NEW PROPOSAL FOR A MULTI-OBJECTIVE TECHNIQUE USING TRIBES AND TABU SEARCH

Nadia Smairi, Sadok Bouamama
National School of Computer Sciences, University of Manouba, Manouba 2010, Tunisia

Khaled Ghedira, Patrick Siarry
High Institute of Management, University of Tunis, Tunisia
University of Paris 12 (LiSSi, E.A. 3956),France

Keywords: Particle Swarm Optimization, Tribes, Tabu Search, Multi-objective Optimization.

Abstract: The aim of this paper is to present a new multi-objective technique which consists on a hybridization between a particle swarm optimization approach (Tribes) and tabu search technique. The main idea of the approach is to combine the high convergence rate of Tribes with a local search technique based on Tabu Search. Besides, in our study, we proposed different places to apply local search: the archive, the best particle among each tribe and each particle of the swarm. As a result of our study, we present three versions of our hybridized algorithm. The mechanisms proposed are validated using twelve different functions from specialized literature of multi-objective optimization. The obtained results show that using this kind of hybridization is justified as it is able to improve the quality of the solutions in the majority of cases.

1 INTRODUCTION

One of many drawbacks of evolutionary algorithms is that each one of them has many parameters to be tuned each time we want to solve a different problem. Tribes, an adaptative Particle Swarm Optimization (PSO) technique, has the advantage to be designed as a black box; the user defining only the search space, the function to minimize, the required accuracy and a maximum number of evaluations. At the beginning, it was designed to treat mono-objective problems. The aim of this work is to design a competitive multi-objective algorithm free from parameters based on Tribes. However, it has become evident that the concentration on a sole metaheuristic is restrictive. A skilled combination of Tribes with other optimization techniques can provide a more efficient behaviour and higher flexibility when dealing with the real-world problems. Therefore, in this paper, we propose a new multi-objective technique based on Tribes and Tabu Search (TS). In fact, TS is used to cover widely the solution space and to avoid the risk of trapping in non Pareto solutions and Tribes is used to accelerate the convergence. In our study, we use twelve well-known multi-objective test functions in order to find the best one from the proposed techniques and to justify the use of the local search.

In section 2 of this paper we present the existing multi-objective PSO techniques. In section 3, we consider Tribes. In addition, in section 4, we present our proposed approach. Then comparative results are described in section 5, from which conclusions are drawn in section 6.

2 STATE OF ART

In the last few years, several PSO algorithms have been proposed to tackle the multi-objective optimization problem. Here we briefly review the most relevant of them.

Parsopoulos and Vrahatis (2002) propose three different types of aggregation: a classic linear aggregation, for which the weights are fixed, a dynamic aggregation where the weights are gradually modified during the treatment and an

Smairi N., Bouamama S., Ghedira K. and Siarry P. (2010).
NEW PROPOSAL FOR A MULTI-OBJECTIVE TECHNIQUE USING TRIBES AND TABU SEARCH.
In *Proceedings of the 7th International Conference on Informatics in Control, Automation and Robotics*, pages 86-91

aggregation the weights of which are brutally modified during the treatment.

Hu, Eberhart and Shi (2003) propose an algorithm optimizing each time one single objective using a lexicographical order.

The VEPSO strategy was introduced by Parsopoulos, Tasoulis and Vrahatis (2004). It presents an adaptation of VEGA to the particle swarm optimization.

Moore and Chapman (1999) propose an algorithm based on the Pareto dominance and a PSO algorithm with a circular topology of the neighbourhood. In this approach, the choice of the personal guide, for every particle, is arbitrarily made from a list containing the not dominated positions that are found.

Ray and Liew (2002) propose a PSO algorithm using the Pareto dominance. They combine evolutionary techniques with those of the OEP. They also use an operator of density on the neighbourhood to promote the density in the swarm.

This approach, proposed by Coello and Lechuga (2002), is based on having an external archive to store the not dominated positions. Furthermore, the updates of the archive are executed considering a geographical system which decomposes the space of the objectives to a set of hypercubes. The archive is also used to identify a leader which will drive the search.

The authors propose a multi-objective PSO algorithm, called DOPS in which several techniques are integrated for the selection of the leaders and the update of archive (Bartz-Beielstein, Limbourg, Parsopoulos, Vrahatis, Mehnen and Shmitt, 2003).

