OPTIMIZATION OF DISTRIBUTED OLAP CUBES WITH AN ADAPTIVE SIMULATED ANNEALING ALGORITHM

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Abstract: The materialization of multidimensional structures is a sine qua non condition of performance for OLAP systems. Several proposals have addressed the problem of selecting the optimal set of aggregations for the centralized OLAP approach. But the OLAP structures may also be distributed to capture the known advantages of distributed databases. However, this approach introduces another term into the optimizing equation: space, which generates new inter-node subcubes' dependencies. The problem to solve is the selection of the most appropriate cubes, but also its correct allocation. The optimizing heuristics face now with extra complexity, hardening its searching for solutions. To address this extended problem, this paper proposes a simulated annealing heuristic, which includes an adaptive mechanism, concerning the size of each move of the hill climber. The results of the experimental simulation show that this algorithm is a good solution for this kind of problem, especially when it comes to its remarkable scalability.

1 INTRODUCTION

The multidimensional vision, a main characteristic of On-Line Analytical Processing (OLAP) systems, makes their success. But the increasing complexity and size of the multidimensional structures, denoted as materialized views or subcubes, the support of a fast query answering, independently of the aggregation level of the required information, imply new approaches to their optimization, beyond the classical cube selection solutions, e.g. (Harinarayan et al., 1996), (Gupta & Mumick, 1999), (Liang et al. 2001), using greedy heuristics, (Zhang et al., 2001), (Lin & Kuo, 2004), using genetic approaches or in (Kalnis et al. 2002), using randomized approaches. One of the new solutions is the distribution of the materialized subcubes, aiming to capture the known advantages of database distribution: a sustained growth of processing capacity (easy scalability) without an exponential increase of costs, and an increased availability of the system, as it eliminates the dependence from a single source and avoids bottlenecks. This distribution may be achieved in different ways; in this paper, we focus in one of them: distributing the OLAP cube by several nodes, inhabiting in close or remote sites, interconnected by communication links, generating a multi-node OLAP approach (M-OLAP). The traditional cube selection problem (the materialization of only the most beneficial subcubes) is now extended, as we have a new dimension: space. It's not enough to select the most beneficial subcubes; they also have to be conveniently located. In the distributed scenery, we have n storage and processing nodes, named OLAP server nodes (OSN), with a known processing power and storage space, interconnected by a network, being able to share data or redirecting queries to other nodes.

The authors in (Bauer & Lehner, 2003) introduced the distributed aggregation lattice and proposed a distributed node set greedy algorithm that addressed the distributed view selection

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problem, being shown that this algorithm has a superior performance than the corresponding standard greedy algorithm, using a benefit per unit space metric. But they didn't include maintenance costs into the general optimization cost goal and also didn't include communication and node processing power parameters into the cost formulas. This distributed lattice framework is used in (Loureiro & Belo, 2006a), but including real communication cost parameters and processing node power, which led to heterogeneity in the nodes and the network. To this modified model, several estimation cost algorithms were proposed (Loureiro & Belo, 2006a), (Loureiro & Belo, 2006b), which used the intrinsic parallel nature of the distributed OLAP architecture and time as the cost unit. Framed on this model, in (Loureiro & Belo, 2006c), a genetic co-evolutionary approach is applied to the selection and allocation of cubes in M-OLAP systems, where the genotype of each specie is mapped to the subcubes to materialize in each node. This problem is also addressed in (Loureiro & Belo, 2006d), using another heuristic: discrete particle swarm optimization. Globally, the reported tests' results show that both genetic (especially in its co-evolutionary version) and swarm approaches (both normal and cooperative versions) have low complexity (lower for the normal Di-PSO), being shown that they have a good scalability, supporting easily an M-OLAP architecture with several nodes and also suited for moderate OLAP dimensionalities. Now, we use a simulated annealing meta-heuristic to this same problem, but using a more comprehensive cost model, that introduces non-linearities, a better support to maintenance cost estimation and different algorithms to estimate the costs, which include the use of a pipelining approach to simulate the parallel tasks' execution (Loureiro & Belo, 2006b). This new approach is expected to have a good scalability, regarding the results referred in (Kalnis et al. 2002), which also will be welcome in M-OLAP architectures.

