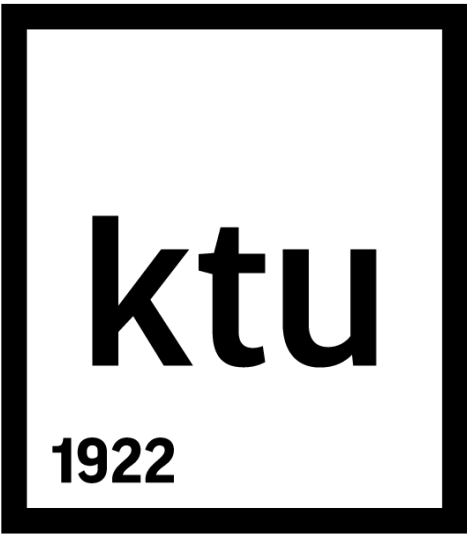


Exploring the Behaviour of the Descent-Ascent Heuristic Optimization Algorithm

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INTRODUCTION

- The essence of the proposed descent-ascent (DA) algorithm lies in the general principle that progress may (often) require temporary setbacks (failures) (Fig. 1)
- In the context of heuristic algorithms, this implies that effective performance may be attained by combining solution improvements (i.e., descents, in the context of minimization problems) with some perturbations (mutations, “invasions” (i.e., ascents)

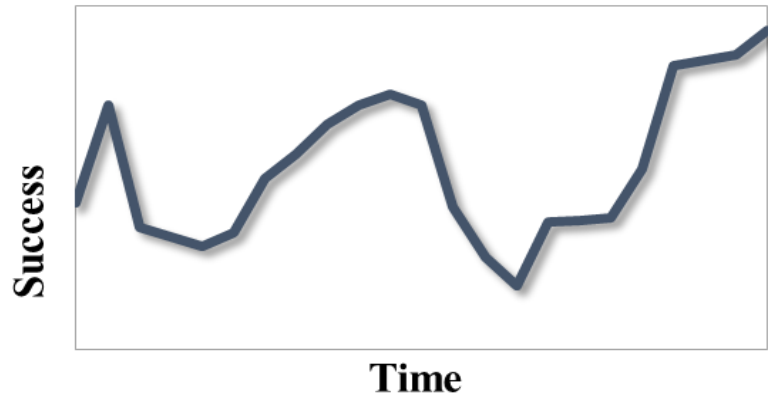


Fig 1. Success vs. time

THE DA ALGORITHM. PSEUDOCODE

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Algorithm 1 Top-level pseudocode of the descent-ascent principle based algorithm
Descent-Ascent-Principle-Based-Algorithm;
// input: n – the problem size, A, B – data matrices,
// DA_iter_N – total number of iterations of the DA algorithm,
// LS_iter_N – the number of iterations of the local search algorithm (descent procedure),
// RP_iter_N_Fact – random perturbation factor (ascent factor),
// Q1, Q2 – the user-defined parameters (integers) (lower and higher (prime) numbers) (Q1 < Q2 – 1)
// output: p* – the best found solution
01 begin
02   create the initial solution p;
03   i ← 1;
04   j ← Q1;
05   if j is the prime number then
06     perform random move with respect to p
07   else begin // j is not a prime number
08     if the previous number (j – 1) is the prime number then begin
09       try to improve the current solution p (if it is possible);
10       if the solution is improved then goto 35 else goto 36
11     endthen
12   else begin // j – 1 is not a prime number
13     if there was improvement of p in the previous iteration
14       then begin
15         try to improve the current solution p (if it is possible);
16         if the solution is improved then goto 35 else goto 36
17       endthen
18     else begin // there was no improvement in the previous iteration
19       if Random_Number(0, 1) < 1/3 then begin
20         perform random move with respect to p;
21         try to improve the current solution p
22       endthen
23       else if Random_Number(0, 1) < 2/3 then begin
24         perform increased random move with respect to p;
25         try to improve the current solution p
26       endthen
27       else begin // Random_Number(0, 1) >= 2/3
28         perform random move or increased random move
29         with the equal probability (1/2) with respect to p;
30         try to improve the current solution p
31       endelse
32     endelse // there was no improvement in the previous iteration
33   endelse // j – 1 is not a prime number
34 endelse; // j is not a prime number
35 if z(p) < z(p*) then p* ← p; // the best so far solution is memorized
36 if j < Q2 then j ← j + 1 else j ← Q1; // go to the next number
37 i ← i + 1; // go to the next iteration
38 if i <= DA_iter_N then goto 05 else goto 39;
39 return p*
40 end.