Quintero, Santiago and Coello (2008) suggest a hybridization of a PSO algorithm with local search techniques such as scatter search and rough sets theory.

The proposed algorithm (Sierra and Coello, 2005) is based on the dominance of Pareto: every not dominated position presents a potential candidate to be selected as a leader. A crowd function is also used to filter all the leaders. This approach (Sierra and Coello, 2007) also integrates the concept of the ε-dominance to fix the size of the archive.

The author has developed a multi-objective version of Tribes. In fact, Mo-Tribes use an approach based on the Pareto dominance. The not dominated particles are stored in an external archive which size and updates are automatically defined. Furthermore, the variety is maintained thanks to a criterion of maximization of the crowd distance and also thanks to the multiple restarts of the swarm. The results of Mo-Tribes are very encouraging (Cooren, 2008).

3 TRIBES

Tribes is a PSO algorithm that works in an autonomous way. Indeed, it is enough to describe the problem to be resolved and the way of making it at the beginning of the execution. Then, it is the role of the program to choose the strategies to be adopted (Clerc, 2006).

At the beginning, we start with a single particle forming a tribe. After the first iteration, the first adaptation takes place and we generate a new particle which is going to form a new tribe, while keeping in touch with the generative tribe. In the following iteration, if the situation of both particles does not improve, then every tribe creates two new particles: we form a new tribe containing four particles. In this way, if the situation deteriorates, then the size of the swarm grows (creation of new particles). However, if we are close to an optimal solution, the process is reversed and we begin to eliminate particles, even tribes. In fact, the removal or the generation of a particle are not arbitrary. The removal of a particle consists in eliminating a particle without risking the missing of the optimal solution. For that purpose, only the good tribes are capable of eliminating their worst elements. The creation of a particle is made for bad tribes as they need new information to improve their situations.

4 OUR APPROACH

4.1 Preliminary Study

The adaptation of Tribes to the multi-objective optimization consists in using the Pareto dominance to respect the completeness of every objective and to add an external archive to save the found not dominated solutions. Furthermore, as the PSO algorithm, Tribes can be considered neither a global optimization algorithm nor a local optimization one (Bergh, 2002). Therefore, the hybridization between Tribes and a local search algorithm can be considered as a competitive approach to handle difficult problems of multi-objective optimization. In order to improve the capacity of exploitation of Tribes, we apply a local search technique: TS. In fact, the local search is not going to be inevitably applied in a canonical way that is on all the particles of the swarm: we also propose two other manners, the first one consists in applying the local search only among the best particle of every tribe. The second one consists in applying it among the particles of the archive. We shall have then three versions of the algorithm.

The first one consists in applying the TS only to the particles of the archive which are situated in the least crowded zones. Let us note that, in this case, the local search is not applied unless the archive is full so that some time is allowed to the information to propagate in the swarm.

```
Begin
  Swarm initialization
  Swarm evaluation
  Archive initialization
  While f<fmax
    For each tribe
      For each particle i
        Determination of the state of the particle
        Choice of the strategy of movement
        Choice of the informer
        Update of the position
        Evaluation
        Update of pi (best position visited by i)
        Update the best particle of the tribe
        Update the archive
      EndFor
    EndFor
    If criterion of adaptation verified
      Determination of the quality of the tribe
      Adaptation of the swarm
      Update of the adaptation criterion
    EndIf
    For each particle of the archive situated in
    the least crowded zones
      TS (stopping criterion)
    EndFor
  EndWhile
End
```

Figure 1: TS-TribesV1 pseudo-code.

The second version of the algorithm consists in applying the TS only to the best particles of the tribes. In fact, we consider that those particles are situated in promising zones and probably they need further intensification to find out other solutions.

The third version consists in applying the TS to all the particles of the swarm. It is made at the moment of the swarm adaptation.

The detailed description of TS-TribesV2 and TS-TribesV3 was omitted due to space restrictions.

4.2 Updating the External Archive

The update of the archive consists in adding all the not dominated particles to the archive and deleting the already present dominated ones. If the number of particles in the archives exceeds a fixed number, we apply a crowd function to reduce the size of the archive and to maintain its variety. Indeed, Crowd divides the objective space into a set of hypercube.

