Different Versions of Particle Swarm Optimization for Magnetic Problems

Tomasz M. Gwizdałła
Dept. of Solid State Physics, University of Łódź
Pomorska 149/153
90-236 Łódź, Poland
tomgwizd@uni.lodz.pl

ABSTRACT

The paper presents the application of Particle Swarm Optimization into the magnetic problems where the structure of sample, its stoichiometry and the character of magnetic interactions is described by some well known models. We use three different models or approximations what enables to use three different versions of PSO: binary, real-number and discrete (multi-state). We show that, in order to prepare the efficient code leading to the correct results, we have to include some changes. The most important is the modification of the relative strength of the cognitive and social factors determining the value of velocity. We show also that the computational hardness of the optimization problem depends on the choice of physical parameters. This feature makes it possible to use the presented cases as an interesting testing tool. We compare also our results with the results obtained by using genetic algorithms found either in references or generated by our own code.

Categories and Subject Descriptors

G.1.6 [**Optimization**]: [Global optimization]

General Terms

Algorithms

Keywords

Ising model, Blume-Emery-Griffiths model, Genetic Algorithm, Particle Swarm Optimization

1. INTRODUCTION

The analysis of many physical models lead to the problems which can be understood as NP-hard problems. They are often related to the minimization of the energy of a system described by the specific form of interaction equations, like e.g. the magnetic one.

Although another global optimization techniques (especially GA) has been applied in the area of magnetism (see [4] and references therein) there is very small number of papers which use the Particle Swarm Optimization to solve the pure magnetic problems. Some existing applications concerns rather technical issues. In our paper we propose to pay attention to the basic magnetic models, like the Ising or Blume-Emery Griffiths one. The Ising model is of large historical significance and now is still used in different areas like image analysis [2] or estimation of distribution algorithms [7]. The BEG model has many practical applications (for the extensive list see e.g. [6]).

GECCO'11, July 12–16, 2011, Dublin, Ireland.
ACM 978-1-4503-0690-4/11/07.

2. MODELS

We studied three magnetic models which need different PSO approaches.

1. The two-state Ising model [3]. The behavior of particles is defined by the model proposed in[5] it means velocity values are mapped onto the $[0, 1]$ interval using the sigmoid/logistic curve:

$$sig(v) = \frac{1}{1 + e^{-v}}, \tag{1}$$

and the new states are determined according to the formula:

$$x_{ij}(t+1) = \begin{cases} -1, \; if \; rnd \geq sig(v_{ij}(t)) \\ +1, \; if \; rnd < sig(v_{ij}(t)) \end{cases} \tag{2}$$

2. The spin-1 Blume-Emery-Griffiths model, where 3 possible states $\{-1, 0, +1\}$ are accepted [1]. We relate to this model as to the BEG model on spins. For this case we must define the procedure of new states determination. We do it modifying the formula 2:

$$x_{ij}(t+1) = \begin{cases} x_{ij}(t) - 1, \; if \; rnd \geq sig(v_{ij}(t)) \\ x_{ij}(t) + 1, \; if \; rnd < sig(v_{ij}(t)) \end{cases} \tag{3}$$

3. The spin-1 BEG model on densities. For the so-called first CVM approximation the BEG hamiltonian can be simplified and expressed in the terms of the densities X_i of successive states. Here the basic Kennedy-Eberhart PSO model without constriction factor and inertia weight was used. The crucial problem was keeping the constraints $\sum_{i=-1}^{1} X_i = 1$.

For higher temperatures we must consider free energy $F = U - TS$ instead of internal energy U as a value to be minimized. The method of entropy calculation for individual models can be found in [3] and [1].

3. RESULTS

In Fig.1 we show the efficiency of optimization (the percentage of optimization runs which lead to the best result) for $T = 0$ in the function of cognitive and social factors c_1

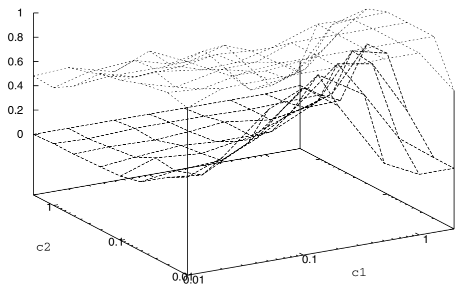

Figure 1: The efficiency of PSO algorithm for Ising model. L_x=L_y=10, $T = 0$, **the lower (thicker line) surface corresponds to** $N_{swarm} = 50$, **the upper one to** $N_{swarm} = 1000$.

