutionary algorithms and nature-inspired algorithms for real-parameter optimisation has increased noticeably in the last years.
- The speed at which the number of publications of each family increases substantially vary from one another. At the extremes, we may point out the rapid increase (steepest slopes) of publications in PSO, DE, ACO, and ABC families and the slower one (moderate slopes) of ES and EP. Between these extremes, we find BFO, HS, DE, and GA, although DE and GA records are sustained by a sig-

nificantly higher and regular amount of publications per year.

3 Benchmarks for research on real-coding optimisation

Several benchmarks have been proposed for real-coding optimisation since 2005. Though some attempts have been published in journal articles (Addis and Locatelli 2007; Jamil and Yang 2013; Jamil et al. 2013; Omidvar et al. 2015; Qu et al. 2016; Rönkkönen et al. 2011), the most popular ones have been presented for special sessions on real-coding optimisation in international congresses, such as the *IEEE Congress on Evolutionary Computation* (CEC) or the *Genetic and Evolutionary Computation Conference* (GECCO), called Black-Box Optimisation Benchmarking (BBOB). Both are popular, and they have evolved, incorporating different and interesting characteristics, according to the contribution of several authors:

- In the CEC competitions, all the functions were initially addressed for 10, 30, and 50 variables, focussing in the optimisation of functions with higher dimensionality in subsequent years. On the other hand, the BBOB benchmark set has functions with different dimensionalities, from two to higher dimensions (but always lower than those in the CEC competitions).
- While the CEC benchmarks have few functions with noise, BBOB emphasised the relevance of noise treatment from the first year, presenting two sets of functions: noiseless and noisy ones.
- The characteristics of the functions are very different, as was shown in Garden and Engelbrecht (2014). For example, contrary to the BBOB functions, several of CEC ones are composed by similar subfunctions, so algorithms that perform well on these fewer subfunctions may probably get good results on this benchmark. This is in line with the fact that the functions of CEC share more similarities among themselves than those of the BBOB (Garden and Engelbrecht 2014). On the other hand and contrary to the CEC functions, the BBOB ones emphasise ill-conditioning with low and high gradients, so methods that apply a type of hill-climbing process might be expected to prosper better than others.
- The analyses on the CEC benchmarks are usually carried out on each function, or group of functions with similar features, separately. This helps researchers to extract conclusions connecting the performance of the algorithms with the features of the functions. On the other hand in BBOB, results are usually compared by means of cumulative distributions of the necessary runtime to achieve a certain maximal error. This helps researchers to provide general conclusions on the general performance of the methods.

More information about the CEC benchmarks for real-coding optimisation can be obtained in Liang et al. (2005) and the webpage of P.N. Suganthan.[1] More information about the BBOB benchmark can be obtained in Hansen et al. (2016) and the official website.[2]

To carry out studies on new algorithms for real-parameter optimisation, it is advisable that researchers follow the most recent version of one of these benchmarks and comparison methodologies. The selection of one or the other depends on the aspects the researcher seeks to analyse, although real-world problems often have more variables than those considered in some of the BBOB functions. This way, results can be directly compared with those of previous and recognised approaches, such as state-of-the-art ones.

4 The progress: significant contributions and their comparative analysis' weaknesses

Here, we analyse how the increment in the number of publications might have pushed forward the real-parameter optimisation field in the last decade. To carry out this goal, we analyse five algorithms published in the most prominent journal of the field, *IEEE Transactions on Evolutionary Computation*, between 2009 and 2011, around 5 years after the CEC 2005 competition: SADE (2009) (Qin et al. 2009), JADE (2009) (Zhang and Sanderson 2009), DEGL (2009) (Das et al. 2009), Frank-PSO (2009) (Montes de Oca et al. 2009), and OLPSO (2011) (Zhan et al. 2011).

In Sect. 4.1, we compare previous algorithms against which was considered the state-of-the-art in 2005, IPOP-CMAES (Auger and Hansen 2005a) and under the empirical framework defined at the CEC 2005 competition. In Sect. 4.2, we examine the comparisons carried out in their respective publications.