2 HILL CLIMBING WITH SIMULATED ANNEALING

The hill climbing heuristic is simple: a hill climber moves randomly through the search space, trying to find good solutions to the problem, restricted only by constraints that may be imposed to the optimizing process. This heuristic may be improved only allowing moves (Mov^{+}) which improve the quality of the solution. This is called iterative improvement or local search. But if the hill climber falls into a local optimum, it cannot escape from there, and the search process ends abruptly. In (Kirkpatrick et al., 1983) a simulated annealing meta-heuristic able to solve this problem was proposed: the hill climber could move to a worst place, jumping then out of the local minimum. This trick is good, but must be restricted, including an adaptive probabilistic mechanism: the probability of accepting "bad" moves (Mov^{-}) decreases with the on-going process. The annealing schema explores the thermodynamic analogy of the cooling of a melted solid: T (the temperature) controls the probability of accepting Mov^{-} moves (and its extent). A simplified version of the simulated annealing algorithm is shown in Algorithm 1. As we can see, T (temperature) is a parameter that controls the possibility of allowing movements which degrade the solution. As Δ is the loss of solution's quality (in terms of the objective function f), if $\Delta < 0$, the new position is accepted (the referred local search heuristic), but with a probability $e^{-\Delta/T}$ a movement with $\Delta > 0$ (a Mov^{-} move) will be possible, allowing the hill climber to escape from local optima.

This probability has two immediate consequences:

– Movements which imply low values of delta will be admitted more often than the opposite: jumps that imply a great loss in the solution's quality will have a low probability of happening.
– The value of T will be a factor which controls this probability. Its value controls the exploration *versus* exploitation trade-off: for the same delta's value, a high T implies a higher probability of accepting moves which imply a higher degradation of the quality's solution (accepting worst moves) and conversely.

```
Simulated Annealing Meta-Heuristic
Select a initial solution $S$ and an initial temperature
   $T_0>0$
Begin
   $T \leftarrow T_0$
   $S_{best} \leftarrow 0$
   While not achieved stop criterion
      $s' \leftarrow$ solution in the neighbourhood of $S$
      $\Delta \leftarrow f(s) - f(s')$  // f(s) defines the quality of s
      if $\Delta < 0$ then $s \leftarrow s'$  // the new solution is better
      else if $e^{-\Delta/T} >$ rnd[0,1) then $s \leftarrow s'$
      if $f(s) > f(s_{best})$ then $s_{best} \leftarrow s$
      $T \leftarrow T * \alpha$
   WhileEnd
   Return $s_{best}$
End
```

Algorithm 1: Simulated annealing meta-heuristic.

This way, a high initial T value allows the hill climber to escape from local optima. However, if *T* remains the same for all the search process, the algorithm will keep the exploration, without seeking for a deep inspection in a particular region, what would be achieved if the probability of accepting Mov^- moves was low. We face then with two conflicting objectives. But if *T* had initially a high value which would decrease until a low value, the algorithm would have an initial phase where the exploration was favored, being the situation reversed at the end of the process, where almost (or even only) the exploitation was allowed. In fact, as *T* decreases with the iteration's number, when *T* approaches zero, the probability of accepting Mov^- moves almost reaches 0: $T \to 0 \Rightarrow e^{-\Delta/T} \to 0$. Summarizing, *T* is set at an initial high value T_0. After a pre-defined iterations' number, it is reduced by an α factor, $T_n \leftarrow \alpha * T_{n-1}$, being $0 < \alpha < 1$. Other cooling mechanisms were possible, e.g. 1) decreasing *T* by a constant value, after a pre-defined number of iterations or 2) even the decreasing value could be successively lower as the end of the search process approached.

3 PROBLEM DEFINITION AND ALGORITHM'S APPLYING

The problem that we must solve may be defined like this:

Definition 1: *Selection and allocation of distributed M problem.* Let *Q={q₁, …, qₙ}* be a set of queries with access frequencies $\{fq_1, \ldots, fq_n\}$, query extension $\{qe_1,\ldots,qe_n\}$; let update frequency and extension be $\{fu_1, \ldots, fu_n\}$ and $\{ue_1,\ldots,ue_n\}$, respectively, and let S_{Ni} be the amount of materializing space by OLAP node *i*. A solution to the selection and allocation problem is a set of subcubes $M=\{s_1,\ldots,s_n\}$ with a constraint,

$$\sum_j |s_{jN_i}| \leq S_{N_i} \qquad \text{where} \qquad \sum_j |s_{jN_i}|$$

is the materializing space of all subcubes S_j in node N_i, so that the total costs of answering all queries *Q* and maintaining *M*, *Cq(Q, M)+Cm(M)* are minimal.

