Parallel Divide-and-Evolve: Experiments with OpenMP on a Multicore Machine

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ABSTRACT

Multicore machines are becoming a standard way to speed up the system performance. After having instantiated the evolutionary metaheuristic DAE$_X$ with the forward search YAHSP planner, we investigate on the global parallelism approach, which exploits the intrinsic parallelism of the individual evaluation. This paper describes a parallel shared-memory version of the DAE$_{YAHSP}$ planning system using the OpenMP directive-based API. The parallelization scheme applies at a high level of abstraction and thus can be used by any evolutionary algorithm implemented with the Evolving Objects framework. The proof of concept is validated on a 48-core machine with two planning tasks extracted from the last international planning competition. Experiments show significant speedups with an increasing number of cores. This preliminary work opens an avenue for parallelizing any evolutionary algorithm developed with EO that would target multicore architectures.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search; D.1.3 [**Programming Techniques**]: Concurrent Programming—*Parallel Programming*

General Terms

Algorithms, Experimentation, Performance.

Keywords

Evolutionary Computation, Automated Planning, Parallel Shared-Memory, Multicore.

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1. INTRODUCTION

The classical planning problem in Artificial Intelligence [10] is to find a path in a transition system: a sequence of actions which maps an initial state I into a state G satisfying a set of desired goals. Usually, a metric is associated with the solution plan such as length, cost or duration (where concurrent actions are allowed). In domain-independent planning, problems are described with the Planning Domain Description Language (PDDL) [9]. In the simplest STRIPS model, states of the world are defined by sets of atoms instantiated from a set of predicates and a set of objects, and actions are triples of sets of atoms: preconditions, add effects, del effects. Instances of the planning problem, called planning tasks, can model many kinds of abstract reasoning problems and are known to be PSPACE-hard.

To solve such planning tasks, several heuristic search algorithms have been proposed in the past but none of them can be easily parallelized. They require a great amount of work to provide efficiency while preserving correctness [5, 6].

Recently, the DAE$_X$ evolutionary metaheuristic has been proposed to solve such planning tasks [3, 21]. As an evolutionary algorithm, DAE$_X$ provides an intrinsic parallelism: the individual evaluation stage, which is often the most time-consuming stage during the evolutionary generation loop. This nice property opens an avenue towards the design of a parallel planning system without going deeply inside a whole reconstruction of the sequential version.

Moreover, the implementation of DAE$_X$ has been made with the STL-based Evolving Objects framework[1] which provides an abstract control structure to develop any kind of evolutionary algorithm. Therefore, our parallelization scheme is easily transposable to any evolutionary algorithm developed within the EO framework.

As a proof of concept, we implemented a multi-threaded version of DAE$_{YAHSP}$, the instantiation of DAE$_X$ with the heuristic forward search YAHSP planner [23], using the OpenMP directive-based API[2]. The design of experiment is built on problems extracted from the last international planning competition[3] with the multi-threaded DAE$_{YAHSP}$ release mapped onto a 48-core parallel machine.

While clusters is the most common distributed memory

[1] `http://eodev.sf.net`
[2] `http://www.openmp.org`
[3] `http://ipc.icaps-conference.org`

system for high performance computing, multicore architectures are gaining popularity as they become the *de facto* standard in computer mass market. The GPGPU-based architectures share similar characteristics, but require a specific programming language. As a consequence we would have to rewrite entirely the YAHSP solver called by our evaluation function.

The paper is outlined as follows. We first review related works in the fields of parallel evolutionary computation and AI planning, before presenting in more details the main algorithms on which our parallel system is based: the evolutionary metaheuristic DAE$_{\text{X}}$ and the forward-chaining heuristic search planner YAHSP. The parallel implementation of DAE$_{\text{YAHSP}}$ is then described, as well as the specific problems, due to the shared-memory programming model, that arose during this implementation. After having demonstrated the effectiveness of our parallel implementation of DAE$_{\text{YAHSP}}$ on two planning benchmark tasks, we conclude and provide some insights of possible future works.