4.3 Choosing the Particle Informer

The choice of the particle informer or guide is similar to the case of mono-objective Tribes. Indeed, if we take a particle which is not the best of its tribe, his guide is then the best particle of the tribe. If we consider, on the other hand, the best particle of a given tribe, the informer is then some random particle from the archive.

4.4 Hybridizing Tribes with TS

The TS is introduced by Glover. It consists in the examination of a neighbourhood of a current solution x and retains the best neighbour x_0 even if x_0 is worse than x. However, this strategy can pull cycles. To prevent this kind of situation from appearing, we store the k last visited configurations in a short-term memory and we forbid to hold any other configuration which is already a part of it.

However, TS is essentially intended for the resolution of the combinatorial problems. Few works considered its adaptation for the continuous optimization. Among whom we can mention the approach of Chelouah and Siarry (2000). In that case, this method is similar to the classic TS. The difference lies essentially in the generation of the neighbourhood. It is necessary to define first of all a way to discretize the search space. In fact, the neighbourhood is defined by using the concept of “ball”. A ball B(x, r) centered on x (current solution) with radius r. To obtain a homogeneous exploration of the space, we consider a set of balls centered on the current solution x with radius r_0, r_1, r_2,…r_n. Hence the space is partitioned into concentric crowns. The n neighbours of x are obtained by random selection of a point which does not belong to the tabu list inside each crown C_i, for i varying from 1 to n. Finally, we select the best neighbour x' even if it is worse than x and we insert it in the tabu list.

5 EXPERIMENTATIONS AND RESULTS

5.1 Test Functions

In order to compare the proposed techniques, we perform a study using twelve well-known test functions taken from the specialized literature on evolutionary algorithms. The detailed description of these functions was omitted due to space restrictions. However, all of them are unconstrained, minimization and have between 3 and 30 decision variables. Indeed, we fix the maximal size of the archive to 100 for the two-objective functions and to 150 to the three-objective ones. We also varied the size of the neighbourhood for the TS algorithm: 5, 10 and 20. Moreover, we fix the maximal number of evaluations in the experimentations to 5e+4.

Table 1: Properties of the test functions.

Test functions	Objective	Modality	Geometry
Oka2	f_1 f_2	Uni-modal Multi-modal	Concave
Sympart	$f_{1:2}$	Multi-modal	Concave
S_ZDT1	$f_{1:2}$	Uni-modal	Convex
S_ZDT2	$f_{1:2}$	Uni-modal	Concave
S_ZDT4	f_1 f_2	Uni-modal Multi-modal	Convex
R_ZDT4	$f_{1:2}$	Multi-modal	Convex
S_ZDT6	$f_{1:2}$	Multi-modal	Concave
S_DTLZ2	$f_{1:3}$	Uni-modal	Concave
S_DTLZ3	$f_{1:3}$	Multi-modal	Concave
WFG1	$f_{1:3}$	Uni-modal	Convex
WFG8	$f_{1:3}$	Uni-modal	Concave
WFG9	$f_{1:3}$	Multi-modal	Concave

5.2 Metrics of Comparison

For assessing the performance of the algorithms, there are many existent unary and binary indicators measuring quality, diversity and convergence. In the literature, there are many proposed combination in order to perform a convenient study and comparison. We choose the combination of two binary indicators that was proposed in (Knowles, Thiele and Zitler, 2006): R indicator and hypervolume indicator.

5.2.1 R indicator (I_{R2})

It computes the difference between the maximum value of the augmented Tchebycheff utility function of the reference set and the obtained solutions from the procedure.

5.2.2 Hypervolume Indicator ($I_{\bar{H}}$)

The hypervolume indicator measures the hypervolume of that portion of the objective space that is weakly dominated by an approximation set A, and is to be maximized. Here we consider the hypervolume difference to a reference set R; where smaller values correspond to higher quality.

5.2.3 Results

The binary indicators used to make the comparison measure both convergence and diversity. The results regarding the R indicator are given in tables 2, 3 and 4 (R can take values between -1 and 1 where smaller values correspond to better results). The hypervolume difference is given for all test functions in table 5, 6 and 7. Again, smaller values mean better quality of the results because the difference to a reference set is measured.