To use the simulated annealing meta-heuristic we must, as we can see, referring to Algorithm 1:

1. find a way to code the problem;
2. generate the initial position of all hill climbers;
3. define the neighborhood of any position s;
4. define the hill climber's movement scheme;
5. know how to evaluate the quality of each solution (delta computing);
6. define T_0 and α (or any other cooling mechanism).

Figure 1 shows a functional presentation of Hill Climber with Simulated Annealing M-OLAP (HC-SA M-OLAP) algorithm.

Concerning to the first referred issue, as we have a space paradigm of the solutions, we must map each possible M into the position of a hill climber. As M may have a maximal number of subcubes *nS=n.Ls* (where *n* is the number of OSNs and *Ls* is the number of subcubes into the lattice), we must have a multidimensional space of *d=nS* dimensions, being each dimension mapped to a possible subcube in M (in right lower corner of Figure 1, we have shown the multidimensional space for a node with 8 possible subcubes). A position=1 for a dimension d_i, means that the corresponding subcube in M is materialized and conversely. E.g., in Figure 1, subcube S0 is mapped into the X dimension: as S0 is materialized, the HC is at a 1 position. Summarizing, as the search space has *d* dimensions, the position of the hill climber is coded by a binary string where each bit is then mapped to a subcube that may be (or not) materialized into each node.

Relating to the second issue, as for the generation of the initial genome in genetic algorithms or the generation of the initial position of a particle in particle swarm algorithms that we tested in other research works, we opted for the random generation of the initial position of each hill climber.

Concerning to the definition of the neighborhood of a given position, as $s = M$, any other $s' = M' \neq M$ will be a new solution in the s's neighborhood. We may define a maximal Hamming distance, *mhd*, which will limit the range of the move of each step for any hill climber. Viewing this scheme under the spatial paradigm, this will imply that each journey of the HC is limited to a given maximal range. In terms of the problem to solve, this implies that the number of subcubes to dematerialize or materialize in each iteration is limited and may be changed, by specifying a different value.

The forth item, the hill climber's movement scheme (shown in the second round cornered rectangle of Figure 1), is directly related to the former definition of neighborhood: in each iteration the dematerialization of *dsc* subcubes is allowed, $ddh_{\min} \leq dsc \leq ddh_{\max}$, as is the rematerialization of *rsc* subcubes $rdh_{\min} \leq rsc \leq rdh_{\max}$, selecting both values randomly inside the specified interval. Once again, the balance of the relation exploration *versus* exploitation is changed along the search process, by decreasing *dsc* and *rsc* range (at each *fudri* – update frequency of dematerialization and rematerialization interval). In practice, the algorithm randomly selects a node and subcube to dematerialize, changing the corresponding position of the HC from 1 to 0. This operation is repeated *dsc* times, as long as there are subcubes to dematerialize.