2. RELATED WORKS

2.1 Parallel Evolutionary Algorithms

A large literature deals with the parallelization techniques of Evolutionary Algorithms (EAs). Depending on the targeted architecture, the parallelization scheme may be chosen accordingly. The main approaches may be classified among: simple *run level parallelism*, EA with *global parallelism* where the evaluation stage is parallelized but not the other operators, and *island-based* in which the population is partitioned into separate subpopulations. These structured EAs further split into cellular EAs (cEA) where the selection and reproduction steps are parallelized, and distributed EAs *dEA* with a controlled migration between islands [2].

The run level parallelism being trivially achieved by running several runs concurrently, the first step when parallelizing a new algorithm is often to try the global parallelization approach, because the evaluation step is often the most costly part of EAs and because individual evaluations are generally intrinsically independent.

A parallel extension of EO, ParadisEO, has been proposed by Cahon et al. [7]. It is based on the Message Passing Interface (MPI) and proposes several parallelization schemes, available by calling wrappers around common functions of EO. ParadisEO targets multiprocessor machines, especially clusters and grids, for running large-scale, general purpose EAs. As we are targeting a multicore architecture, and since our evaluation function has a large memory footprint, message passing may introduce a time consuming memory copy overhead. This reason discards the ParadisEO framework.

Another attractive parallel architecture is the GPGPU card with a very good processor-price ratio. The work described in [16] shows how a simple general scheme can be designed for EAs, by parallelizing the evaluation step. But the limitations that are pointed out can hardly be avoided in our case. Firstly, without stack, functional calls are forbidden on a GPGPU card: the whole code must be inlined; this would entail to inline the YAHSP solver entirely, which would overcome the available length limit. Secondly, it necessitates flat genome representations, which in our case would imply a lot of copies of the atoms objects instances, which can be numerous on large problems. Moreover, YAHSP uses a memoization mechanism which is a global shared-memory that save previous computations. It greatly speeds up the search but cannot be used on a GPGPU because it may need up to several gigabytes of memory on hard problems, where GPGPU cards have heavy limitations on memory space. And finally speedups may be obtained for very large sizes of population (e.g. 5000, 20000) which is not the average case here. For these reasons we also discarded this type of architecture.

2.2 Parallel Planning

Several approaches to parallel planning have been proposed in recent years. Parallel Retracting A* [8], was implemented on a Connection Machine and had to deal with very severe memory limitations. In that algorithm, a distributed hash function is used to allocate generated states to a unique processing unit and avoid unnecessary state duplications. PRA* deals with the memory limitation through a retraction mechanism which allows a processor to free its memory by dropping states. In order to confirm the transfer of a state, synchronous communication channels must be used, which seriously slows down the search process. Transposition-table driven work scheduling [20], similarly to PRA*, uses a hash function to avoid duplication. It is based on IDA* and, running on a standard architecture, does not necessitate any retraction mechanism and can efficiently exploit asynchronous communication channels. Parallel Frontier A* with Delayed Duplicate Detection [17] uses a strategy based on intervals computed by sampling to distribute the workload among several workstations, targeting distributed-memory systems as opposed to previous approaches. In [15], the authors introduce Hash Distributed A* (HDA*) which combines successful ideas from previous parallel algorithms. HDA* uses a hash function which assigns each generated state to a unique processing unit in order to avoid the duplication of the search efforts. This mechanism was introduced in PRA*, which unfortunately combined it with synchronous communication channels which cause a lot of waiting. This problem was addressed in HDA* by the use of non-blocking communication (as in [20]). In [6, 5] the authors present Parallel Best-NBlock-First (PBNF). It uses an abstraction to partition the state space. PBNF allows each thread to expand the most promising nodes while detecting duplicate states. Rather than sleeping if a lock cannot be acquired, a thread can perform "speculative" expansions by continuing the expansion of its current part of the space. This technique keeps cores busy at the expense of duplicate work. [22] adapts for planning a technique called dovetailing, in which several instances of a search algorithm with different parameter settings are run in parallel. Finally, [24] proposed a multicore version of the planner [23] where many concurrent threads expand nodes from a common open list, yielding to early exploration of branches of the search tree that would have been delayed by a classical search, which can speedup search by several orders of magnitude.

3. METHODS

3.1 Algorithms

Divide and Evolve.