4.1 Performance analysis

We have used the benchmark functions, dimensions, and stopping condition proposed at the CEC 2005 competition to compare the aforementioned methods. Though other methodologies have been proposed, they did not appear until 2009 (GECCO-BBOB'09; CEC06-09 were focused on other aspects, such as constraints, multi-objective…). Thus, the CEC 2005 specifications were the clear framework reference at the time the considered approaches were being conceived,

[1] http://www.ntu.edu.sg/home/epnsugan/index_files/cec-benchmarking.htm.

[2] http://coco.gforge.inria.fr/.

Table 1 Wilcoxon results on the CEC 2005 functions with $D = 10$

IPOP-CMAES vs.	$R+$	$R-$	p value
Frank-PSO	278	22	6.39e−5
OLPSO	310	15	8.166e−6
SADE	263	37	6.498e−4
DEGL	325	0	5.960e−8
JADE	298	27	7.498e−5

Table 2 Wilcoxon results on the CEC 2005 functions with $D = 30$

IPOP-CMAES vs.	$R+$	$R-$	p value
Frank-PSO	286.5	38.5	4.03e−4
OLPSO	325	0	5.96e−8
SADE	217	83	0.0564
DEGL	277	48	0.0013
JADE	216.5	108.5	0.1524

Table 3 Wilcoxon results on the CEC 2005 functions with $D = 50$

IPOP-CMAES vs.	$R+$	$R-$	p value
Frank-PSO	276	24	9.084e−5
OLPSO	281	44	8.082e−4
SADE	205	120	0.2457
DEGL	276	49	0.0015
JADE	217	108	0.148

and the most straightforward way to analyse their performance against those of the state-of-the-art ones. Despite of this, some of these works considered a set of functions appearing in previous publications and some others partially followed the CEC 2005 specifications, but none used the full benchmark or a more recent one.

Wilcoxon's matched-pairs signed-ranks test (Demsar 2006; Wilcoxon 1945) was applied to compare these algorithms over all the functions. This test computes the performance differences of two algorithms and ranks them according to their magnitudes. Rankings are subsequently aggregated according to their sign, $R+$ for IPOP-CMAES and $R-$ for the other method. Finally, we compute the probability that supports the null-hypothesis, the p value, which assumes that both algorithms' performances are equivalent. Tables 1, 2 and 3 show the results of the Wilcoxon test for each dimension.

According to the results in Tables 1, 2 and 3, we observe that none of the analysed algorithms outperforms IPOP-CMAES. On the contrary, IPOP-CMAES often provides statistically better results, in general, even when it was published four or six years before.

4.2 Who compares with whom?

In this section, we take previous algorithms, Frank-PSO, OLPSO, SADE, DEGL, and JADE, and analyse which other methods they were compared with. Figure 2 depicts that comparison social network. Nodes are algorithms, and arcs represent the comparisons that were carried out in their respective publications. Nodes are vertically organised according to their respective publication year (see Table 4), so the most recent methods are located near the bottom of the figure and arcs always go downward. Year 2005 is highlighted to differentiate those methods published before the CEC 2005 competition and those published afterwards, for which competing methods are included in the graph, too. The following facts can be observed from Fig. 2:

- IPOP-CMAES is hardly considered in subsequent experiments, even though it was declared the state-of-the-art method for real-parameter optimisation in 2005. The exceptions are NSDE and DEGL. However, NSDE is not clearly better than IPOP-CMAES from the results in Yang et al. (2007): 11 functions with better results, 9 functions with worse ones, and 5 functions without statistical performance differences, and the functions used to compare DEGL and IPOP-CMAES in Das et al. (2009) are not those of the CEC 2005 competition. This contradiction with our results shows that different empirical frameworks, functions or problems, may favour the generation of different results, and it raises some issues with *no free lunch* theorems commented in Sect. 6. Finally, in case the transitive relation was assumed, which would be a very optimistic hypothesis, we could consider that there is a comparison relation between IPOP-CMAES and JADE and OLPSO, though we observed in Sect. 4.1 that IPOP-CMAES outperformed them.
  We shall comment that IPOP-CMAES was beaten by BIPOP-CMAES (Hansen 2009) at the GECCO in 2009. But this new version is not considered in OLPSO publication either, which is the only one after 2009 among those analysed.
- The average number of algorithms considered for comparisons purposes from 2005 onwards is 7, being OLPSO, OPSO, and NSDE extreme cases with 13, 13, and 2 algorithms considered, respectively.
- Differences between the year of publication of the algorithms compared may vary significantly. Considering the minimal difference, just one algorithm is compared with a method published the year before, jDE, and the maximal min-difference is 6 (OPSO). Recall that the graph does not show comparison relations for algorithms published before 2005.

