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A Honey Bee Algorithm to Solve Quadratic Assignment Problem

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Abstract

Assigning facilities to locations is one of the important problems, which significantly is influence in transportation cost reduction. In this study, we solve quadratic assignment problem (QAP), using a meta-heuristic algorithm with deterministic tasks and equality in facilities and location number. It should be noted that any facility must be assign to only one location. In this paper, first of all, we have been described exact methods and heuristics, which are able to solve QAP; then we have been applied a meta-heuristic algorithm for it. QAP is a difficult problem and is in NP-hard class, so we have been used honey bee mating optimization (HBMO) algorithm to solve it.This method is new and have been applied and improved NP-hard problems. It's a hybrid algorithm from Honey-Bee Mating system, simulated annealing and genetic algorithm.

Keywords: Honey-Bee mating optimization; Quadratic assignment problem; Heuristic methods; Meta- heuristic methods; Simulated annealing; Genetic algorithm.

1. Introduction

In recent decades, nature inspired algorithms have been used widely to solve different optimization problems. Swarm intelligence and evolutionary algorithms are favorite methods for search and optimization. Calculating of optimum solution for most of optimization problems is difficult. The QAP is one ofthemost difficult combinatorial optimization problems: in general, instances of order n >20 cannot be solved within reasonable time. Therefore, it implies the necessity of using heuristic algorithms to achieve a *good solution.* So, we use meta-heuristic algorithms in these cases. Most of the time, meta-heuristics solve problems in the short time, but they don't ensure to find optimized solutions (Fattahi 2009).

In recent years meta-heuristics algorithms like simulated annealing, genetic algorithm, tabu search, and bee colony algorithms have been applied to solve NP-Hard problems increasingly.Beealgorithmis able to solve combinatorial problems under uncertain conditions, and also deterministic combinatorial problems. So it has been presented good results in real world problems (Fattahi 2009).

Integer programming, dynamic programming and graph theory (combinatorial), are traditional approaches to solve Combinatorial optimization problems. To solve the majority of combinatorial optimization problems are difficult, because these problems are large scale and decomposing them to smaller one is difficult. The mentioned models application in real world problems is considerable. Some of them are building layout in hospitals, storage management and distribution strategies, and minimizing wire length in electronic boards.The other application of QAP is to assign plants to locations, design of control panels and typists keyboard (Fattahi 2009).

To design a meta-heuristic, we should take into consideration to contradictory criterion. These are exploration in search area and exploitation from the best solutions. In exploitation from the best solution, exploration has a limited area among the achieved initial best solutions. So we should search the whole area. If we note the exploration, the algorithm will tend to a random behavior, while in exploitation it investigates the solution in good solution area (Fattahi 2009).

In this study we want to use honey bee mating optimization algorithm to solve deterministic Quadratic Assignment Problem (QAP) within reasonable time.

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2. Literature Review

2.1. Quadratic Assignment Problem

In this paper we study the model of integer linear programming as follow:

$$\min \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n} f_{ij} d_{kl} x_{ik} x_{jl} \quad (1)$$

s.t.

$$\sum_{i=1}^{n} x_{ij} = 1 \; 1 \le j \le n \quad (2)$$

$$\sum_{j=1}^{n} x_{ij} = 1 \; 1 \le j \le n \quad (3)$$

$$x_{ij} \in \{0,1\} \; 1 \le i, j \le n \quad (4)$$

Which f_{ij} is the flow between facility *i* to facility *j*, d_{kl} is the distance between location *k* to location *l* (Loiola et al. 2007). If we take into consideration the assignment cost of facilities to locations we have the below model (Loiola et al. 2007):

$$\min \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n} f_{ij} d_{kl} x_{ik} x_{jl} + \sum_{i}\sum_{k} C_{ik} x_{ik} \quad (5)$$

s.t. equs (2), (3) and (4)