DAE$_{\text{X}}$, the concrete implementation of the *Divide-and-Evolve* paradigm, is a domain-independent satisficing planning system based on Evolutionary Computation [21]. The

basic principle is to carry out a *Divide-and-Conquer* strategy driven by an evolutionary algorithm. The algorithm is detailed in [3] and compared with state-of-the-art planners. In order to solve a planning task $\mathcal{P}_D(I, G)$, the basic idea of DAE$_X$ is to find a sequence of states $S_1, \ldots, S_n$, and to rely on an embedded planner X to solve the series of planning tasks $\mathcal{P}_D(S_k, S_{k+1})$, for $k \in [0, n]$ (with $S_0 = I$ and $S_{n+1} = G$). A DAE$_X$ individual is a sequence of goals which define a sequence of subproblems to be solved (a *decomposition*). These subproblems are submitted successively to an embedded planner X and the global solution is obtained after the compression of these intermediate solutions. The overall optimization process is controlled by an evolutionary algorithm.

The fitness implements a gradient towards feasibility for unfeasible individuals and a gradient towards optimality for feasible individuals. Feasible individuals are always preferred to unfeasible ones. Population initialization as well as variation operators are driven by the critical path h^1 heuristic [11] in order to discard inconsistent state orderings, and atom mutual exclusivity inference in order to discard inconsistent states. Beside a standard one-point crossover for variable length representations, four mutations have been defined: addition (resp. removal) of a goal in a sequence, addition (resp. removal) of an atom in a goal. The selection is a comparison-based deterministic tournament of size 5.

For the sequential release, Darwinian-related parameters of DAE$_X$ have been fixed after some early experiments [21] whereas parameters related to the variation operators have been tuned using the Racing method [4].

All experiments were done with DAE$_{YAHSP}$: the instantiation of DAE$_X$ with the YAHSP heuristic forward search solver [23]. We added two novelties to the version described in [3]. One important parameter is the maximum number of expanded nodes allowed to the YAHSP sub-solver which defines empirically what is considered as an easy problem for YAHSP. As a matter of fact, the minimum number of required nodes varies from few nodes to thousands depending of the planning task. In the current release this number is estimated during the population initialization stage. An incremental loop is performed until the ratio of feasible individuals is over when a given threshold or a maximum boundary has been reached. By default this number is doubled at each iteration until at least one feasible individual is produced or 100000 has been reached.

Furthermore we add the capability to perform restarts within a time contract in order to increase solution quality.

Yet Another Heuristic Search Planner.

The YAHSP planning system [23] extends a technique introduced in the FF planner [13] for calculating the heuristic, based on the extraction of a solution from a planning graph computed for the relaxed problem obtained by ignoring deletes of actions. It can be performed in polynomial time and space, and the length in number of actions of the relaxed plan extracted from the planning graph represents the heuristic value of the evaluated state. This heuristic is used in a forward-chaining search algorithm to evaluate each encountered state.

A novel way has been introduced in YAHSP for extracting information from the computation of the heuristic, by considering the high quality of the relaxed plans extracted by the heuristic function in numerous domains. Indeed, the beginning of these plans can often be extended to solution plans of the initial problem, and there are often a lot of other actions from these plans that can effectively be used in a solution plan. YAHSP uses an algorithm for combining some actions from each relaxed plan, in order to find the beginning of a valid plan that can lead to a reachable state. Thanks to the quality of the extracted relaxed plans, these states frequently guide search closer to a solution state. The lookahead states thus calculated are then added to the list of nodes that can be chosen to be expanded by increasing order of the numerical value of the heuristic.

This lookahead strategy can be used in different search algorithms. In YAHSP, a classical best-first search algorithm has been modified in such a way that completeness is preserved. It simply consists in augmenting the list of nodes to be expanded (the open list) with some new nodes computed by the lookahead algorithm. The branching factor is slightly increased, but the performances are generally better and completeness is not affected.

A first motivation in the use of YAHSP in DAE$_X$ is that experiments about the use of this lookahead strategy in a complete best-first search algorithm have demonstrated that in numerous planning benchmark domains, the improvement of the performance in terms of running time and size of problems that can be handled are been drastically improved (cf. [23]). The YAHSP planner has been awarded a second place in the 4^{th} International Planning Competition [12] and some recent results [19] demonstrate that it is still extremely competitive with more recent planners. A second motivation in the use of YAHSP in DAE$_X$ is its ability to answer very fast to the considerable number of planning requests emanating from DAE$_X$, as opposed to modern techniques such as the landmark heuristics implemented in the LAMA planner [18] (winner of the 6^{th} International Planning Competition) which require a costly analysis for each new initial state.