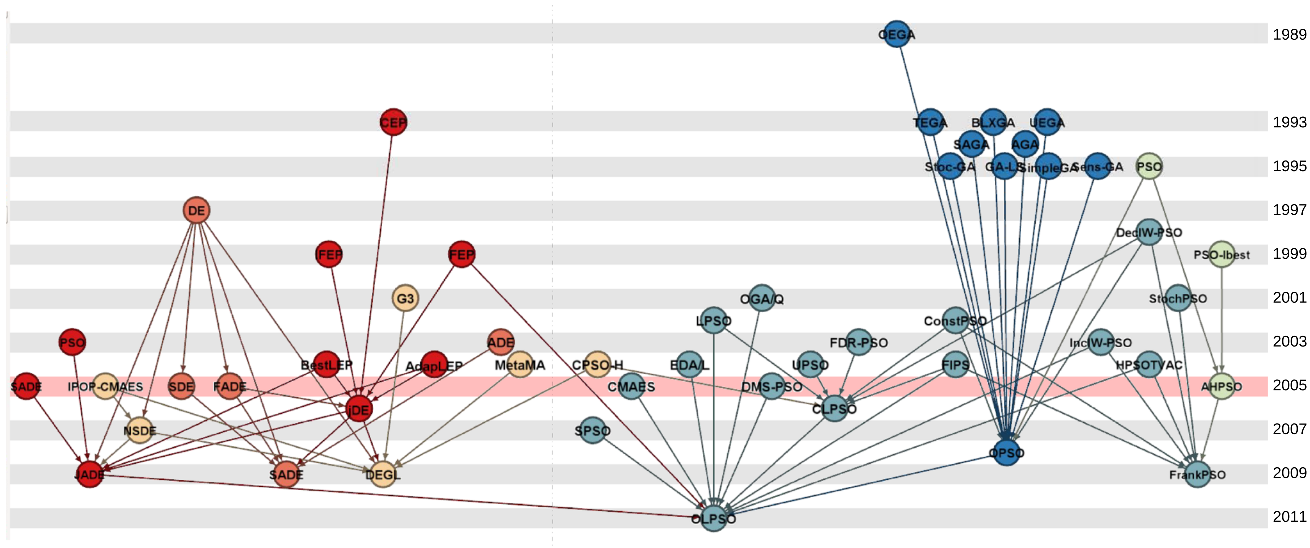

Fig. 2 Algorithms comparison social network

– Very interestingly, we observe that there appear some communities where algorithms are compared among themselves, but share few relations with algorithms from other communities. Particularly, notice that the graph can be divided into two components, separated by a dashed line, where just three algorithms, FEP, JADE, and CPSO-H, establish connections with algorithms from the other community, the two formers with OLPSO and the latter with DEGL. In addition, two of these three relations connect algorithms with five or more years difference of date of publication.

To conclude, we may point out the significant failure of many publications that do not compare their respective proposals with the state-of-the-art of the real-parameter optimisation discipline, even when it appeared around five years before. In our opinion, that is a weakness scientific studies should avoid, given that real progress should be measured with regard to the current state-of-the-art of the field.

5 Ten years after the CEC 2005 competition

There is a very recent publication in the IEEE Trans. on Evolutionary Computation journal, 10 years after the CEC 2005 competition, where authors propose a new crossover operator for DE algorithms and show its advantages when applied in two classic methods and three advanced ones (Guo and Yang 2015): DE/rand/1/eig, DE/best/1/eig, DEGL/eig, JADE/eig, and SADE/eig. Each of these new versions of the algorithm was proved to get better results than its corresponding original method.