In assignment problem, if distance between locations, flow between facilities, and the assignment cost has determined, only a facility can assign to a location and a location can assign to a facility. International literature defines QAP as a problem to find minimum cost for assigning facilities to locations. Koopmans and Beckman (1957) introduced QAP as a model for economic activitiesfor the first time. Steinberg (1961) used QAP to minimize the number of connections between the elements in backboard wiring. Heffly (1972, 1980) applied it for economic problems. Francis and White (1974) develop a decision making frame, to assign a new facility (like police post, supermarkets, schools locations) for service to determined number of clients. Geoffrion and Graves (1976) focused on scheduling problem. Pollatshek et al (1976) used QAP to define best design for typist keyboards and control panels. Krarap and Pruzan (1978) applied it to archeology; Hubert (1987) in statistical analysis; Forsberg et al. (1994) used it in the analysis of reaction chemistry and Brusco and Stahl (2000) in numerical analysis. Nevertheless, the facilities layout problem is the mostpopular application for QAP; Dickey and Hopkins (1972) applied QAP to the assignment of buildingsin a University campus, Elshafei (1977) in a hospital planning and Bos (1993) in a problem related toforest parks. Benjaafar (2002) introduced a formulation of the facility layout design problem in order tominimize work-in-process (WIP). In his work, he shows that layouts obtained using a WIP-based formulationcan be very different from those obtained using the conventional QAP-formulation. For example, aQAP-optimal layout can be WIP-infeasible. Rabak and Sichman (2003), Miranda et al. (2005) studied the placement of electronic components (Loiola et al. 2007).

Sirirat Muenvanichakul and Peerayuth Charnsethikul (2007) presented an algorithm combining dynamic programming (DP), benders decompositionand meta-heuristics for solving a dynamic facility layout problem. The problem is proposed as anextended model of quadratic assignment problem (QAP) called the dynamic quadratic assignment problem (DQAP) (Sirirat Muenvanichakul et al. 2007). Mohamed Saifullah Hussin and Thomas Stützle (2009) applied hierarchicaliterated local search to solve QAP problem.Hui Li and Dario Landa- Silva applied an elite greedy randomized adaptive search method to solve multi objective QAP (Hui Li et al. 2009). Artur Alves Pessoaet al (2010) used lagrangian decomposition and linear reformulation methods for solving generalized assignment problem (ArturAlves et al. 2010). Ramkumar et al (2009) applied a quick iterative local search heuristic method to solve QAP in facility layout problem. They modified the method by a new recombination from crossover operator (Ramkumar et al. 2009). Huizheng zhung et al (2010) considered the formulation reduction for QAP under Adams and Johnson integer linear programming. They indicated the result by solving 30 instances from QAPLIB with dimension between 12to32. Demirel and Toksari (2006) applied ant colony algorithm to solve QAP. Linzhong Liu and Yinzheng Li (2006) solved fuzzy QAP by new models and GA. Özbakir et al (2010) applied honey bee foraging algorithm for solve GAP.

Sahni and Gonzales (1976) had shown that QAP is NP-hard and that, unless P = NP, it is not possible to find an *f*-approximation algorithm, for a constant *f*. Such results are valid even when flows and distances appear as symmetric coefficient matrices.