In order to speed up the search process, a memoization mechanism has been introduced in YAHSP and carefully controlled to leave memory space for DAE. Indeed, most of the time during a run of YAHSP, and as a consequence during a run of DAE$_{YAHSP}$, is spent in computing the h^{add} heuristic for each encountered state. During a single run of YAHSP, duplicate states are discarded; but during a run of DAE$_{YAHSP}$, the same state can be encountered multiple times. Therefore, we keep track of the h^{add} costs of all atoms in the problem for each state, in order to avoid recomputing these values each time a duplicate state is reached. This generally leads to a speedup comprised between 2 and 4. When DAE$_{YAHSP}$ runs out of memory, which obviously happens much faster with the memoization strategy, all stored states and associated costs are flushed. For the parallel scheme, we experimented two strategies: a global memoization shared by all individual evaluations against a memoization local to each individual evaluation. Results are presented in section 4.3.

Parts that can theoretically be parallelized.

As shown in section 2.2, heuristic search algorithms used in automated AI planners can be parallelized in many ways, although there is no obvious and natural way to do so. However, our goal in this work is not to parallelize the underlying planner, but the evolutionary algorithm which controls the planner, which can be made in a very efficient way. Indeed, in typical population-based algorithms such as evolutionary

algorithms, the evaluation of individuals can be made independently of each other, a fortiori in a parallel way since there is no data-dependencies. Applying variation operators can also be performed in parallel; and depending on the application, parallelism on variation operators or individual evaluation will have a different impact on the running time and utilization of the computational resources. In DAE$_X$, the running time of applying the variation operators is negligible w.r.t. the running time required by the individual evaluations by an embedded planner, which is the reason why we only parallelized the latter.

3.2 Implementation

Locks, thread-Safe & reentrant subroutines.

Even if being very natural in the context of evolutionary algorithms, parallelizing individual evaluations in DAE$_X$ requires to be carefully made in order to avoid some typical problems that can happen with shared-memory parallel implementations. Indeed, even if individual evaluations are made independently of each other, some concurrent accesses to shared memory are still required (for example, a basic one is incrementing some global counter), especially in YAHSP (detailed below). Furthermore, the original implementations of DAE$_X$ and YAHSP were not designed with parallelism in mind, which implied some modifications to render them thread-safe.

One problem that can happen in a shared-memory parallel implementation is *deadlocks*, which are situations where at least two concurrent threads are each waiting for the other one to finish, and thus neither ever does. This can happen for example when a thread t_1 acquires a lock on a shared variable x, and then tries to acquire a lock on another shared variable y; while in the same time a thread t_2 acquired a lock on y and then tries to acquire a lock on x. Each thread waiting for the other one to release the lock on the next variable locked by the other thread, nothing happens. A variation of deadlocks is *livelocks*, where the threads are still able to continue doing some work but cannot go through some portion of the code due to a similar phenomenon.

Another problem that can arise is the concurrent use of a given subroutine by several threads, when such a subroutine or some subroutines called, it modifies some global data. This is a typical problem of reentrancy, which must be carefully analyzed in order to render thread-safe a parallel implementation. Two cases can then occur: either the global data must be shared by some threads, which requires to protect its access, or it can be made private to each thread, thus necessitating to change the scope of this data.

EO & OpenMP.

In order to guarantee a non-blocking algorithm, we apply the Concurrent Read Exclusive Write (CREW) strategy[4] of the Parallel Random Access Machine (PRAM). In this work, we used OpenMP which defines a set of compiler directives to tell which part of a program should be parallelized and which part of memory can be shared out. The main advantage of OpenMP is that it is designed to make easy to parallelize an existing program [1]. The parallel shared-memory scheme may also be used as a simple approach to program clusters, either with a dedicated method, or through a virtual symmetric multiprocessing machine [14].

Considering that the evaluation of the population is the most costly part of the algorithm, this step is our first target to parallelize. Moreover, in most cases the evaluation done on individuals can be made in parallel without data dependencies. There are several classes in EO implementing evaluation operators but all of them call a common function to apply the evaluation on a population. The `apply` function takes a functor as argument. The advantages of the `Functor` pattern is to meet the genericity and the modularity offered by object-oriented programming while keeping the simplicity of a single call to a function. EO functors generally take a population (a vector of individuals) as argument. In order to enable OpenMP to build a multi-threaded algorithm without memory bounds, the evaluation functor (`proc` in the apply function) must fulfill certain requirements. In EO, the evaluation functors are supposed to be instantiated only once. In a sequential mode, the same instance is used to evaluate every individuals in a population. In a parallelized mode, one must ensure that the evaluation functor have thread-local data structures.