Hereafter, we analyse if any of these recent algorithms may outperform IPOP-CMAES in the context of the CEC 2005 competition. We also include SHADE (Tanabe and Fukunaga 2013), which, though it has not been published in any journal, to our knowledge, was the best non-CMAES-based approach in the CEC 2013 real-parameter competition. Tables 5, 6 and 7 compare these methods with IPOP-CMAES according to the guidelines commented in Sect. 4.

As in Sect. 4, we observe that these recent versions of previous algorithms can not clearly surpass IPOP-CMAES, in general, in the context of the CEC 2005 competition. On the contrary, IPOP-CMAES often obtains statistically better results. The only exception is SHADE, which is the sole approach, among those considered in this study, that attains a very slightly superior performance than IPOP-CMAES in the context with the highest number of dimensions ($R-$ is greater than $R+$ in Table 7). Although the analysis does not reveal statistical differences among these results, we observed that SHADE reaches better outcomes in functions f_4, f_9, f_{12}, f_{13}, f_{14}, f_{17}, f_{21}, f_{23}, and f_{24}.

6 Discussion: What are researchers doing in the experimental analysis?

A group of potential problems arise from the question 'What are researchers doing in the experimental analysis?': the consequences of comparing against algorithms of the same community and ignoring the current state-of-the-art; how the diversity of proposals complicates determining the line of real improvements, or even delays the progress of the research field; the difficulties to identify the current state-of-the-art; whether there is a example of a clear and real

Table 4 Year and reference of nodes in Graph 2

Name	Year	References
OEGA	1989	Goldberg (1989)
CEP	1993	Bäck and Schwefel (1993)
TEGA	1993	Eshelman and Schaffer (1993)
BLXGA	1993	Eshelman and Schaffer (1993)
UEGA	1993	Eshelman and Schaffer (1993)
SAGA	1994	Esbensen and Mazumder (1994)
AGA	1994	Srinivas and Patnaik (1994)
Stoc-GA	1995	KrishnaKumar et al. (1995)
GA-LS	1995	KrishnaKumar et al. (1995)
SimpleGA	1995	KrishnaKumar et al. (1995)
Sens-GA	1995	KrishnaKumar et al. (1995)
PSO	1995	Kennedy and Eberhart (1995)
DE	1997	Storn and Price (1997)
DecIW-PSO	1998	Shi and Eberhart (1998a), Shi and Eberhart (1998b), Shi and Eberhart (1999)
IFEP	1999	Yao et al. (1999)
FEP	1999	Yao et al. (1999)
PSO-lbest	1999	Keenedy (1999)
G3	2001	Deb et al. (2001)
OGA/Q	2001	Leung and Wang (2001)
StochPSO	2001	Eberhart and Shi (2001)
LPSO	2002	Kennedy and Mendes (2002)
ConstPSO	2002	Clerc and Kennedy (2002)
PSO	2003	Trelea (2003)
ADE	2003	Zaharie (2003)
FDR-PSO	2003	Peram et al. (2003)
IncIW-PSO	2003	Zheng et al. (2003a), Zheng et al. (2003b)
BestLEP	2004	Lee and Yao (2004)
AdapLEP	2004	Lee and Yao (2004)
MetaMA	2004	Ong and Keane (2004)
CPSO-H	2004	Bergh and Engelbrecht (2004)
EDA/L	2004	Zhang et al. (2004)
UPSO	2004	Parsopoulos and Vrahatis (2004)
FIPS	2004	Mendes et al. (2004)
HPSOTVAC	2004	Ratnaweera et al. (2004)
SADE	2005	Qin et al. (2009)
IPOP-CMAES	2005	Auger and Hansen (2005a)
SDE	2005	Omran et al. (2005)
FADE	2005	Liu and Lampinen (2005)
CMAES	2005	Auger and Hanse (2005b)
DMS-PSO	2005	Liang and Suganthan (2005)
AHPSO	2005	Janson and Middendorf (2005)
jDE	2006	Brest et al. (2006)
CLPSO	2006	Liang et al. (2006)
NSDE	2007	Yang et al. (2007)
SPSO	2007	Particle swarm Central (2007)
OPSO	2008	Ho et al. (2008)
JADE	2009	Zhang and Sanderson (2009)
SADE	2009	Qin et al. (2009)
DEGL	2009	Das et al. (2009)
Frank-PSO	2009	Montes de Oca et al. (2009)
OLPSO	2011	Zhan et al. (2011)

