An Indicator-Based Chemical Reaction Optimization Algorithm for Multi-objective Search

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ABSTRACT

In this paper, we propose an Indicator-based Chemical Reaction Optimization (ICRO) algorithm for multiobjective optimization. There are two main motivations behind this work. On the one hand, CRO is a new recently proposed metaheuristic which demonstrated very good performance in solving several mono-objective problems. On the other hand, the idea of performing selection in Multi-Objective Evolutionary Algorithms (MOEAs) based on the optimization of a quality metric has shown a big promise in tackling Multi-Objective Problems (MOPs). The statistical analysis of the obtained results shows that ICRO provides competitive and better results than several other MOEAs.

Categories and Subject Descriptors

I.2.8 [**Computing Methodologies**]: Articial Intelligence—*Problem Solving, Control Method, and Search.*

General Terms

Algorithms, Design.

Keywords

Multi-objective optimization, chemical reaction optimization, indicator-based selection

1. INTRODUCTION

Most real world optimization problems encountered in practice have a multi-objective nature. In fact, Evolutionary Multi-objective Optimization (EMO) is new branch in the optimization research field and it represents actually one of the most attractive and active research fields in computer science. One of the emerging fitness assignment schemes proposed in the EMO literature is the indicator-based schemes which is based on the use of performance indicators. Furthermore, a new CRO metaheuristic was proposed recently by Lam and Li [1] in 2010. The CRO algorithm has demonstrated its effectiveness and efficiency in solving different single-objective real world and benchmark problems [1]. It has several nice features rendering it one of the most efficient metaheuristics for mono-objective optimization. Till now, the CRO has not been investigated in indicator-based multi-objective optimization. For this reason, we seek in this paper to exploit the nice CRO characteristics in solving MOPs and to propose then a new multi-objective general based indicator CRO (ICRO).

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2. INDICATOR-BASED CHEMICAL REACTION OPTIMIZATION

2.1 Basic scheme

This section gives the main algorithmic scheme of ICRO. The first step of the algorithm consists on applying the CRO variation operators in order to generate the offspring population Q_t. We should mention here that differently to other metaheuristics, CRO performs environmental selection within the variation operators [1]. As well, each CRO operator defines its replacement strategy based on PE value. For this reason, we seek firstly to relax the CRO verification in the variation step. So, thus we generate the offspring population Q_t and after that we can turn back to apply the PE energy management laws of CRO. It looks like we control moves in the search space in order to avoid visiting non-promising regions thanks to these energy management rules. The PE value corresponds here to the usefulness of such solution according to Q_t. As a result, the second step of the algorithm consists on computing this value based on the used quality indicator (cf. section 2.2). Now, we are ready to apply the CRO energy management laws to obtain the updated offspring population Q'_t. After this stage, we can form the combined population $R_t = P_t \cup Q'_t$. The population size of R_t is larger than the predefined population size N, since both parent and offspring population members are included in R_t. As a consequence, elitism is ensured. After this step, environmental selection is implemented. We iteratively remove from R_t the worst population members and therefore updating the fitness values of the remaining ones.

2.2 Fitness assignment

The usefulness of an individual regarding to a whole population P and a binary indicator I was suggested by many authors in the last decade. The ICRO is focused upon binary indicator-used fitness assignement in which we use the following recent and popular addidative $\epsilon-$indicator-based selection method proposed by Ziztler and Kunzli [2].

Table 1: GD and HV median values of ICRO, SMS-EMOA, IBEA and MOEA/D. The Wilcoxon test is performed so that the ith "+" means different with the ith algorithm, and "-" means the opposite.

	ICRO		SMS-EMOA		IBEA		MOEA /D	
	GD	HV	GD	HV	GD	HV	GD	HV
DTLZ1	7,27E-4(+++)	7,49E-4(+++)	**3,55E-4**(+++)	**8,16E-1**(+++)	3,57E-3(+++)	3,10E-1(+++)	4,02E-4(+++)	7,77E-1(+++)
DTLZ2	**4,40E-4**(-++)	**4,68E-1**(-++)	4,47E-4(-++)	4,65E-1(-++)	1,22E-3(+++)	4,28E-1(+++)	4,96E-4(+++)	4,09E-1(+++)
DTLZ3	**1,34E-3**(+++)	2,42E-1(+++)	7,77E-1(+++)	1,20E-3(+--)	8,87E-3(++-)	1,8E-4(+--)	1,72E-2(++-)	**7,08E-1**(+--)
DTLZ4	4,28E-3(-++)	**4,32E-1**(+++)	3,94E-3(-++)	3,44E-3(+++)	**1,01E-3**(++-)	4,21E-1(+++)	1,55E-3(++-)	3,17E-1(+++)
DTLZ5	2,66E-4(+++)	9,46E-2(-++)	1,83E-4(+++)	9,35E-2(---)	8,66E-5(+++)	9,42E-2(+-+)	**1,71E-5**(+++)	**9,47E-2**(+-+)
DTLZ6	2,65E-4(+++)	9,25E-2(+++)	3,43E-2(+++)	8,32E-3(+-+)	3,35E-4(+++)	9,23E-2(+-+)	**3,81E-5**(+++)	**9,53E-2**(+++)
DTLZ7	**7,55E-4**(+++)	**3,07E-1**(-++)	7,89E-4(+++)	2,95E-1(-++)	1,85E-2(+++)	2,41E-1(++-)	3,72E-3(+++)	2,27E-1(++-)
SDTLZ1	6,30E-4(+++)	6,69E-1(+++)	**3,90E-4**(+++)	**8,16E-1**(+++)	3,41E-3(++-)	3,53E-1(+++)	2,48E-3(++-)	5,46E-1(+++)
SDTLZ2	**4,57E-4**(+++)	**4,48E-1**(--+)	4,69E-4(+++)	4,46E-1(-++)	1,22E-3(+++)	4,28E-1(-++)	2,79E-3(+++)	2,65E-1(+++)
WFG5	**1,25E-3**(-++)	**4,11E-1**(+++)	1,66E-3(-++)	4,07E-1(+++)	1,26E-3(+++)	3,91E-1(+++)	7,04E-4(+++)	3,58E-1(+++)