EO::apply.

The `apply` function takes as parameters a population and a function to be applied to each individual. The parallelization of this region of code is done thanks to the pragma `omp for`.

Algorithm 1 apply(proc, pop)

```
template < typename EOT >
void apply< EOT >(eoUF< EOT, void >& proc,
                  std::vector< EOT >& pop)
{
   for (size_t i = 0; i < pop.size(); ++i)
       proc(pop[i]);
}
```

Algorithm 2 apply(proc, pop) parallelized using OpenMP

```
template < typename EOT >
void apply< EOT >(eoUF< EOT, void >& proc,
                  std::vector< EOT >& pop)
{
#pragma omp for
   for (size_t i = 0; i < pop.size(); ++i)
       proc( pop[i] );
}
```

When parallelizing the evaluation loop in an evolutionary algorithm, there exists a synchronization step at each generation, this ensure that no race-condition may occurs. Indeed, individuals being evaluated are all independent, which is the case in the majority of evolutionary algorithms, and also in DAE$_X$.

YAHSP & OpenMP.

The design of YAHSP has been made in C with efficiency in mind, and kept as light as possible. This is typically the kind of implementation, making heavy use of global variables, not designed for a concurrent use by several paral-

[4]Multiple processors can read a memory cell but only one can write at a time.

lel threads, and where thread-safety is clearly not ensured. However, OpenMP offers a facility to deal with global variables, in order to change their scope: the `omp threadprivate` pragma. It takes as parameter a list of global variables whose scope must be changed from shared by all threads to private (local) to each thread. And finally, specifying which global variable should be rendered private to each thread was the only thing we had to do to ensure thread-safety in YAHSP. For example, the global arrays used to compute the heuristic, the relaxed plans and the lookahead plans are made private to each thread, ensuring that concurrent executions of YAHSP do not use the same portions of the global memory.

Specific parallelization issues.

DaE$_{\text{YAHSP}}$ evaluation step calls the YAHSP solver several times on the same decomposition and thus uses several variables to keep the state of the evaluation over the searches between intermediate goals (namely k, B and U in the original article). As the evaluation functor is a single instance, it must be guaranteed reentrant by not using static variables nor attributes. A way to achieve the re-entrancy is to define those variables as attributes of the decomposition itself, and not as attributes of the evaluation functor.

Static and dynamic scheduling.

OpenMP lets the choice between static (the default) and dynamic task scheduling. In the static scheduling, a loop iterating through a set of tasks will be divided in several tasks relative to the number of available processors. In dynamic scheduling, if one thread has finished its tasks it gets the next available one, using a queue structure.

4. EXPERIMENTAL STUDY

4.1 Setup

Platform.

The algorithm is programmed in C++ using GCC and the GNU OpenMP threading library (GOMP), both release 4.4.4. It is run on a 48-core DELL PowerEdge R815 Rack Server set up with four 12-core AMD Opteron(tm) 6174, 2.2GHz (12x512 KB cache) processors with 192GB of RAM, under Linux x86_64 2.6.32.

The speedup and the efficiency are measured with the operating system `time` command which gives the percentage of the CPU that the process being timed got[5]. For instance 3182% means a speedup of 31.82. The efficiency, or processor use rate, equals the speedup divided by the number of processors available. For instance $31.82/48 = 0.66$ is the efficiency for a speedup of 31.82% on 48 processors.

Benchmarks.

Although there are several families of problems, we concentrate here on cost planning and temporal planning. In cost planning a cost is attached to each action and the objective is to minimize the sum of all costs for a sequential plan whereas in temporal planning actions have a duration and can be run in parallel. In temporal planning the objective is to minimize the total makespan of the parallel plan.

[5]computed as (Total number of CPU-seconds that the process spent in user mode + Total number of CPU-seconds that the process spent in kernel mode) / Wall clock time.