Table 5 Wilcoxon results on the CEC 2005 functions with $D = 10$

IPOP-CMAES vs.	$R+$	$R-$	p value
DE/rand/1/eig	312.0	13.0	0.000054
DE/best/1/eig	322.0	3.0	0.000017
DEGL/eig	299.0	26.0	0.000228
JADE/eig	272.0	28.0	0.000465
SADE/eig	263.0	37.0	0.001183
SHADE	221	104	0.04679

Table 6 Wilcoxon results on the CEC 2005 functions with $D = 30$

IPOP-CMAES vs.	$R+$	$R-$	p value
DE/rand/1/eig	317.0	8.0	0.00003
DE/best/1/eig	278.0	47.0	0.001801
DEGL/eig	239.0	86.0	0.038281
JADE/eig	195.0	130.0	0.374579
SADE/eig	242.0	83.0	0.031354
SHADE	184.5	140.5	0.5383

Table 7 Wilcoxon results on the CEC 2005 functions with $D = 50$

IPOP-CMAES vs.	$R+$	$R-$	p value
DE/rand/1/eig	303.0	22.0	0.000148
DE/best/1/eig	278.0	47.0	0.001801
DEGL/eig	215.0	110.0	0.153849
JADE/eig	227.0	98.0	0.0803
SADE/eig	210.0	115.0	0.196519
SHADE	134.5	190.5	0.4938

evolution in any community; and open questions about the convenience of empirical benchmarks. We discuss all these subjects in more detail below.

The lack of a comparison with state-of-the-art algorithms Examples given in Sects. 4 and 5, representative for a large number of articles that have been published, show that a significant portion of the publications on real-parameter optimisation in the last decade can not outperform IPOP-CMAES (or BIPOP-CMAES), at least in the empirical context defined by the CEC 2005 competition. But the striking fact is that most of them do not consider neither IPOP-CMAES or BIPOP-CMAES as a competitor in their experiments.

The papers have the tendency of comparing among proposals of the same community The analysis of the graph illustrating the social network of comparisons in Sect. 4.2 suggests that the emergence of communities associated to specific metaheuristic families, which compare new proposals with algorithms in the same community, and less frequently with methods from other communities, may promote the growth of their respective number of publications and not necessarily the real progress on the real-parameter optimisation field. Authors might find it easier, and therefore purposely choose , to attain certain progress within these particular communities, instead of in the general area.

The diversity of proposals complicates determining the line of real improvements Though diversity has a positive effect on the field, since it promotes the conception of new ideas and the complimentary contribution with other research lines, researchers should be aware that it may have undesirable consequences on scientific research and engineering applications, too. Particularly, since the literature becomes populated with too many alternatives with unclear exclusive advantages, it is difficult for newcomers to identify the best ones. We have shown that choosing the most recently published real-parameter optimisation alternative from the most important journal of the field, might not be sufficient to get an idea of the current state-of-the-art in the field. As an example, the most recent publication, among those analysed in this work, does not cite the latest and most relevant CMAES variants for general real-parameter optimisation, IPOP-CMAES and/or BIPOP-CMAES.

Excessive diversity in proposals without a clear objective can even delay the progress in the field In our opinion, although diversity is clearly positive, researchers should not avoid the main goal, and invest their efforts in attaining a clear progress at the frontier of the current state-of-the-art in the field. New algorithms, and specially those leading the inspiration on a new metaphor, might not be better than the state-of-the-art for the general context, but their specific benefits over the state-of-the-art should be clearly stated. Therefore, the comparison should be mandatory. Diversity is good if concrete objectives of achieving new goals are targeted.