For both indicators, we present the summary of the results obtained. In each case, we present the average of I_{R2} and hypervolume measures over 10 independent runs. These values are given for the different sizes of neighbourhood. According to these tables, we notice that:

- The found fronts for test functions S_ZDT1, S_ZDT2 and S_DTLZ2 are very close to the reference set (for all the versions). Moreover, the found fronts for test functions OKA2, WFG8 and WFG9 are better than the proposed reference fronts (for all the versions).
- Bad performance behaviour is noticed for S_ZDT4 and R_ZDT4 for all the versions except TS-TribesV3. We note that bad convergence behaviour is detected also with another PSO algorithm for ZDT4 in (Hu, Eberhart and Shi, 2003).
- TS-TribesV1 outperforms generally the other versions except for test functions S_ZDT4 and R_ZDT4 where TS-TribesV3 gives the best results.
- The neighbourhood size has no big effect on the performances of the considered algorithms. In fact, they keep the same tendency with the neighbourhood size variation.

Finally, we recapitulate that TS-Tribes is very competitive as it supports both intensification and diversification. In fact, the choice of particle's informer is done in order to accelerate the swarm's convergence towards the search space zones where are situated the archive's particles. This can be considered as an intensification process. Moreover, the archive's updating is done thanks to the Crowd function that maintains the archive's diversity. This can be considered as a diversification process. Indeed, TS supports both intensification and diversification. The good neighbourhood exploration intensifies the search towards specific zones in the search space. Besides, the TS mechanisms such as tabu list allow avoiding the risk of trapping in non Pareto solutions.

Table 2: Results for R indicator (neighbourhood size = 5).

Test Functions	TS-TribesV1	TS-TribesV2	TS-TribesV3
OKA2	**-1.23e-3**	-1.22e-3	-1.21e-3
Sympart	6.74e-5	**2.91e-5**	8.38e-5
S_ZDT1	**7.21e-4**	1.26e-3	1.05e-3
S_ZDT2	4.01e-5	1.48e-3	**3.27e-5**
S_ZDT4	**2.84e-3**	4.84e-3	4.10e-3
R_ZDT4	8.21e-3	**2.24e-3**	1.46e-2
S_ZDT6	4.50e-3	7.78e-3	**2.19e-3**
S_DTLZ2	2.52e-4	**2.19e-4**	2.70e-4
S_DTLZ3	4.24e-4	**2.99e-4**	7.68e-4
WFG1	**2.44e-2**	3.93e-2	4.94e-2
WFG8	**-2.01e-2**	-1.18e-2	-2.25e-3
WFG9	**-6.73e-3**	-6.10e-3	-2.63e-3

Table 3: Results for R indicator (neighbourhood size = 10).

Test Functions	TS-TribesV1	TS-TribesV2	TS-TribesV3
OKA2	**-1.15e-3**	-1.03e-3	-1.02e-3
Sympart	**2.99e-5**	3.20e-5	4.68e-5
S_ZDT1	**5.17e-4**	1.19e-3	1.21e-3
S_ZDT2	**3.72e-5**	1.02e-3	1.23e-4
S_ZDT4	2.82e-3	8.78e-3	**1.68e-4**
R_ZDT4	4.24e-3	3.35e-3	**2.38e-3**
S_ZDT6	3.05e-3	8.79e-3	**2.42e-3**
S_DTLZ2	**1.69e-4**	2.32e-4	2.13e-4
S_DTLZ3	**2.08e-4**	3.37e-4	4.72e-4
WFG1	**2.49e-2**	4.39e-2	4.89e-2
WFG8	**-1.69e-2**	-1.22e-2	-2.26e-3
WFG9	**-9.21e-3**	-4.93e-3	-8.44e-3

Table 4: Results for R indicator (neighbourhood size = 20).

Test Functions	TS-TribesV1	TS-TribesV2	TS-TribesV3
OKA2	-1.01e-3	-1.01e-3	**-1.03e-3**
Sympart	**4.03e-5**	4.84e-5	5.40e-5
S_ZDT1	**6.26e-4**	1.26e-3	1.26e-3
S_ZDT2	**3.93e-5**	1.35e-3	3.95e-5
S_ZDT4	2.31e-3	9.67e-3	**2.53e-6**
R_ZDT4	8.30e-3	2.78e-3	**1.08e-4**
S_ZDT6	**3.37e-3**	6.02e-3	4.32e-3
S_DTLZ2	**1.52e-4**	1.71e-4	2.41e-4
S_DTLZ3	**1.43e-4**	2.96e-4	7.36e-4
WFG1	**2.88e-2**	4.33e-2	3.02e-2
WFG8	**-1.96e-2**	-1.32e-2	-8.68e-3
WFG9	**-1.18e-2**	-7.59e-3	-8.26e-4

Table 5: Results for $I_{\bar{H}}$ (neighbourhood size = 5).