We have tested the above implementation on two benchmarks from the satisficing track of the 6^{th} International Planning Competition: Elevators-12 for cost planning and Openstacks-17 for temporal planning.

The Elevators domain is stated as follows: there is a building with $N + 1$ floors, numbered from 0 to N. The building can be separated in blocks of size $M + 1$, where M divides N. Adjacent blocks have a common floor. The building has K fast (accelerating) elevators that stop only in floors that are multiple of $M/2$. Each fast elevator has a capacity of X persons. Furthermore, within each block, there are L slow elevators, that stop at every floor of the block. Each slow elevator has a capacity of Y persons (usually $Y < X$). There are costs associated with each elevator starting/stopping and moving. There are several passengers, for which their current location and their destination are given. The objective function is to minimize the total cost of moving the passengers to their destinations. The total cost is increased each time an elevator starts/stops or moves.

The Openstacks domain is based on the "minimum maximum simultaneous open stacks" combinatorial optimization problem, which can be stated as follows: a manufacturer has a number of orders, each for a combination of different products, and can only make one product at a time. The problem is to order the making of the different products so that the maximum number of stacks that are in use simultaneously, or equivalently the number of orders that are in simultaneous production, is minimized. The problem is NP-hard and known to be equivalent to several other problems. In the temporal case a maximum number of stacks is given and the goal is to find the plan with the minimum makespan, without violating the maximum number of stacks constraints.

Algorithm parameters.

All the experiments were done with the parameter set described in [3] except for the population size which varies depending on the experiment. The fixed evolution engine is a (popsize + 7× popsize)-ES: n individuals generate $7 \times n$ offspring without selection. For all runs, the following steady-state stopping condition has been applied: after at least 10 generations, evolution is stopped if no improvement of the best fitness in the population is made during 50 generations, with a maximum of 1000 generations.

The DaE$_{\text{X}}$ algorithm being stochastic, each run is repeated 11 times and the resulting distributions are presented as standard boxplots.

4.2 Experiments

Two types of experiments were conducted to analyze the algorithm behavior when increasing the number of cores on one hand and when increasing the size of the population on the other hand.

Competition settings, varying the number of cores.

This experiment tests four versions of the algorithm, combining the memoization scheme (local or shared) and the parallelization scheme (static or dynamic), with a population of 48 and 96 individuals. Number of cores used range from 6 to 48, testing each 6 cores. 21 runs are performed for each setting which are stopped when the algorithm reached 50 generations without improvement.

Alternative version, varying the population size.

This experiment uses the same version of DAEYAHSP as the one used for the International Planning Competition, in a similar experimental environment. The algorithm uses the shared memoization and a static parallelization scheme. It has 30 minutes to achieve its search, and performs a complete restart each time it is stuck after 50 generations without improvement, 11 runs being performed on the 48 available cores, for the following population sizes: 48, 1152, 2304, 3456, 4608, 5760.

4.3 Results

Speedup against the number of processors.

Results show that the speedup raises linearly with the number of processors, for every parallel/memoization combination and every problem tested (see Figure 1 for an example on two combinations).

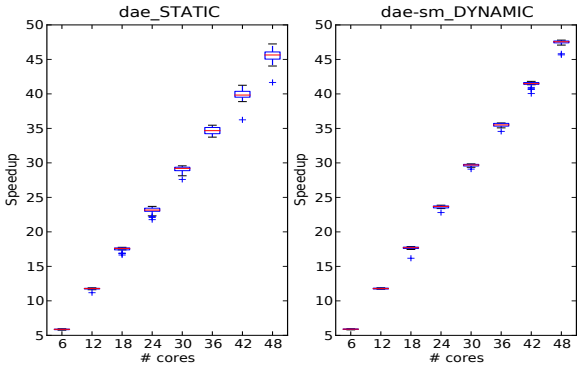


Figure 1: Speedup of DAEYAHSP relative to the number of processors, on OPENSTACKS-17. On the left: with local memoization and the static parallelization scheme, on the right: with shared memoization and the dynamic parallelization scheme.

This observation meets the expected behavior and is classical when considering the parallelization of the evaluation step of an evolutionary algorithm. Nevertheless, the difference among combinations and problems can be seen when considering efficiency.

Figures 2 and 3 shows that for the benchmark ELEVATORS-12, shared memoization may perform better for larger population sizes but that there is no difference between static an dynamic parallelization schemes. On OPENSTACKS-17, the dynamic scheme performs slightly better when used along with the shared memoization.