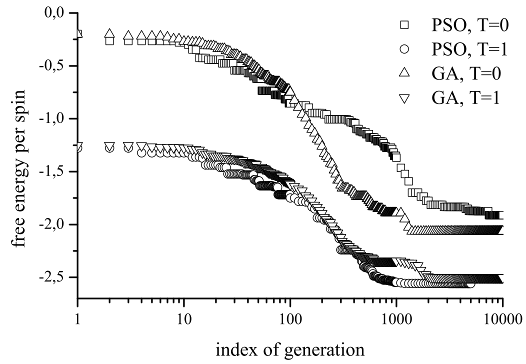

Figure 3: The dynamics of optimization. The values of minimum energy for different algorithms and swarm sizes. Upper plot - $N_{swarm} = 50$, **lower plot -** $N_{swarm} = 500$.

and c_2. We can observe that by assigning different weights to a social and to a cognitive factors we can increase the efficiency. The values of c_1 are usually about 10 times greater so it seems that the social behavior is here more important than a personal memory.

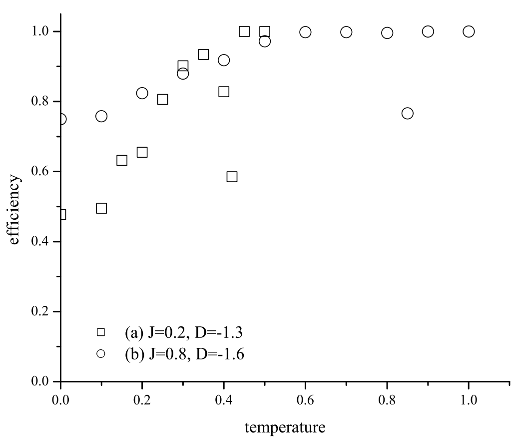

Figure 2: The dependence of efficiency on the temperature for two selected sets of physical parameter values. Number of update steps is equal 1000. N_{swarm}**=50.**

In Fig.2 we show the efficiency vs. temperature plot for two sets of physical parameters taken from ref. [1]. This results correspond directly with the "BEG on densities" model. We observe problems for two regions of temperatures. The visible decrease exist for temperatures about $T = 0.4$ (a) and $T = 0.8$ (b). These temperatures correspond to the phase transition and are of great importance for physical reasons.

The calculations performed for the "BEG model on spins" confirm that the effects mentioned before are visible also in the current calculations. The increase of the swarm size lead to the improvement of efficiency however the magnitude of change is not so big as it was earlier. On the other hand the worsening is obtained for the temperatures close to the phase transition point.

We also performed the comparison between the GA and PSO optimization dynamics (see Fig.3) and we present it as a plot of minimum free energy vs. the number of generation/update step. We selected 4 exemplary runs. Comparing the plots we can point out that the curves for PSO tend to the minimum rather slower and at the uniform rate while those for GA changes rapidly achieving better value.

4. REFERENCES

[1] O. Canko, M. Şahin, and A. Erdinç. Application of the genetic algorithm to Blume-Emery Griffiths model:. test cases. *Int. J. Mod. Phys. B*, 19:4229, 2005.

[2] J. Giovannelli. Estimation of the Ising field parameter thanks to the exact partition function. In *17th IEEE International Conference on Image Processing (ICIP), 2010*, pages 1441–1444, 2010.

[3] T. M. Gwizdałła. Ising model studied using evolutionary approach. *Mod.Phys.Lett.B*, 19:169, 2005.

[4] T. M. Gwizdałła. The role of crossover operator in the genetic optimization of magnetic models. *Applied Mathematics and Computation*, In Press, DOI: 10.1016/j.amc.2011.04.025, 2011.

[5] J. Kennedy and R. C. Eberhart. A discrete binary version of the particle swarm algorithm. In *Systems, Man, and Cybernetics, 1997. 'Computational Cybernetics and Simulation'., 1997 IEEE International Conference on*, volume 5, pages 4104–4108 vol.5, 1997.

[6] M. Keskin, C. Ekiz, and O. Yalçin. Stable, metastable and unstable solutions of the Blume-Emery-Griffiths model. *Physica A*, 267:392–405, 1999.

[7] H. Mühlenbein and R. Höns. Approximate factorizations of distributions and the minimum relative entropy principle. In *Proceedings of the 2005 workshops on Genetic and evolutionary computation*, GECCO '05, pages 199–211, New York, NY, USA, 2005. ACM.