2.2. HBMO

Honeybees are among the most closely studied social insects. Honeybee mating mayalso be considered as a typical swarm-based approach for optimization, in which the searchalgorithm is inspired by the process of marriage in real honey-bee. Honeybees have beenused to model agent-based systems (Bozorg haddad et al. 2007). Abbas for the first time proposed mating bee optimization approach in 2001. Afshar, Bozorg haddad, Marino and Adams (2007) had presented the HBMO algorithm to demonstrate the efficiency of the algorithm in handling the single reservoir operation optimization problems. Afshar, Bozorghaddad and Marino (2008) had applied HBMO to non-convex hydropower systemdesign and operation. In this study they considered two problems: single reservoir and multi-reservoir. Ming Huwi Horng et al (2009) had introduced a new approach for multi-level thresholding adopted the honey bee mating optimization based on the minimum cross-entropy criterion. Soltanjalali et al (2011) had studied the effects of breakage level one using HBMO algorithm to design of water distribution networks (WDNs). Niknam (2008) had presented a new approach based on honey-bee mating optimization to estimate the state variables in distribution networks including distributed generators. Niknam (2011) presented an efficient multi-objective HBMO evolutionary algorithm to solve the multi-objective distribution feeder reconfiguration, too. Ming-Huwi Horng and Ting-Wei Jiang (2011) applied a new swarm algorithm based on HBMO to construct the codebook of vector quantization. Ming-HuwiHorng (2010) had presented a new multilevel maximum entropy thresholding (MET) algorithm based on HBMO [12]. Marinaki et al (2010) applied HBMO algorithm to financial classification problems. Bozorg haddad et al (2010) applied it to find shortest path in project management problems with constrained/unconstrained resources. Bernardino et al (2010) proposed a new approach to assign terminals to concentrators in communication networks using HBMO algorithm. Marinakis et al (2011) had proposed a new hybrid algorithmic nature inspired approach using HBMO to solve the Euclidean Traveling Salesman Problem. They combined HBMO with multiple phase neighborhood search-greedy randomized adaptive search procedure (MPNS-GRASP) and the expanding neighborhood search strategy (ENS). Fathian et al (2007) applied HBMO algorithm in clustering using K-means as popular clustering method and combine it with HBMO (HBMK-means).

3. Honey Bee in Nature

HBMO is a new swarm intelligence based on meta-heuristic inspired by honey bee social organized, and their mating process. The method characteristic is to hybrid simulated annealing, genetic algorithm and local search meta-heuristic principles. Simulated annealing has consideredin honey bee mating process; genetic algorithm reflects the mating method, and local search simulate the queen bee and broods feeding process.

Honey bee mating algorithm can be considered as a general method based on insect behavior for optimization which, the search algorithm inspired from mating process in real bees life. Honey bee behavior is an interaction among genetic potential, physiologic and ecologic environment of hive social conditionsand the hybrid of mentioned cases. A honey bee hive including: a queen with long life for laying eggs, about 10000 to 60000 worker bee, and up to hundreds of drone (according to the season). Queens have the main roll to generate some honey bee species, and laying eggs. Drones are the hive father. They are mono-sexual and intensify the mother genes without changing in their genetic combination. Worker bees do laying eggs and mother-craft.

Queen bee would feed by "royal jelly" that is a milky white jelly. Worker bees hide the dietary substances and consume it for the queen. This kind of feeding makes the queen larger than the others. The queen lives between 5-6 year, while the worker bees live about 6 months. Mating flight starts with a special dance by queen. Drones follow the queen and mate with her in the air. In a usual mating flight, she mates with about 7 to 20 drones. Sperms would collect in spermatheca and store there in any mating operation. Drones will die after mating, but their sperm would store in spermatheca. It means that queen will mate for several times and with several drones, but drones are able to mate for only one time. This kind of mating will make exclusive bees mating in comparison with the other insects.

At the beginning of mating flight, queen's energy is determined and at the end of any iteration – when queen return to the hive– her energy may reduce. If her spermatheca has got full or her energy has reduced to zero, the queen would return to the hive.

Any worker as an investigative function, promote the generation or take care a set of broods.At the beginning of a mating flight, drones are generated randomly and the queen selects a drone using the probabilistic rule in Eq. (6).Any drone will mate with the following probabilistic function:

$$prob(Q,D) = e^{-\Delta f / S(t)} \qquad (6)$$

Which *prob* is the probability of collecting drones (D) sperm to queen (Q) spermatheca, or the probability of a successful mating. Δf Is the absolute differentiation between drone objective function (f(D)) and queen objective function (f(Q)), and s(t) is the queen's speed at time *t*. The function indicate the mating probability at the beginning of mating operation, which the queen speed is high or the drone fitness function is suitable and near the queen fitness function. Initially, the speed and the energy of the queen are generated randomly, also the number of mating flights are determined. Gradually and after any queen move in the air, her speed and energy will reduce as Eq. (7). It should be noted that Eq. (7) is different than the one proposed by Abbass (ArturAlves et al. 2010),(Ramkumar et al. 2009).