It is important, although difficult sometimes, to identify the current state-of-the-art for comparison purposes A difficult issue is to distinguish the current state-of-the-art of the field. In our work, we had expected that new proposals published in relevant journals could have improved IPOP-CMAES, which was considered the best algorithm in 2005. BIPOP-CMAES (Hansen 2009) is one of those algorithms, and there are others with similar results, but without statistical differences. Even so, the good results of BIPOP-CMAES in the CEC benchmark and BBOB do not imply that this algorithm be the best one. It has been observed that it does not scale well with the dimensionality, even though tuning its parameters (Liao et al. 2015). Another algorithm that can be considered state-of-the-art for medium dimensionalities is SHADE (Tanabe and Fukunaga 2013) and its extensions, commented below.

Is there any example of clear and real evolution in any community? L-SHADE JADE (Zhang and Sanderson 2009) was proposed in 2009 as a DE with a new mutation operation and an adaptive mechanism that controls two of its parameters, crossover rate (CR) and weighting factor (F), according to previous improvements. SHADE (Tanabe and Fukunaga 2013) was proposed four years later, whose main difference with JADE was the usage of several possible values in the adaptive mechanism. Then, L-SHADE (Tanabe and Fukunaga 2014) extended SHADE in 2014. While the population size was fixed in SHADE, L-SHADE reduced it during the search, to increase exploitation over the best sampled regions of the search space.

In each publication, the new proposal was compared against advanced and modern DEs, including the previous one and showing statistically better performance. This is a good example of evolution, leading eventually to an algorithm that shows to be robust on several benchmarks. In Table 7, we observed that SHADE had a good performance, and it was fourth in the CEC'2013 competition. In addition, not only L-SHADE was the winner in the CEC'2014 competition, but the winners of subsequent competitions were versions of it (SPS-L-SHADE-EIG (Guo et al. 2015) in 2015 and LSHADE_EpSin (Awad et al. 2016) in 2016 with the CEC'2014 benchmark). Thus, this can be seen as an excellent example of a clean evolution in a certain community, although these algorithms should also have been compared with competitive algorithms from other communities.

There are still many open questions about the convenience of current benchmarks We shall mention that the CEC 2005 functions and empirical frameworks might not be the most appropriate context for comparing real-parameter optimisation approaches. Some authors have criticised its artificial nature (Piotrowski 2015), and efforts are regularly invested in designing alternatives in journal publications (Addis and Locatelli 2007; Jamil and Yang 2013; Jamil et al. 2013; Omidvar et al. 2015; Qu et al. 2016; Rönkkönen et al. 2011) and special sessions in conferences (Sect. 3). Besides, given the computational bound of algorithms addressing real-parameter optimisation in a finite representation manner, we should not expect finding algorithms with superior general performances for artificially designed problems. This is a consequence of the *no free lunch theorems* (Wolpert and Macready 1997). Instead, benchmarks that represent the characteristics of problems with practical interest in the real world, where no free lunch theorems improbably hold

(García-Martínez et al. 2012), would be more advisable. In any case, this argument should not be used for avoiding the comparison with the widely accepted state-of-the-art method for real-parameter optimisation at the time.

7 Conclusions

In this work, we have examined the research on real-parameter optimisation since the CEC 2005 competition. We have shown that the exponential growth in the number of publications has not necessarily contributed to the progress in the field. A comparative analysis of selected publications with regard to the state-of-the-art approach in 2005 has exhibited that they can not attain the good results of this latter. But more intriguing, we have observed that they were not compared with the state-of-the-art in the respective studies, despite it was published several years before. Instead, many publications limit their experiments to the comparison with some approaches of the same family, and exceptionally consider methods from other communities.

We advocate that the comparison with the state-of-the-art should always be mandatory, particularly in the case of real-parameter optimisation. This is necessary to promote a real progress in the field, which becomes blurred for outsiders otherwise.

Finally, Sect. 3 has provided a snapshot of other benchmarks proposed after the CEC 2005 competition, such as those of the CEC or BBOB series (Auger et al. 2012; Pošic et al. 2012; Pošic and Kubalík 2012). We consider the comparative analysis under these posterior scenarios for future works.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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