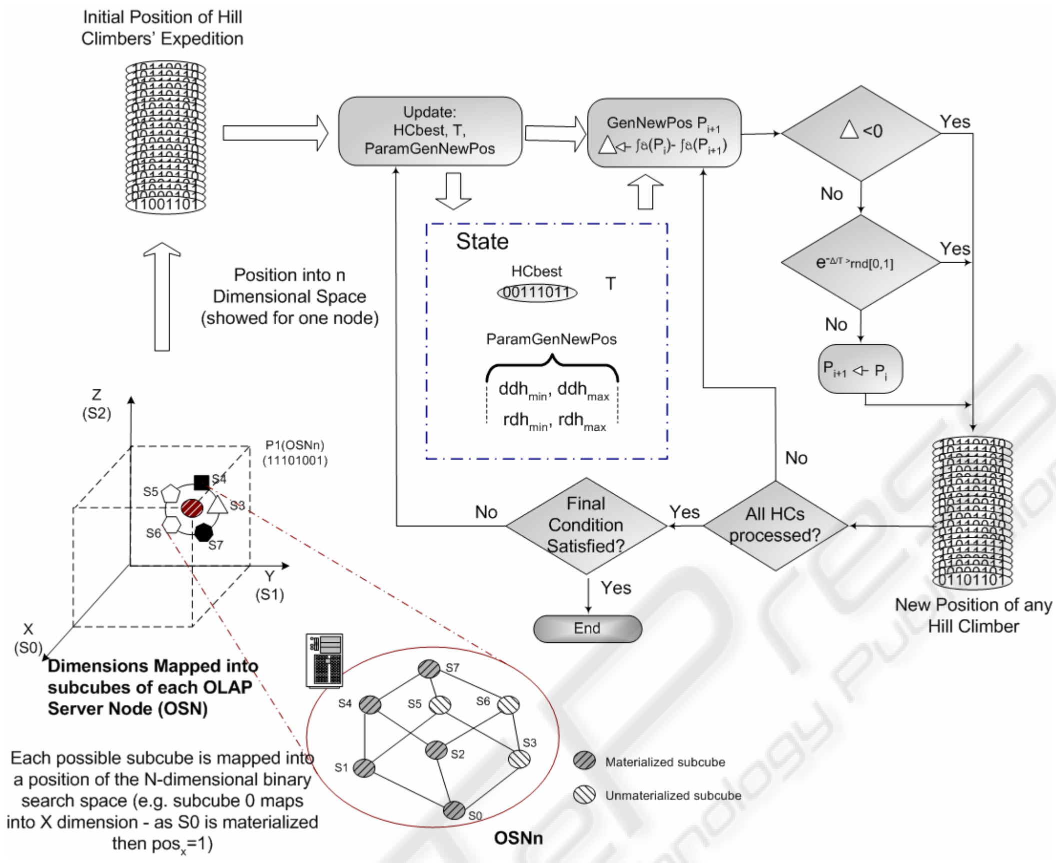

Initial Position of Hill Climbers' Expedition
Update: HCbest, T, ParamGenNewPos
GenNewPos P_{i+1} $\triangle \leftarrow fa(P_i) - fa(P_{i+1})$
$\triangle < 0$
Yes
No
$e^{-\Delta/T} > rnd[0,1]$
Yes
No
$P_{i+1} \leftarrow P_i$
State
HCbest
00111011
T
ParamGenNewPos
ddh_{min}, ddh_{max}
rdh_{min}, rdh_{max}
Position into n Dimensional Space (showed for one node)
Z (S2)
Y (S1)
X (S0)
P1(OSNn) (11101001)
Final Condition Satisfied?
All HCs processed?
No
Yes
End
New Position of any Hill Climber
Dimensions Mapped into subcubes of each OLAP Server Node (OSN)
Each possible subcube is mapped into a position of the N-dimensional binary search space (e.g. subcube 0 maps into X dimension - as S0 is materialized then pos_x=1)
Materialized subcube
Unmaterialized subcube
OSNn

Figure 1: Functional scheme of HC-SA M-OLAP algorithm.

The process of rematerialization is made in an identical way. The algorithm selects randomly a dimension where the HC is at a 0 position and changes its position to 1. In practice, the corresponding subcube is materialized. All parameters concerning this issue are user specified, allowing the tuning of the algorithm.

Concerning to the fifth issue, the fitness function (`fa`) of Figure 1, referring to definition 1, the objective function is the minimizing of *Cq(Q, M)+Cm(M)*. We used the algorithms *Multipipelining Parallel Query Cost Calculation Algorithm with Node Allocation by Constrained Reordering* (PQA) (Loureiro & Belo, 2006b) and *Two Phase Hierarchical Sequence with Multipipelining Parallel Processing* (2PHSMPP) (Loureiro & Belo, 2006b) for estimating query and maintenance costs, respectively.

Finally, for T_0 and the cooling mechanism, we decided for its setting by the user, implying a preliminary tuning, having adopted a type 1 cooling mechanism (as referred in section 2).

4 HC-SA M-OLAP ALGORITHM

Algorithm 2 presents the formal definition of the proposed algorithm. As we can see, it uses the solutions for the issues described in the last section. The algorithm is divided into four main sections:

1. the initialization of parameters and objects, e.g. the expedition of HCs;
2. the generation of the initial position of each HC, its repairing to obey to the space constraint, the computing of its fitness and the display of the state;
3. the iterative module, where the moves of the HCs are performed, as well as the evaluation of its fitness, the updating of move's control parameters and the display of the state;
4. the returning of the best solution achieved.