Since the evaluation times are varying (given the fact that decompositions have different lengths and that each subproblem may be more or less difficult), by construction a queue-based scheduling should be more efficient in average. But the behavior is dependent of the algorithm instance and ability to avoid premature convergence that would produce an homogeneous population. Hence the difference between the two schemes may not be immediately notable.

An explanation for the poor performance gain of using shared memoization might be that the benefit obtained when memoization is shared among individuals is lost with the bottleneck due to multiple access locking.

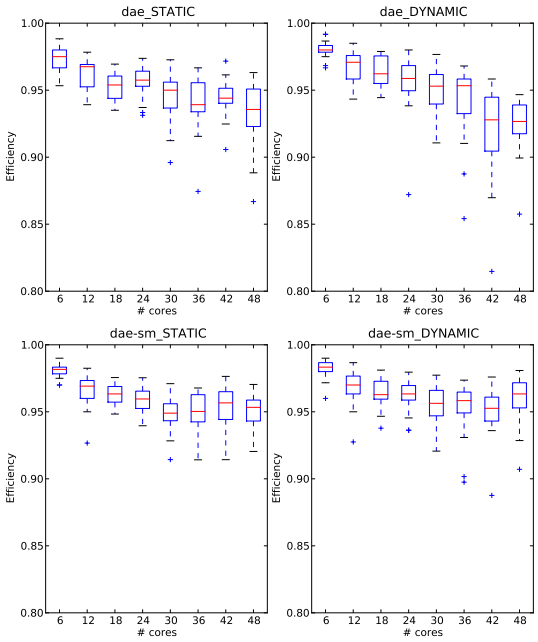


Figure 2: Efficiency of DAEYAHSP relative to the number of processors, on ELEVATORS-12.

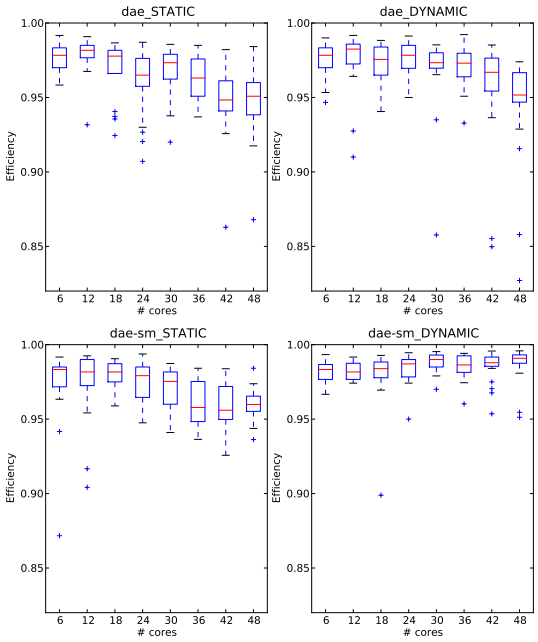


Figure 3: Efficiency of DAEYAHSP relative to the number of processors, on OPENSTACKS-17.

Figures 4 and 5 show that the solution quality remains unaffected by the number of cores used.

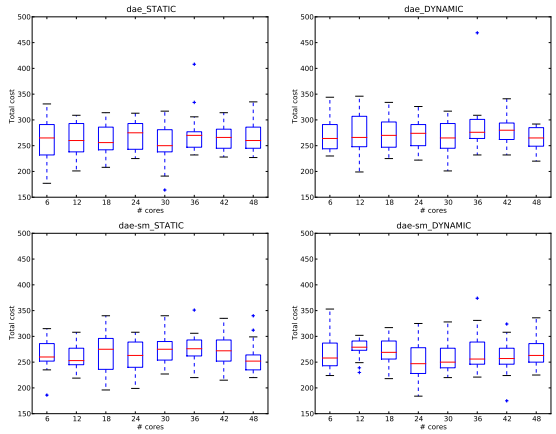


Figure 4: Total costs of the 4 parallel/memoization combinations of DAEYAHSP on ELEVATORS-12.