$$I_\epsilon(x_1, x_2) = max_{i\in\{1,...,n\}}(fi(x_1) - fi(x_2)) \quad (1)$$

where $x_1 \in X$, $x_2 \in X$ and then $I_\epsilon(x_1, x_2)$ expresses the minimal translation in the objective pace on which to execute x_1 thus it dominates x_2. So thus, $PE\,(x_1) = \sum_{x_2 \in p} -e^{-I_\epsilon(x_1,x_2)}$. Note that the translation may take negative values which means that x_1 dominates x_2. ICRO scheme can apply other indicators to adapt the search according arbitrary performance measure and the diversity of the population should be improved by the used binary indicator defined by DM.

3. RESULTS AND DISCUSSION

Our experiments are divided into two parts. The first one is devoted to compare ICRO against three well-cited MOEAs which are: (1) MOEA/D, (2) SMS-EMOA, and (3) IBEA. The second one is dedicated to CPU time analysis in order to assess the efficiency of our ICRO from a computational time viewpoint. The ICRO algorithm was tested on well-known benchmark problems: the first seven test problems of DTLZ suite [3] in addition to the WFG5 test problems [4]. Moreover we use two variants of DTLZ1 and DTLZ2 called Scaled DTLZ1 (SDTLZ1) and Scaled-DTLZ2 (SDTLZ2). The generated results of the different EMOA are evaluated using two performance metrics: (1) Generational Distance (GD), and (2) HyperVolume (HV) indicators [4]. As well, the performance comparison was carried out using the Wilcoxon statistical test. Therefore, thirty one runs for the bi-objective case and eleven runs for the tri-objective one are performed.

We present only the comparative results for the tri-objecti ve in Table 1 due to limitation space where the best value for each problem is highlighted in bold. For GD results, ICRO gives good results on DTLZ2, DTLZ3, DTLZ7, SDTLZ2 and WFG5. This result could be explained by the fact that ICRO operators perform explicitly local search techniques, which allows it to give a good convergence rate in the majority test problems. However, for some other test problems e.g. DTLZ4, no comparaison results can be deduced between ICRO and SMS-EMOA. For the HV comparative results we show that ICRO presents a good results on several test problems e.g., DTLZ2, DTLZ3, DTLZ4, DTLZ7, SDTLZ2 and WFG5. However it performs poorer than MOEA/D on DTLZ6 which is characterized by a curve front. Indeed, ICRO generates a challenging results regarding to SMS-EMOA and IBEA on DTLZ3 which is a difficult task problem involving multiple local fronts. For the CPU time analysis, we observe from Table 2 that ICRO represents a CPU times less than SMS-EMOA and IBEA. While, compared to MOEA/D, it takes more CPU times. MOEA/D is a decomposition based algorithm so it requires lower computational complexity.We should mention here that based on Wilcoxon test, all results are statistically different from each others. In summary, the CPU times analysis shows clearly that ICRO outperforms SMS-EMOA and IBEA which can make it an efficient Indicator based-MOEA.

Table 2: CPU time results of the four algorithms on DTLZ2 and WFG5 for the bi-objective case and the tri-objective one.

	Bi-objective case		Tri-objective case	
	DTLZ2	WFG5	DTLZ2	WFG5
ICRO	1,49s	1,64s	9,39s	10,52s
IBEA	3,02s	3,02s	19,15s	20,99s
SMS-EMOA	67,61s	125,96s	22879,90s	23981,13s
MOEA/D	0,12s	0,12s	0,36s	0,36s

4. CONCLUSIONS

In this paper, we have suggested an Indicator-based CRO which has shwon its performance for the tri-objective case in terms of finding a well-converged and well-distributed approximation of the Pareto front in a reasonable time. Therefore, it is interesting to design a many-objective version of ICRO and to investigate it to tackle real-world problems.

5. REFERENCES

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