$$S(t+1) = S(t) - \alpha \qquad (7)$$
$$E(t+1) = E(t) \times \beta$$

With considering the QAP nature, we can see that the objective function value is too larger than queen speed value. Therefore the related probability for mating would get to zero wrongly. So, in order to remove the error we present a new formula for queen speed. To present itapplied a hyperbolic sinus function as follow:

$$\sinh^2 \beta = (e^{\beta} - e^{-\beta})/2 \qquad (8)$$

$$speedt = \min\{\alpha + \sinh^2 \beta, \gamma\} \qquad (9)$$

Which α is a random number between [1,100], β is a value for queen energy reduction in a mating process and is a random number between [1, 10], and γ is a random number between [100, 1000]. It should be noted the mentioned spans is the best and have been achieved by several algorithm runs.
In a mathematical formulation, drone and queen imply a string of genes which indicate an expected solution for problem. Thus, in any mating flight, some drone genes has no change and the other, selected randomly and will change. Worker bees which promote broods generation in hiveare defined as some investigating functions.
Queens have the main role in mating both in nature and HBMO algorithm. Any queen has known by a string of genes, speed, energy and determined spermatheca size. So energy, speed and spermatheca size should be defined by user at the beginning of algorithm. Sperms will store in spermatheca after any successful mating process. Then in brood generation process, any brood has generated by placing some drone genes and completing other genes with queen gene.
In this manner, the queens egg laying has defined as an investigative function and promotes the generation.
By ending queen's mating flight, broods generating start. In order to generate defined number of broods -algorithm input data-, the queen, is mate with a number of sperms stored in her spermatheca, randomly. Then worker bees promote broods according to their fitness function. If their fitness function is better, the improved brood will replace with the previous one, after that the broods should sort in order to find the best one. Selected brood replace with queen bee if her fitness function is better than the queen. A group of broods -defined by user- with better fitness function also replace with the worst drones have been generated at the beginning of algorithm. Rested broods will kill and the next iteration would start. The algorithm would continue until all mating flights done or termination criteria satisfied (Bozorg-Haddad 2008).

4. Proposed Algorithm

In this section the proposed algorithm is applied to solve QAP problem. To apply HBMO, the following steps have to be taken.
Step1. *Define the input data*
The input data including maximum mating flights or problem maximum iterations (mfmax), maximum number of broods (bmax), maximum number of drones (dr), queen spermatheca size (spmax), and the percentage of broods would be replaced with the worst drones (darsad) are defined by user.
Step 2.*Generate the initial population*
Generate m drone as a$n \times n$ matrix like f and d in dimensions, randomly, with considering that there is only one member in a row and column with number 1 (other members of that row and column should be zero (0)).
Calculate all drones fitness function, sort the achieved values, and select the individual that has the minimum fitness function as queen.
Step3. *Calculate mating probability*
By using simulated annealing, select the best drone to mate. The drones the highest speed can mate to queen. So, select a drone, randomly, and calculate mating probability using annealing function. If probability function is greater than a random number between [0, 1], the mating flight would be successful and drone's sperm would store in spermatheca. Queen bee energy also should be calculated. Ifher energy is zero, the mating process will stop.
Step4. *Breeding process*
In this step, a population of broods is generated based on mating between the queen and the drones stored in the queen's spermatheca according to proposed method (see section 4.1). For this process we use one-point crossover operator and roulette wheel to generate new broods.
Step5. *Local search*
In this step we apply local search and searching a new neighborhood. Select a random number between [1, n] whichn is the row number to change the place with next and previous row for selected solution after crossover operation. Then calculate new solutions fitness function. If the new one is better than the old, we should replace it. Otherwise the old solution remains as a brood.
Step6. *Selection of new queen*
Sort all calculated values of fitness function. Select the best one and compare it to the queen fitness function. If the best brood value is better than the queen, replace the new best brood with queen. A determined percentage of remained best broods will replace with the worst existing drones.
Step7. *Termination criteria*
All mating flights should perform according to abovealgorithm (termination criteria). When termination criteria had satisfied best fitness function, the queen would select as best solution.
The pseudo code for the algorithm and local search method has shown in figure 1 and 2 (Appendix1).