Given the comments included, the algorithm auto-explainable, and then we choose not to add any further discussion. Among all rules, we highlighted the one which accepts or rejects the movement of the HC and the one which implements the movement.

```
Input: L // Lattice (all granularity's combinations and subcubes' dependencies)
  S=($S_1$... $S_{n}$.) ; Q=($Q_1$... $Q_n$) // Max. storage nodes' space, query set (freq., dist.)
  Pb // Base Parameters: Tf (type of Hc fixing), nOSN (number of OSNs),
    MaximalSizeMaintWindow
  Psa // Parameters of simulated annealing algorithm (NumHC, NumIter,
    DefMovim, $T_0$, α, tpGerac)
  Mt // maintenance costs' dependencies
  P=($P_1$... $P_{n}$.); X=($X_1$... $X_{n}$.)  // Nodes' processing power; connections' param.
Output: M // Materialized subcubes selected and allocated
Begin
1. Initialization:
  M← { $c_0$ } // initialize with all empty nodes; node 0 has the base virtual relation
  E← { };  d← NSCubes * nOSN // HC' expedit. empty; d=dim. of search space
2. Generation, repairing, evaluation and showing the state of the  initial HC' expedit.
  Repeat NumHC Times: // NumHC is the number of HCs of the expedition
    While (MaintCost(hc))>MaximalSizeMaintWindow Do: // while position of
      // generated hill climber (HC) doesn't satisfy the maintenance constraint
      hc ← GenerateHC(d) // generates the HC into a random position in d
      For Each n Into MOLAP, Do: // for each OSN in MOLAP architecture
        If (size(pos(hc),n)) >$S_n$ Then // if size of materialized subcubes proposed
          // by solution of HC for node n > available mat. space in node n ($S_n$)
          Reposition(hc); // relocate HC into the dimensions mapped to node n
            // to observe the space constraint
      Next n
    End While
    E ←E ∪ hc; // add the hill climber to the expedition
    fitness(hc)= f (hc, Q, M, X);
    If fitness(hc)>hcBest Then hcBest ←fitness(hc); // updates hcBest (not really
      // necessary, but interesting to show the initial best position)
  End Repeat
  ShowState(E); // shows the instant state of all hill climbers and hcBest
3. Expedition's movement, fitness evaluation of each solution and state show:
  Iter  ←0; // iterations counter
  While (Itr < NumIter) Do: // final condition is the number of iterations
    T  ← update (T); // T varies from $T_0$ until T→ 0 at each fuT iterations;
    If iter>frozenI OR T<frozenT Then frozen  ← true; // after frozenI
        // iterations or when T is lower than a given value, the system is frozen
    interv_Max_Unmat ←update(interv_Max_UnMat); // updates maximal
      // number of bits which represent the position of each HC that was allowed
      // to change from 1 to 0 in each iteration
    intervMaxRemat ←update(intervMaxRemat) ; // updates maximal number of
      // bits which represent the position of each HC that was allowed to change
      // from 0 to 1 in each iteration
    wU←rnd(interv_Max_UnMat); // generates the number of bits
      // to change from 1 to 0 (un-materialize)
    wR←rnd(interv_Max_ReMat);  // generates the number of bits
      // to change from 0 to 1 (materialize corresponding subcubes)
    // Moves each HC according to the defined movement scheme
    For Each hc Into E, Do:
      While (MaintCost(hc))>MaximalSizeMaintWindow Do: // while new
        // position of HC doesn't verify the maintenance cost constraint
        Repeat wU Times: // un-materilize wU sbcubes (changing bits - 1 to 0)
          d ← select (D); // randomly selects node and subcube to un-materialize
          hc(d) ← 0; // turns the bit (which represents the HC's position) - 1 to 0
        End Repeat
        Repeat wR Times: // rematerilize wR sbcubes (changing bits - 0 to 1)
          d ← select (D);// selects node and subcube to un-materialize with a
            // prob. proportional to the available space into each node or to the
            // relation available space x total space of each node; the subcube to
            // rematerialize cannot imply the break of imposed space constraint
          hc(d) ← 1; // turns the bit (which represents the HC's pos. from 0 to 1)
        End Repeat
      End While
      // Accepting or rejecting HC's movement
      delta  ← f (hc (iter-1), Q, M, X) – f  (hc (iter), Q, M, X); // computes the
        // delta (loss of quality) concerning to HC movement,
        // f is the fitness function
      If delta > 0 AND frozen=true OR delta > 0 AND rnd([0,1))>$e^{-\Delta/T}$ Then
        hc(iter) ← hc(iter-1); // restore prev. pos. of the HC, reject. the new pos.
      fitness(hc)= f (hc, Q, M, X);
      If fitness(hc)>hcBest Then hcBest ←fitness(hc); // updates hcBest
    Next hc;
    ShowState(E); // shows the instant state of all hill climbers and hcBest
    iter ← iter ++; // increments iterations' counter
  End While
4. Returning of result:
  Return M(hcBest) // ret. M corresp. to the best posit. ever achieved by any HC
End
```