```

THE EXPLORED COMPONENTS/PARAMETERS OF THE DA ALGORITHM

- N - the total number of iterations of the DA algorithm;
- T - the number of iterations of the tabu search (TS) procedure within the iterated tabu search algorithm;
- IT - the number of iterations of the iterated tabu search (ITS) algorithm within the DA algorithm itself;
- MN - the number of multistarts (restarts).

CONCLUDING REMARKS. RECOMMENDATIONS

- Overall, it can be stated that the introduced idea has demonstrated (quite) strong *potential* (and *effectiveness*).
- The proposed DA algorithm exhibits high *flexibility*: by appropriately *tuning different control parameters*, the algorithm’s search behavior and overall performance can be *effectively shaped* (substantially *improved*).
- It would be valuable in the future work to experiment with *other types of improvement and/or perturbation algorithms* serving as the “descent” and “ascent” components.
- Another promising research direction would be to *integrate* the DA algorithm within *population-based or evolutionary frameworks*, such as genetic algorithms, memetic algorithms, or swarm intelligence methods, to *exploit synergistic hybridization effects*.

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CASE STUDY: THE QUADRATIC ASSIGNMENT PROBLEM (QAP)

— QAP: the goal is to find a (globally optimal) permutation $p=(p(1), p(2), \dots, p(n))$, such that the following objective function is minimized (among all permutations for given matrices A, B):

$$z(p) = \sum_{i=1}^n \sum_{j=1}^n a_{ij} b_{p(i)p(j)}$$

— The following benchmark instances have been used in the experiments: tai40a, tai50a, tai60a, tai80a, tai100a, tai27e1..tai27e5, tai45e1..tai45e5, tai75e1..tai75e5, tai125e1..tai125e5, tai175e1..tai175, bl49. They are from the acknowledged sources (QAPLIB - Quadratic Assignment Problem Library, / Burkard