4.1. Computational Results and Discussion

The main parameters for HBMO algorithm described below:

- Flow matrix between facilities (f)
- Distance matrix between locations (d)
- Number of drones or feasible solutions in any generation (dr)
- Queen bee spermetheca size (spmax)
- The maximum number of broods should generate (trial solution) (bmax)
- The percentage of broods should be replaced with drones (darsad)

- The maximum number of mating flights or iterations (mfmax)

This algorithm had coded by MATLAB software and it had runs with a Intel® Pentium DualCPU, T3200@2.00 GHZ, 997 MHZ, 0.99 GB of Ram, for several times.
In our experiment, We run the coded algorithm for two kind of experiment as follow:

4.1.1. First Experiment

Our goal here is to study algorithm accuracy with considering the problem dimensions. It has been done by two kind of iteration as short term and long term.
We select problem with 30, 60, 90 dimensions of lipa*a from QAPLIB, which one of its primary matrices has generated, randomly; and problemwith 49 to 100 dimensions of sko* from above website in short term iterations (10 iterations).
The results presented in table 1. In this experiment we compared the results with some methods mentioned in QAPLIB. Figs 3 and 4 indicate the results graphically in shortterm iterations (Appendix 2).

Table1
Results for HBMO algorithm in short term runs (10iteration)

Problem name	B.K.V	n	Average gap for HBMO (%)	Time (sec)
Lipa30a	13178	30	3.74	8.5
Lipa60a	107218	60	2.25	114
Lipa90a	360630	90	1.67	550
Sko49	23386	49	16.11	52.5
Sko56	34458	56	18.49	87.5
Sko64	48498	64	16.91	152
Sko72	66256	72	14.34	161
Sko81	66256	81	13.57	367
Sko100a	152002	100	12.74	578

As shown in short term runs, by increasing problem dimensions, the gap between algorithm results and the problem optimum solution, reduces and it implies the algorithm application to solve problem with higher dimensions.
The experiment had repeated for long term runs (100 iterations) and results have shown in table 2.Figs 5 and 6 indicate the results graphically in long term iterations (appendix2).

Table2
Results for HBMO algorithm in long term runs (100iteration)

Problem name	B.K.V	n	Average gap for HBMO (%)	Time (sec)
Lipa30a	13178	30	3.78	95
Lipa60a	107218	60	2.3	1286
Lipa90a	360630	90	1.65	6215
Sko49	23386	49	18.82	592
Sko56	34458	56	15.88	990
Sko64	48498	64	14.36	1710
Sko72	66256	72	13.78	1831

There is a little difference betweenresults of average gap for short term and long term runs, but as a whole and according to experiment goal the results are the same as short term runs.

4.1.2. Second Experiment

Our goal here is to study influence of input parameters to final solution of QAP. These parameters should defined by user and check their sensitivity after performing experiments. We have done it in two groups of parameters and short term runs. According to first experiment we got that there is no difference between short term and long term runs.
Input parameters have been indicated in table 3.

Table3
Defined parameters to test algorithm

Parameters / experiments	Dr	Bmax	Spmax	Darsad
HBMO-a	30	20	15	50
HBMO-b	60	40	30	20

We have been selected problems in 32 dimensions of *esc32** from *a- h* type, problem in 36 dimensions of *ste36** from *a-c* type, problem in 30, 60, 90 dimensions of *lipa*a* in QAPLIB. The results have been compared with a Hybrid Genetic Algorithm (HGA) [26], and have been shown in tables 4 and 5 for HBMO-a, and tables 6 And7 for HBMO-b.

