Chapter 8
HydroCM: A Hybrid Parallel Search Model for Heterogeneous Platforms

Julián Domínguez and Enrique Alba

Abstract. Here we present HydroCM (HydroCarbon inspired Metaheuristic), a parallel metaheuristic model specifically designed for its execution on heterogeneous hardware environments. With HydroCM we actually propose a schema for describing a family of parallel hybrid metaheuristics inspired by the structure of hydrocarbons in Nature, establishing a resemblance between atoms and computers, and between chemical bonds and communication links. Our goal is to gracefully match computers of different computing power to algorithms of different behavior (GA and SA in this study), all them collaborating to solve the same problem. The analysis will show that our proposal, though simple, can solve search problems in a faster and more robust way than well-known panmictic and distributed algorithms very popular in the literature.

8.1 Introduction

Metaheuristics are an important branch of research since they provide a fast an efficient way for solving problems. In many cases, parallelism is necessary, not only to reduce the computation time, but to enhance the quality of the solutions obtained. Many parallel models exist, both for local search methods (LSMs) and evolutionary algorithms (EAs), and even parallel hybrid models combining both methods are present in the literature [4] [6].

In a modern lab, it is very common the coexistence of many different hardware architectures. It has been proven that such heterogeneous resources can also be used efficiently to solve optimization problems with standard parallel algorithms [7] [20]

Julián Domínguez · Enrique Alba
Universidad de Málaga, Spain
e-mail: {julian,eat}@lcc.uma.es

E.-G. Talbi (Ed.): Hybrid Metaheuristics, SCI 434, pp. 219–235.
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[21], but there exist few works about the design of specific parallel models for an heterogeneous environment.

Here we present HydroCM, a hybrid parallel metaheuristic model. With this work we propose a general model for describing a family of hybrid metaheuristics specifically designed for their execution in heterogeneous hardware environments, being inspired in the structure of the hydrocarbons that can be found in Nature.

Our contribution is not only methodological, but we also have carried out an analysis in order to study the behavior of our proposal. For our analysis, we have implemented two versions of the model making use of two well-known metaheuristics: steady state Genetic Algorithm (ssGA) and Simulated Annealing(SA). We have compared our proposal against the panmictic versions of these algorithms and against a unidirectional ring of ssGA islands executed on the same hardware infrastructure. Our results show that the running times of our proposal are faster in some cases and more robust in the rest than the reference ssGA ring.

We will here present an overview of the proposed model as well as the results of the analysis of the implemented algorithms. Previously, we will start with a brief review on the background concepts used in this chapter.

8.2 Decentralized, Heterogeneous and Hybrid Parallel Metaheuristics

In this section we include a quick review on the existing implementations of decentralized and parallel metaheuristics, as well as on heterogeneity. We also include a description of the metaheuristics used in our hybrid algorithm and how they classify as hybrid metaheuristics.

Many parallel implementations exist for different groups of metaheuristics. We will focus in two of the more common families of metaheuristics: Evolutionary Algorithms (EAs) and Local Search Metaheuristics (LSMs). On the one hand, EAs are population based methods, where a random population is created and further enhanced through a Nature-like evolution process. On the other hand, only one candidate solution is used in LSMs, and it is enhanced by moving through its neighborhood replacing the candidate solution by another one, usually one with a better quality (fitness) value. EAs commonly provide a good exploration of the search space, so they are also called exploration-oriented methods. On the contrary, LSMs allow to find a local optima solution and subsequently they are called exploitation-oriented methods. Many different parallel models have been proposed for each method, and here we present the more representative ones.

8.2.1 Parallel EA Models

A panmictic EA applies its stochastic operators over a single population, which makes them easily parallelizable. A first strategy for its parallelization is the use of

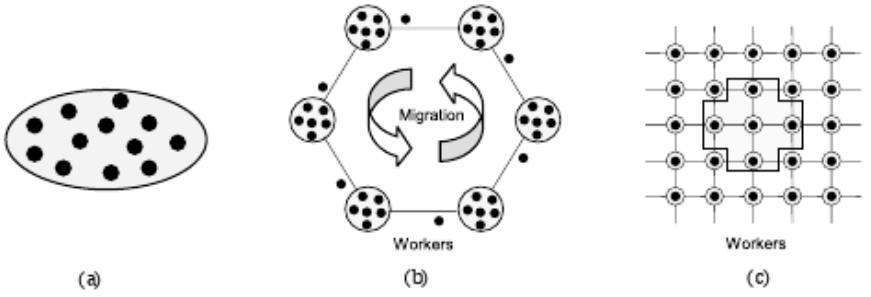


Fig. 8.1 A panmictic EA (a), and two structured EAs: distributed (b) and cellular (c)

a master-slave approach where evaluations are performed in parallel but the population, unless divided, is treated as a whole, maintaining its panmictic behavior. It could be interesting for many tasks, but it does not offer the benefits of a structured population. Therefore, we are going to focus in structured populations, which leads to a distinction: cellular versus distributed EAs [3] (Figure 8.1).

- **Distributed EAs (dEA):** In the case of distributed EAs, the population is divided into a number of islands that run an isolated instance of the EA (Figure 8.1b). Although there is not a single population the sub-populations are not completely isolated: some individuals are sent from one population to another following a migration scheme. It is common that in this model there only exist a few sub-algorithms, loosely coupled among them.
- **Cellular EAs (cEA):** In the cellular model, there exists only one population which is structured into neighborhoods, so that an individual can only interact with the individuals inside its neighborhood (Figure 8.1c). Different neighborhood structures can lead to a different behavior. With the cellular model there exists a large number of sub-algorithms and they are tightly coupled [5].

8.2.2 Parallel LSM Models

Many different parallel models have been proposed for LSMs, but there exist three models that are widely extended in the literature: parallel multistart model, parallel moves model, and move acceleration model (Figure 8.2).