Algorithm 2. HC-SA M-OLAP algorithm.

As we apply a per node space constraint, the hill climbers' moves may produce invalid solutions, as when the materializing space is higher than the maximal allowed space. In this work, we employ a repair method, with the reposition of the HC by randomly turning 1 positions to 0 until the HC's proposal is valid.

5 EXPERIMENTAL PERFORMANCE STUDY

To perform the experimental study of the algorithms we used the test set of Benchmark's TPC-R (TPC-R), selecting the smallest database (1 GB), from which we used 3 dimensions (customer, product and supplier). To broaden the variety of subcubes, we added additional attributes to each dimension, generating hierarchies, as follows: customer (*c-n-r-all*); product (*p-t-all*) and (*p-s-all*); supplier (*s-n-r-all*). Whenever the virtual subcube (base relation) is scanned, this has a cost three times the subcube of lower granularity.

We have used a 3 and 6 nodes' M-OLAP architecture (plus the base node), several randomly generated query sets (of different sizes), and we considered incremental maintenance costs. With this environment we intend to evaluate the impact of the following parameters onto the algorithm's performance: 1) the number of iterations, 2) the value of T, 3) the number of HCs, 4) the number of queries, and 5) the scalability of the algorithm relating to the number of M-OLAP architecture's nodes. Given the stochastic nature of the algorithms, all presented values are the average of 10 runs.

5.1 Parameters Tuning

Several preliminary tests were performed to tune some parameters, whose selected values are shown in Table 1. Other parameters, as *fudri*, the frequency of *T* updating, and the iteration of the freezing of the simulated annealing (when the simulated annealing mechanism stops acting, thus the algorithm starts behaving like a local search algorithm), are changed accordingly to the selected values, for the associated parameters. To make things clear, in this table, all parameters are described.

As said above, the balance of the relation exploration *versus* exploitation is changed along the search process, by decreasing *dsc* and *rsc* range (at each *fudri* – update frequency of dematerialization and rematerialization interval). Reducing the range of each HC's journey with the running of the algorithm implies that, in the beginning, the exploration is favored; in opposite, in the later phases, the same is valid for the exploitation (as the range of the search is lower).

Table 1: Specified values for several parameters of HC-SA M-OLAP algorithm.

Parameter	Description	Value
ddh_{min}	minimal number of subcubes to dematerialize	4
ddh_{max}	maximal number of subcubes to dematerialize	9
rdh_{min}	minimal number of subcubes to rematerialize	3
rdh_{max}	maximal number of subcubes to rematerialize	8
DecrD	the decrease of ddh_{min} and ddh_{max}	1
DecrR	the decrease of rdh_{min} and rdh_{max}	1
InitPosGen	the way of generating the initial position of each hill climber	Random

5.2 Performed Tests

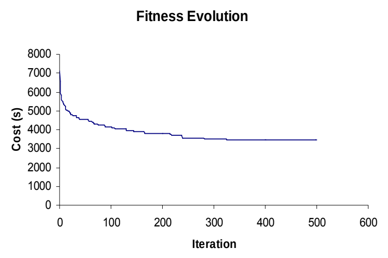
The first test tries to evaluate the impact of the number of iterations over the quality of the achieved solutions and also on the run-time of the algorithm. We used 20 HCs and T_0=30. Figure 2-a shows the evolution of the quality of the solutions proposed by the algorithm. As we can see, the quality of the solutions has an initial fast improvement till about 100 iterations, followed by a slower evolution and an almost null improvement beyond 300 iterations. Moreover, another test, where 1000 iterations were allowed, revealed a small improvement of the quality of the solutions (3435 sec. for 500 iterations *versus* 3411 sec. for 1000 iterations). Moreover, as there is a linear relation between the number of iterations and the run-time execution (as we can see in Figure 2-b), the increase of the run-time doesn't pay off.