Table4
Results of HBMO for short term runs for HBMO-a

Problem name	B.K.V	n	Average gap for HGA(%)	Best gap for HGA(%)	Time –HGA- (sec)	Average gap for HBMO (%)	Best gap for HBMO(%)	Time (sec)
Esc32a	130	32	27.13	21.69	39.4	59.82	54.86	10.7
Esc32b	168	32	27.34	20.75	38.5	54.88	50.56	10.7
Esc32c	642	32	0.47	0	3.2	15.13	9.7	9.5
Esc32d	200	32	6.54	0	3.5	33.54	29.57	10.7
Esc32e	2	32	85.51	0	0.108	76.65	0	10.7
Esc32f	2	32	85.51	0	0.108	81.49	66.67	10.7
Esc32g	6	32	26.83	0	0.395	63.06	40	10.7
Esc32h	438	32	5.28	1.79	3.184	24.74	22.06	10.7

Table5
Results of HBMO for short term runs for HBMO-a

Problem name	B.K.V	n	Average gap for HGA(%)	Best gap for HGA(%)	Time -HGA -(sec)	Average gap for HBMO (%)	Best gap for HBMO(%)	Time (sec)
Ste36a	9524	36	21.36	18.41	50.8	46.02	41.05	16.5
Ste36b	15852	36	32.45	27.1	50.6	70.54	64.48	16.5
Ste36c	8239110	36	18.15	13.27	4.5	43.35	41.47	22.5
Lipa30a	13178	30	2.21	2.01	3.34	3.74	3.47	8.5
Lipa60a	107218	60	1.51	1.48	12.1	2.12	2.12	114
Lipa90a	360630	90	1.18	1.13	25.8	1.62	1.62	550

Table6
Results of HBMO for short term runs for HBMO-b

Problem name	B.K.V	n	Average gap for HGA(%)	Best gap for HGA(%)	Time -HGA -(sec)	Average gap for HBMO (%)	Best gap for HBMO(%)	Time (sec)
Esc32a	130	32	27.13	21.69	39.4	58.52	55.04	21.3
Esc32b	168	32	27.34	20.75	38.5	53.36	51.16	21.3
Esc32c	642	32	0.47	0	3.2	17.59	10.33	21.3
Esc32d	200	32	6.54	0	3.5	30.62	20.36	21.3
Esc32e	2	32	85.51	0	0.108	65.89	0	21.3
Esc32f	2	32	85.51	0	0.108	74.27	0	21.3
Esc32g	6	32	26.83	0	0.395	52.54	0	21.3
Esc32h	438	32	5.28	1.79	3.184	22.23	16.41	21.3

Table7
Results of HBMO for short term runs for HBMO-b

Problem name	B.K.V	n	Average gap for HGA (%)	Best gap for HGA(%)	Time - HGA -(sec)	Average gap for HBMO (%)	Best gap for HBMO(%)	Time (sec)
Ste36a	9524	36	21.36	18.41	50.8	45.23	41.5	33
Ste36b	15852	36	32.45	27.1	50.6	67.34	65.46	33
Ste36c	8239110	36	18.15	13.27	4.5	41.4	42.18	33
Lipa30a	13178	30	2.21	2.01	3.34	3.69	3.44	16.8
Lipa60a	107218	60	1.51	1.48	12.1	2.22	2.14	228
Lipa90a	360630	90	1.18	1.13	25.8	1.63	1.6	1116

We can see that in table 4 in esc32* group, the esc32e and esc32f instances have been improved in comparison with HGA. The reason is about the flow matrix of these problems. There is a same reason for lipa*a. As it's clear the flow matrix for mentioned problems has a special format and less complication than the other instances. These flows lead to spend solving time less than the problems with more complications, and increase their accuracy. But in comparison with improved solutions in table 4 as shown in bold form, we can observe the algorithm efficiency.So in problems with low complexity of flow between facilities; the algorithm has better performance in optimum solution.
In HBMO-b group we can see that the accuracy is more than HBMO-a, but the number of it is not influence on final result. It means that by increasing input parameters we can achieve to more accurate final solution, but the explored time would increase and it’s not economic.
As a whole the experiments indicate that there is no sensitivity for input parameters to solve problem, whether it is influence to final solution.