et. al, 1997/, /Drezner et. al, 2005/, Taillard – QAP (<http://mistic.heig-vd.ch/taillard/problemes.dir/qap.dir/qap.html>), /De Carvalho et al., 2006/)

EMPIRICAL RESULTS

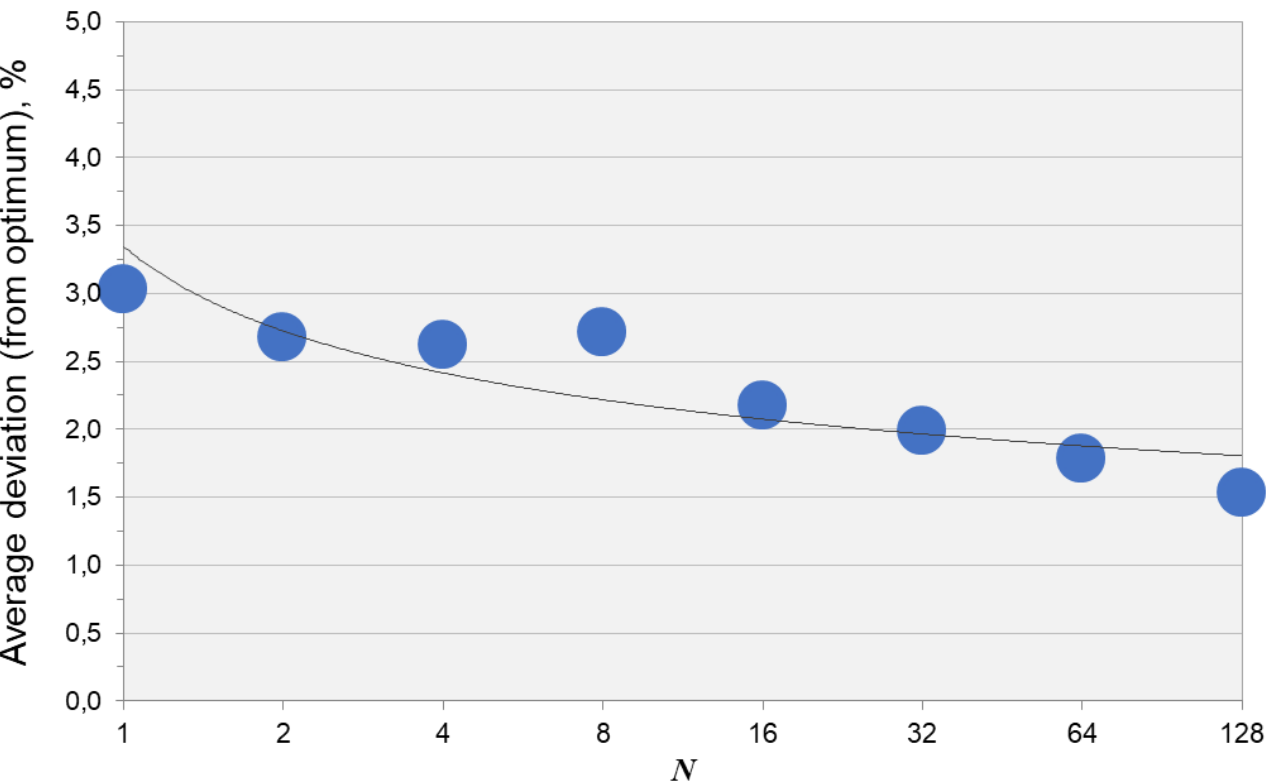


Fig 2. The average percentage deviations from optimum are given for the instance “bl49”. The x-axis of the graph represents the numbers of iterations (N) of the DA algorithm

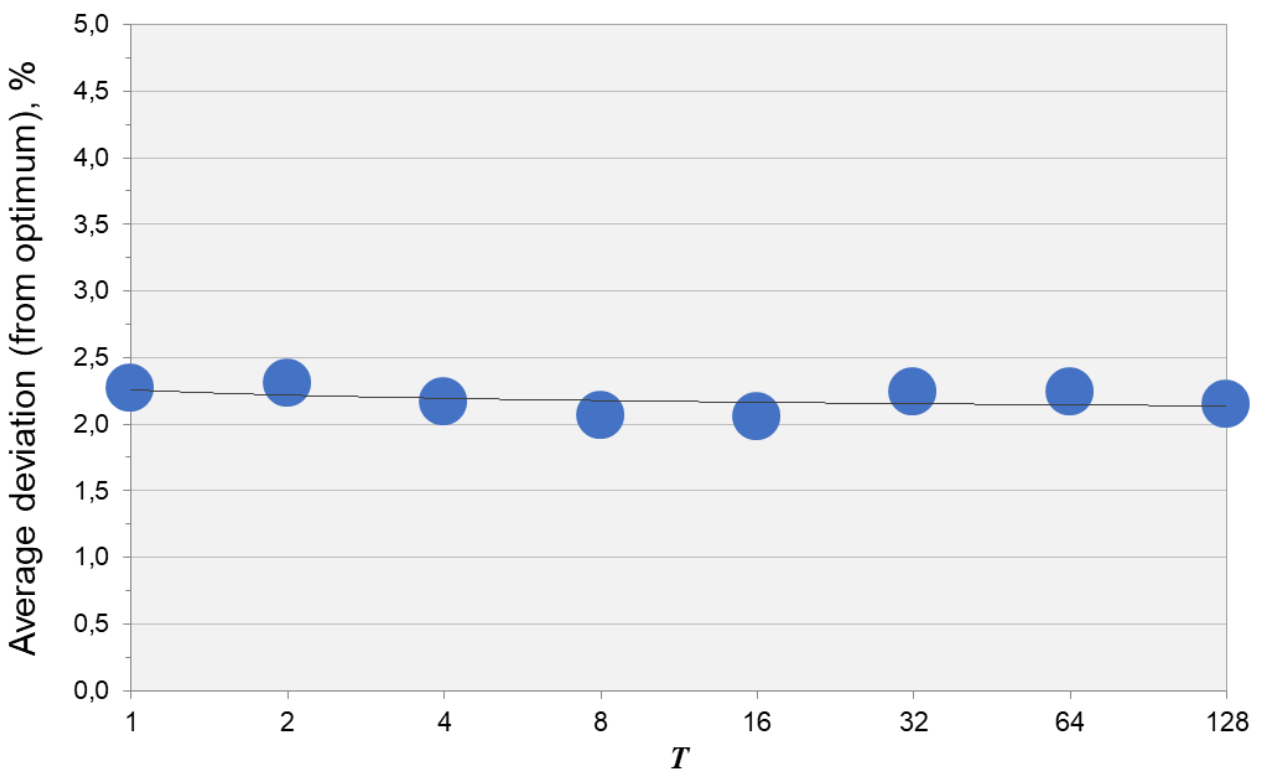


Fig 3. The average percentage deviations from optimum are given for the instance “bl49”. The x-axis represents the numbers of TS iterations (T)

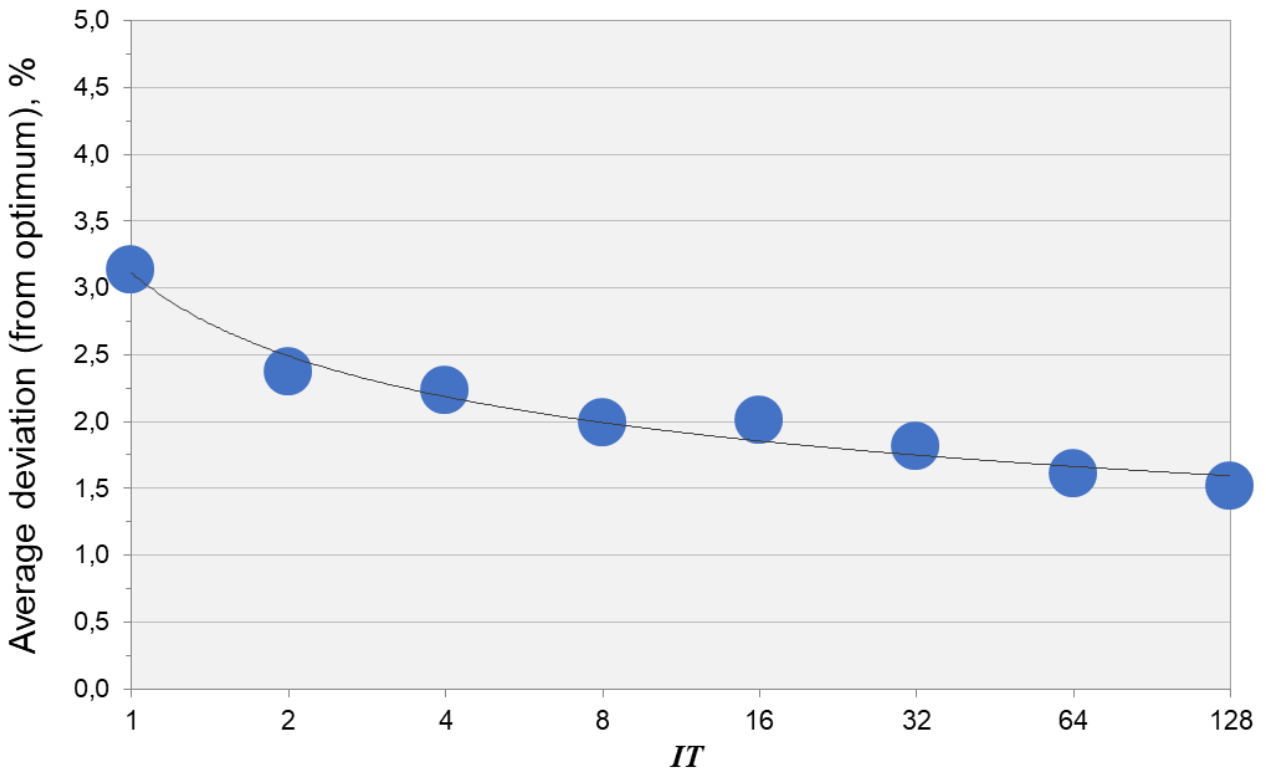


Fig. 4. The average percentage deviations from optimum are given for the instance “bl49”. The x-axis represents the numbers of ITS iterations (IT)

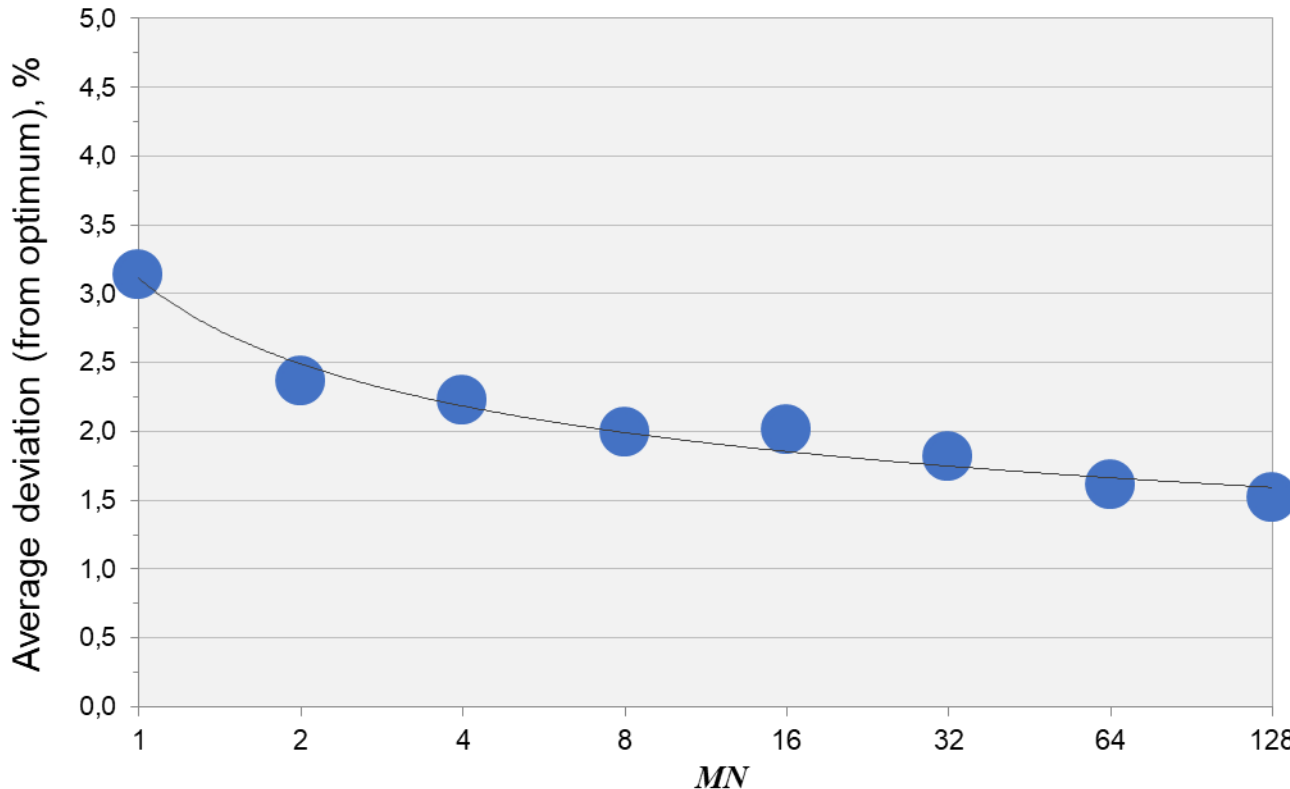


Fig 5. The average percentage deviations from optimum are given for the instance “bl49”. The x-axis represents the numbers of multistarts (MN)