Test Functions	TS-TribesV1	TS-TribesV2	TS-TribesV3
OKA2	**-1.23e-3**	-1.22e-3	-1.21e-3
Sympart	2.01e-4	**8.80e-5**	2.49e-4
S_ZDT1	**5.81e-4**	5.13e-3	4.59e-3
S_ZDT2	3.40e-4	3.87e-3	**3.08e-4**
S_ZDT4	**7.89e-3**	1.38e-2	1.15e-2
R_ZDT4	1.47e-2	**6.85e-3**	4.30e-2
S_ZDT6	6.51e-3	1.65e-2	**4.67e-3**
S_DTLZ2	1.67e-3	**8.78e-4**	1.81e-3
S_DTLZ3	5.62e-3	**8.30e-4**	2.12e-2
WFG1	**1.65e-1**	2.08e-1	2.58e-1
WFG8	**-1.25e-1**	-7.21e-2	-1.42e-2
WFG9	**-4.06e-2**	-3.23e-2	-3.86e-3

Table 6: Results for $I_{\bar{H}}$ (neighbourhood size = 10).

Test Functions	TS-TribesV1	TS-TribesV2	TS-TribesV3
OKA2	**-1.20e-3**	**-1.20e-3**	**-1.20e-3**
Sympart	**8.95e-5**	9.47e-5	1.41e-4
S_ZDT1	**2.45e-3**	5.16e-3	5.11e-3
S_ZDT2	**3.51e-4**	2.74e-3	5.28e-4
S_ZDT4	7.84e-3	2.52e-2	**4.57e-3**
R_ZDT4	1.52e-2	7.07e-3	**1.04e-3**
S_ZDT6	6.38e-3	1.93e-2	**5.21e-3**
S_DTLZ2	**8.09e-4**	8.78e-4	1.81e-3
S_DTLZ3	**6.10e-4**	4.88e-3	1.07e-2
WFG1	**1.70e-1**	2.56e-1	2.55e-1
WFG8	**-1.09e-1**	-7.03e-2	-1.30e-2
WFG9	**-2.29e-2**	-3.01e-2	-5.43e-3

Table 7: Results for $I_{\bar{H}}$ (neighbourhood size = 20).

Test Functions	TS-TribesV1	TS-TribesV2	TS-TribesV3
OKA2	**-1.21e-3**	-1.18e-3	-1.20e-3
Sympart	**1.20e-4**	1.44e-4	1.61e-4
S_ZDT1	**1.50e-3**	1.70e-3	5.24e-3
S_ZDT2	**3.29e-4**	8.65e-4	5.14e-4
S_ZDT4	6.52e-3	2.78e-2	**1.52e-5**
R_ZDT4	2.46e-2	8.55e-3	**3.22e-4**
S_ZDT6	**9.59e-3**	2.19e-2	2.92e-2
S_DTLZ2	**1.30e-4**	5.93e-4	1.94e-3
S_DTLZ3	**2.98e-4**	3.40e-3	1.74e-2
WFG1	**1.63e-1**	2.17e-1	1.70e-1
WFG8	**-1.28e-1**	-8.96e-2	-5.74e-2
WFG9	**-7.22e-2**	-2.49e-2	-1.05e-2

6 CONCLUSIONS

We have introduced a new hybrid multi-objective evolutionary algorithm based on Tribes and TS. This hybrid aims to combine the high convergence rate of Tribes with the good neighbourhood exploration performed by the TS algorithm. Therefore, we have studied the impact of the place where we apply TS technique on the performance of the algorithm. The proposed version TS-TribesV1 gave the best results almost for all the test functions except for S-ZDT4 and R-ZDT4 for which the TS-TribesV3 gave the best results.