With the second test we tried to evaluate the impact of the initial T_0 value over the quality of the solutions. We used a limit of 300 iterations (according to the conclusions of the last test). The results are shown in Figure 2-c. As we can see, we may say that the algorithm's performance is almost independent of T_0 (a difference of 1.2% on average fitness and 4% for final fitness). Also, the plots don't allow deducing a behavior pattern, as they exhibit a non monotonic variation. Watching the plots and inspecting the relative values for the final solution's quality and its average, the value T_0=30 seems to be the one that ensures a better trade-off. Then, we adopted this value for the remaining tests.

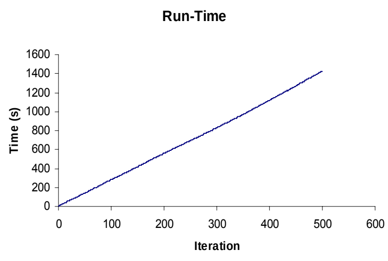
Another characteristic that is important to evaluate, concerning to the algorithm's behavior, is the impact of the HCs' number on the quality of the achieved solutions and on the run-time. The plots of Figure 2-d and 2-e show the obtained results. As we can see, the plot of Figure 2-d shows that the number of HCs has a reduced impact on the quality of the achieved solutions (only 2.7 %). This is something that was expected, given the absence of any competition or cooperation mechanisms. E.g. genetic algorithms are based on struggle for survival and genoma diversity is a condition for evolution. Also the learning process – through Pbest and Gbest – which rules the particles' dynamics in particles swarm algorithm optimization, or *stigmergy*, in ants algorithms, need a population of solutions. Here, each HC acts independently of any other and there isn't any learning process. On the other side, analyzing the plot of Figure 2-e, it is easy to understand that there is an almost linear increase of run-time with the HCs' number. These two evidences allowed us to conclude that it is interesting to keep a low number of HCs, which induces good solutions in a substantially inferior time.

Finally, it is mandatory, as scalability is at premium (recall the algorithm's use to the M-OLAP architecture), to evaluate the impact of the number of queries and especially the nodes' number (as we are using the algorithm for optimizing an M-OLAP system) on the run-time of the algorithm.

This way, for the first case, we used sets with 30, 60 and 90 queries, randomly generated. The run-times are shown in plot of Figure 2-f. Observing this plot, we may see that there is an almost null dependency of the run-time in face of the number of queries (the three lines are almost superposed). Also observing Figure 2-g, we may see that an increase of 3 to 6 nodes in the M-OLAP architecture's has motivated a reduced increase of the run-time: for the 300 iterations there was only an increase of 10.6%. These two observations show that the HC-SA M-OLAP algorithm evidences a very good scalability, being capable to deal with many queries and also with M-OLAP architectures with many nodes. Adding the easy scalability of *hill climbing* with the *simulated annealing*, algorithm concerning to the cube's dimensionality (Kalnis et al. 2002), we have an algorithm capable to scale in all directions.



(a)



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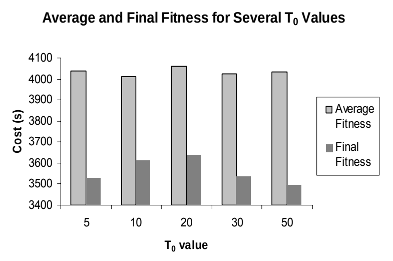

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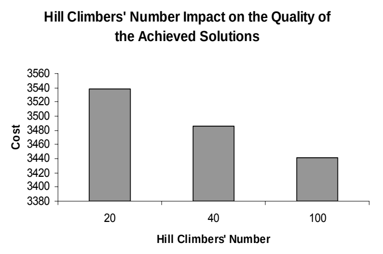