EMPIRICAL RESULTS. LONG RUNS

Instance	Best known value	Deviation, %	Time (sec)
tai40a	3139370	0.000	841.400
tai50a	4938796	0.000	2650.000
tai60a	7205962	0.000	8735.000
tai80a	13499184	0.121	67370.000
tai100a	21043560	0.145	97330.000
tai27e1	2558	0.000	0.106
tai27e2	2850	0.000	0.096
tai27e3	3258	0.000	0.060
tai27e4	2822	0.000	0.071
tai27e5	3074	0.000	0.059
tai45e1	6412	0.000	0.567
tai45e2	5734	0.000	0.457
tai45e3	7438	0.000	0.668
tai45e4	6698	0.000	0.557
tai45e5	7274	0.000	0.487
tai75e1	14488	0.000	5.677
tai75e2	14444	0.000	5.984
tai75e3	14154	0.000	5.749
tai75e4	13694	0.000	5.324
tai75e5	12884	0.000	5.883
tai125e1	35426	0.000	780.200
tai125e2	36178	0.000	845.600
tai125e3	30498	0.000	693.000
tai125e4	33084	0.000	911.900
tai125e5	37210	0.000	915.200
tai175e1	57540	0.000	35440.000
tai175e2	50110	0.000	34830.000
tai175e3	53900	0.000	29950.000
tai175e4	60416	0.000	30170.000
tai175e5	50004	0.000	28550.000