5. Conclusion and Further Research

The algorithm performance, depend on two agents: a) problem dimensions, b) problem nature. With considering the calculated gap for these problems we can see that by increasing in problems dimensions (n) the gap would reduce. As a sample in lipa*a group by increasing dimensions from 30 to 90 accuracy will increase. This is the same for sko* group. Thus, the algorithm is suitable for problems with n≥60.
On the other part we can come to conclusion that flow and distance matrices complexity is influence on algorithm. If the above matrices have more complexity, the gap will increase. That’s important for problem run time.
As a whole HBMO algorithm is acceptable to solve QAP. Also the algorithm has very good convergence according to Figs of 7 and 8 in appendix 3. Most runs for this algorithm are just the same in convergence.
Finally recommended that in future studies, performs some methods like GRASP to generate initial population and then apply the solution in algorithm as initial solution. This will make the algorithm more effective and the

results get better than now because of dwindling in size in search area.

Appendix1

```
Initialization
Generate the initial solutions, randomly (drones)
Selection of best bee as queen
Do while iteration «mating flight(mf_max)»
    Initializing queen spermatheca (SP)
    Calculating initial queen's energy and speed
    Selection of α, β and γ
    Do while energy›0 and spermatheca is not full
        Select a drone
        Prob(Q,D)=exp(-abs(f(Q)-f(D))/speedt)
            If prob(Q,D)›random number
                SP=SP+1
            End if
        Speed (t+1)=speedt-α
        Energy (t+1)=energy*random number between [0,1]
    End do
    Do while S=1: size of spermatheca
        Select a sperm from spermatheca
        Generate brood by a crossover operator by using queen's genotype and the selected sperm
        Select worker bee (local search)
        Use worker to improve brood's fitness function (ff)
            If ff(new brood)‹ff(old brood)
                Brood_old=brood_new
            End if
        Sort brood's according to their fitness function
        Select best brood
        Replace best brood with queen
        Select a percentage of best broods to replace with the worst initial solution (drones)
    End do
End do
Return the queen (best founded solution)
```

Fig. 1.pseudo code for HBMO algorithm

```
Begin
    Select B_j
    Generate a random number
    Change the place of j with j+1 row
    Calculating new fitness function
        If ff(new brood)‹ff(old brood)
            Brood_old=brood_new
        End if
    Change the place of j with j-1 row
    Calculating new fitness function
        If ff(new brood)‹ff(old brood)
            Brood_old=brood_new
        End if
End
```