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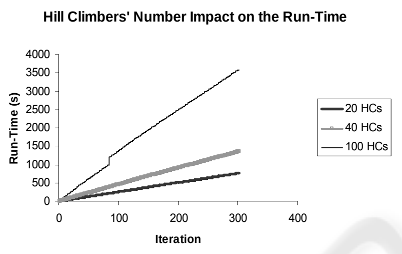
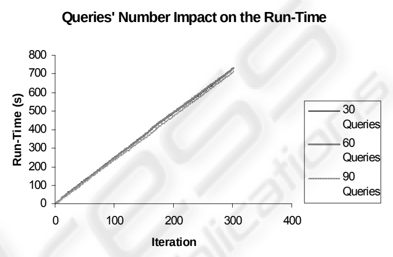
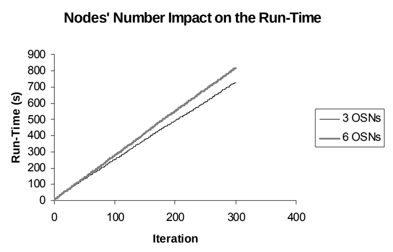


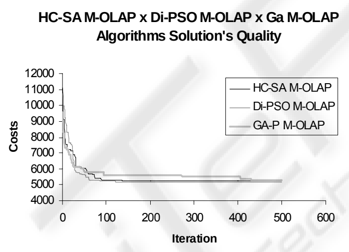
(e)



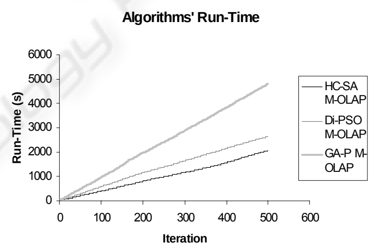
(f)



(g)



(h)



(i)

Figure 2: Plots that show the results of the performed tests.

6 CONCLUSIONS AND FUTURE WORK

This work proposes an adaptive simulated annealing algorithm to optimize the selection and allocation of a distributed cube for multi-node OLAP systems. This algorithm improves existent proposals in three distinct ways: 1) it uses a non-linear cost model to support the estimation of the fitness of each solution, simulating a parallel execution of tasks (using the inherent parallelism of the M-OLAP architecture) which deals with real world parameter values, concerning to nodes, communication networks and the measure value – time (Loureiro & Belo, 2006b); 2) it includes the maintenance cost into the cost equation to minimize; 3) it also introduces simulated annealing meta-heuristic onto the distributed OLAP cube selection problem, extending the work of (Kalnis et al. 2002) into the distributed arena. Also concerning to this work, the HC-SA M-OLAP algorithm includes a mechanism which dynamically reduces the range of searched space in each iteration.

The run-time execution results show an easy scalability of HC-SA M-OLAP in both directions: the cube's complexity and the number of nodes, allowing to manage a distributed OLAP system, capitalizing the advantages of computing and data distribution, with light administration costs.

Also, observing the results of figure 3-h, the HC-SA M-OLAP algorithm is competitive face to standard genetic and particle swarm optimization algorithms for this kind of problem. Moreover, figure 3-i shows that the absolute run-time was also the shortest of the three tested algorithms.

In the near future we intend to include this algorithm into a general framework which includes also a genetic, a co-evolutionary and a discrete particle swarm algorithms. Any of these algorithms may be used in its individuality or combined, where each search agent may assume one of several forms (a particle, an individual or a hill climber), switching through a metamorphosis process. This mechanism is also life inspired, as, in nature, the individuals of many species assume different shapes in their phenotype in different life epochs or under different environmental conditions. Between each phenotypic appearance many transformations occur, during the so called metamorphosis, which many times generates a totally different living being. Assuming completely different shapes seems to be a way for the living being to have a better global adaptation, changing its ways to a particular sub-purpose. E.g. for the butterflies, the larva state seems to be ideal for feeding and growing; the butterfly seems to be perfectly adapted to offspring generating, especially increasing the probability of diverse mating and colonization of completely new environments (recall the spatial range that a worm could run and the space that a butterfly could reach and search). But all these states contribute to the main purpose: struggle for survival.

While designing this algorithm and keeping in mind some knowledge about each meta-heuristics' virtues and limitations that are somewhat disjoint, we figured that, if combined, they may generate a globally better algorithm. What is more, this schema could be easily implemented as a unified algorithm because of the similarities between the solutions' evaluation scheme and the easy transposing of solutions' mapping. This new meta-heuristic may be denoted as "metamorphosis algorithm", which is expected to have an auto-adaptation mechanism.

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