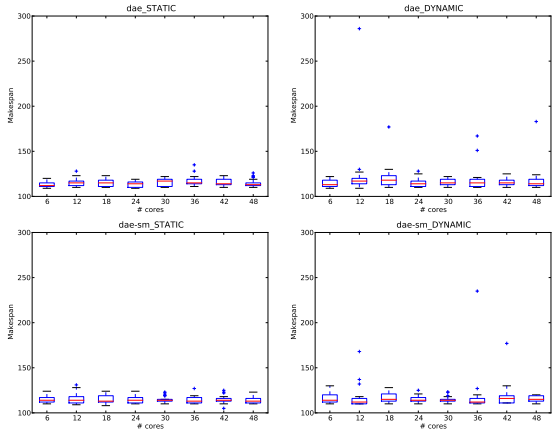
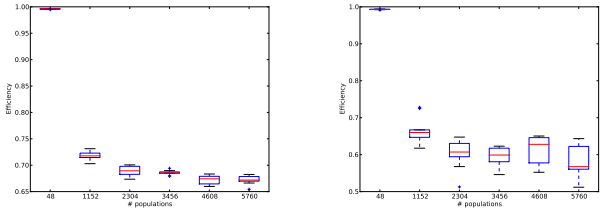


Figure 5: Makespans of the 4 parallel/memoization combinations of DAEYAHSP on OPENSTACKS-17.

It was expected that the shorter time needed to perform a run would lead to more restarts within the 30 minutes time contract and thus to an increasing probability to reach better solutions. Results show that this is not the case. Again, an explanation for those results is that the algorithm converge prematurely and cannot find solutions with a sufficiently high variance to ensure that the probability to find better solutions will increase with restarts.

Speedup against the population size.

Figure 6 shows that the efficiency decreases with the size of the population: while being close to the optimum for a size equal to the available number of processors, it rapidly decreases and reaches a plateau for big populations.

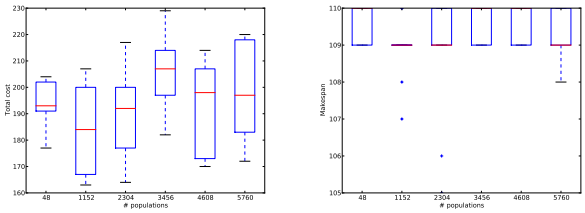


(a) ELEVATORS-12 (b) OPENSTACKS-17

Figure 6: Efficiency of DAEYAHSP relative to the population size.

Using a static parallelization scheme, the decrease in speedup is due to the synchronization step at each generation, when cores have finished the evaluation of easier decompositions and are waiting for the next generation to occur.

Figure 7 shows that no significant difference in solution qualities can be observed when the population size increases.



(a) ELEVATORS-12 (b) OPENSTACKS-17

Figure 7: Solution plans qualities for increasing population sizes.

The hypothesis that a larger population would lead to a greater exploration and thus to a better solution quality is thus not confirmed by experimentation. The algorithm converges too rapidly, independently of the population size.

5. DISCUSSION AND CONCLUSION

We made a proof-of-concept for a shared-memory parallelization of the evaluation step of the DAEX algorithm, based on the OPENMP directive-based API on a common 48-core machine. Thanks to the abstraction level provided by the EO framework, this scheme is immediately available for any evolutionary algorithm as far as the context of the evaluation functor is thread-local and reentrant.

We obtained on our 48-core Dell Machine, a roughly $\times 45$ speedup for the two benchmarks tested, this speedup being the same for all instances.

The dispersion of the measured times is mainly due to the combination of the steady-state stopping criterion with the stochastic nature of the search, which may or may not reach a fitness plateau early. The relationship between this dispersion and the difficulty of the problem solved remains to be explored.

Our results show that the stopping criterion should be chosen carefully, along with the population size, as it has an impact on the dispersion of the computation time distribution. Moreover, the population size may indifferently be chosen small, in order to decrease the computation time.

The dynamic queue mapping management of threads onto cores provides a significant improvement on a single problem instance, when combined with shared memoization. Since it has no special impact on the other problem, it may be preferred, but more tests on other domains are necessary.

The implementation scheme presented here is very simple but works extremely well. A further development will consist in parallelizing other steps of the evolutionary loop in particular the offspring generation (which is also intrinsically parallel) and the selection/replacement operators.

A further research axis deals with the impact on solution quality and in particular how to take advantage of the parallelization scheme to escape from premature convergence.

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