Fig. 2. pseudo code for local search algorithm

Appendix 2

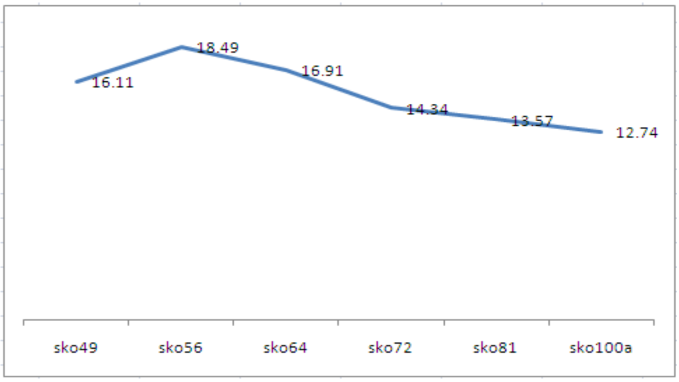

Fig. 3. HBMO algorithm accuracy for sko* problems

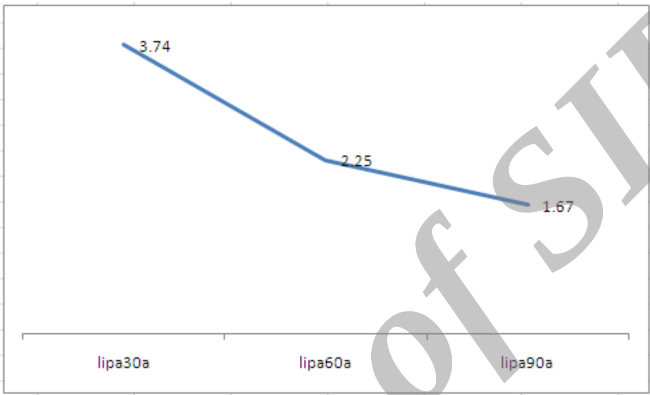

Fig. 4. HBMO algorithm accuracy for lipa*a problems

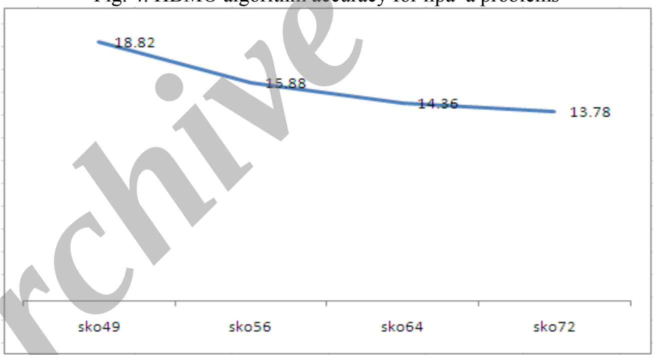

Fig. 5. HBMO algorithm accuracy for sko* problems

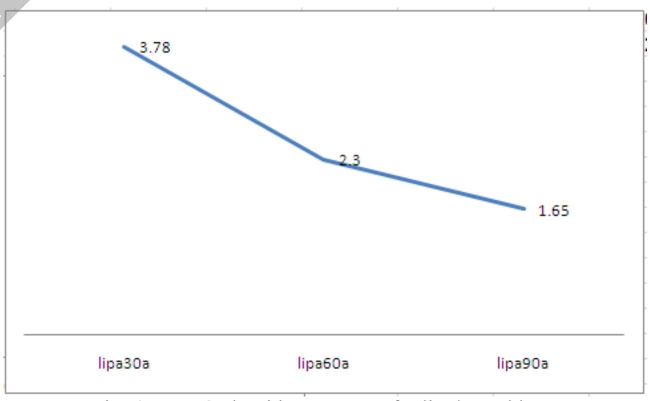

Fig. 6. HBMO algorithm accuracy for lipa*a problems

Appendix 3

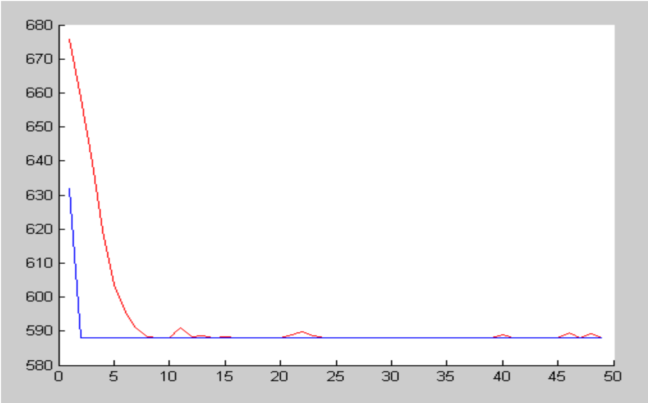

Fig. 7. Convergence speed for esc32h problem

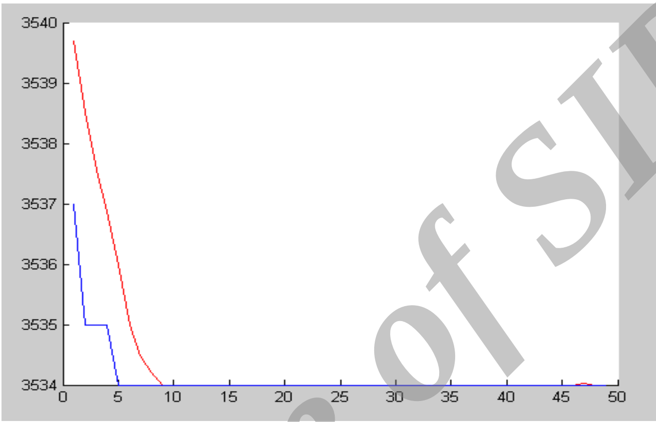

Fig. 8. Convergence speed for lipa60a problem

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