The results showed that the hybridization is a very promising approach to multi-objective optimization. As part of our ongoing work we are going to compare the proposed algorithms with other techniques that are representative of the state of art of the multi-objective optimization. Moreover, we are going to study other hybridization between Tribes and other local search techniques.

REFERENCES

Bartz-Beielstein, T., Limbourg, P., Parsopoulos, K.E., Vrahatis, M.N., Mehnen, J., and Shmitt, K. (2003, December). Particle Swarm Optimizers for Pareto Optimization with Enhanced Archiving Techniques. *In congress on Evolutionary Computation Canberra, Australia*, IEEE Press, Vol. 3, 1780-1787.

Bergh, F. (2002). *An Analysis of Particle Swarm Optimizers*. PhD thesis, Departement of Computer Science, University of Pretoria, Pretoria, South Africa.

Carlos, A. and Coello, C.A.C. (2000, June). An Updated Survey of GA-Based Multiobjective Optimization Techniques. *ACM Computing Surveys*, Vol. 32, No. 2.

Chelouah, R. and Siarry, P. (2000). Tabu Search applied to global optimization. *European Journal of Operational Research 123*, 256-270.

Clerc, M. (2006). *Particle Swarm Optimization*. International Scientific and Technical Encyclopaedia, John Wiley & sons.

Coello, C.A.C and Lechuga, M.S. (2002, May). MOPSO: A Proposal for Multiple Objective Particle Swarm Optimization. *Congress on Evolutionary Computation (CEC'2002)*, IEEE Service Center, Piscataway, New Jersey, Vol. 2, 1051-1056.

Cooren, Y. (2008). *Perfectionnement d'un algorithme adaptatif d'optimisation par essaim particulaire. Applications en génie médicale et en électronique*. PhD thesis, Université Paris 12.

Coello, C.A.C., Pulido, G.T. and Lechuga, M.S. (2004, June). Handling multiple objectives with particle swarm optimization. *IEEE Transactions on Evolutionary Computation*, 8(3), 256-279.

Hu, X., Eberhart, R. and Shi, Y. (2003). Particle swarm with Extended Memory for multi-objective Optimization. *In IEEE Swarm Intelligence Symposium*.

Knowles, J., Thiele, L. and Zitler, E. (2006, February). A tutorial on the Performance Assessement of Stochastic Multi-objective Optimizers. *Tik-Report No-214*, Computer Engineering and Networks Laboratory, ETH Zurich, Switzerland.

Moore, J. and Chapman, R. (1999). *Application of particle swarm to multiobjective optimization*. Departement of Computer Science and Software Engineering, Auburn University.

Parsopoulos, K.E., Tasoulis, D.K. and Vrahatis, M.N. (2004, February). Multiobjective optimization using parallel vector evaluated particle swarm optimization. *In Proceedings of the IASTED International Conference on Artificial Intelligence and Applications (AIA 2004)*, Innsbruck, Austria, ACTA Press, Vol. 2, 823-828.

Parsopoulos, K.E. and Vrahatis, M.N. (2002). Particle Swarm Optimization Method in Multi-objective Problems. *Proceedings of the ACM 2002 Symposium on Applied Computing (SAC'2002)*, 603-607.

Quintero, L.V.S., Santiago, N.R. and Coello, C.A.C. (2008). Towards a More efficent Multi-objective Particle Swarm Optimizer. *Multi-objective Optimization in computational intelligence: Theory and practice*, Information Science Reference, Hershey, USA, In Lam Thu Bui and Sameer Alam (editors), 76-105.

Ray, T. and Liew, K.M. (2002, March). A swarm metaphor for multiobjective design optimization. *Engineering Optimization*, 34(2), 142-153.

Sierra, M.R. and Coello, C.A.C. (2005). Improving PSO-based multi-objective optimization using crowding, mutation and ε-dominance. *In third International Conference on Evolutionary Multi-Criterion Optimization*, Guanajuata, Mexico, LNCS 3410, Springer-verlag, 505-519.

Sierra, M.R. and Coello, C.A.C. (2007). A study of techniques to improve the efficiency of a multi-objective particle swarm optimizer. *Evolutionary Computation in Dynamic and Uncertain Environments*, Springer, 269-296.

Zitzler, E. and Deb, K. (2007, July). Tutorial on Evolutionary Multiobjective Optimization. *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO'07)*, London, United Kingdom.