- **Parallel multistart model:** In this model, several independent instances of the LSM are launched simultaneously (Figure 8.2a). They can exchange individuals following a migration scheme. This model can usually compute better and more robust solutions than the panmictic version.
- **Parallel moves model:** This model is a kind of master-slave model where the master runs a sequential LSM but, at the beginning of each iteration, the current solution is distributed among all the slaves (Figure 8.2b). The slaves perform a

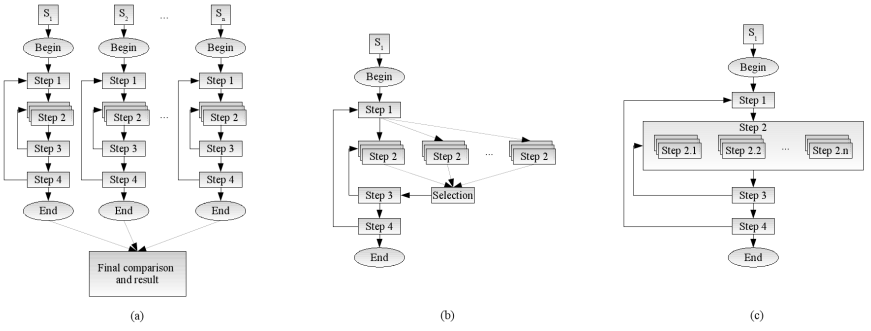


Fig. 8.2 Parallel multistart model (a), parallel moves model (b), and move acceleration model (c)

move and return the candidate solution to the master, which selects one of them. This model does not alter the behavior of the sequential algorithm.

- **Move acceleration model:** The quality of each candidate solution is evaluated in a parallel centralized way (Figure 8.2c). It is useful when the evaluation function can be itself parallelized. The move acceleration model does not alter the behavior of the sequential algorithm.

In both, EAs and LSMs parallel models, each sub-algorithm includes a phase for communication with a neighborhood according to some topology. This communication can be carried out in a synchronous or asynchronous manner. Many works have found advantages in using an asynchronous execution model [8] [11]. Additionally, asynchronism is essential in our study because of the heterogeneous hardware, which could easily produce bottlenecks, so our communications will be carried out in an asynchronous way.

8.2.3 Being Heterogeneous

In the models presented above, all the sub-algorithms share the same search features. But we could modify the behavior of a parallel metaheuristic by changing the search features between sub-algorithms, obtaining a globally heterogeneous hybrid metaheuristic. Also the hardware being used to run the algorithm can be homogeneous or heterogeneous, so we have not to be confused between the hardware platform heterogeneity and the heterogeneous software model. Parallel heterogeneous metaheuristics can be classified into four levels depending on the source of heterogeneity [3]:

- *Parameter level*: At this level, the same algorithm is used in each node, but the configuration parameters are different in one or more of them.
- *Operator level*: At operator level, heterogeneity is achieved by using different mechanisms for exploring the search space, such as different operators.

- *Solution level*: Heterogeneity is obtained using a different encoding for the solutions in each component.
- *Algorithm level*: At this level, each component can run a different algorithm. This level is the most widely used.

Here we present an algorithm level parallel heterogeneous metaheuristic which is later run in heterogeneous hardware. This solver is based in two different methods. We have chosen one method of each of the two well-known families, LSMs and EAs, in order to obtain a good balance between exploitation and exploration. The used methods are a Genetic Algorithm (GA) and a Simulated Annealing (SA).

GAs are one of the more popular EAs present in the literature. In Algorithm 8 we can see an outline of a panmictic GA. A GA starts by randomly generating an initial population $P(0)$, with each individual encoding a candidate solution for the problem and its associated fitness value. At each iteration, a new population $P'''(t)$ is generated using simple stochastic operators, leading the population towards regions with better fitness values.

Algorithm 8. Standard Genetic Algorithm

```
Generate(P(0));
Evaluate(P(0));
t := 0;
while not stop_condition(P(t)) do
   P'(t) := Selection(P(t));
   P''(t) := Recombination(P'(t));
   P''(t) := Mutation(P''(t));
   Evaluate(P'''(t));
   P(t+1) := Replace(P(t),P'''(t));
   t := t+1;
end while
```

In our algorithm, we have actually used a special variant of the generic GA called steady state Genetic Algorithm (ssGA) [22]. The difference between a common generational GA and a ssGA is the replacement policy: while in a generational GA a full new population replaces de old one, in a ssGA only a few individuals, usually one here, are generated at each iteration and merged with the existing population.

Because of its easy utilization SA has become one of the most popular LSMs. SA is an stochastic algorithm which explores the search space using a hill-climbing process. A panmictic SA is outlined in Algorithm 9. SA starts with a randomly generated solution S. At each step, a new candidate solution S' is generated. If the fitness value of S' is better or equal than the old value, S' is accepted and replaces S. As the temperature T_k decreases, the probability of accepting a lower quality solution S' decays exponentially towards zero according to the Boltzmann probability distribution. The temperature is progressively decreased following an annealing schedule.

Based on the classic SA, many different versions have been implemented by using a different annealing schedule. In our algorithm we have used the New Simulated Annealing (NSA) [26], which uses a *very fast* annealing schedule.

Algorithm 9. Standard Simulated Annealing

```
Generate(S);
Evaluate(S);
Initialize(T_0);
k := 0;
while not stop_condition(S) do
   S' := Generate(S,T_k);
   if Accept(S,S',T_k) then
      S := S';
   end if
   T_{k+1} := Update(T_k);
   k := k+1;
end while
```

8.2.4 Classifying Hybrid Metaheuristics

Attending to the classification proposed by E.-G. Talbi [23] (Figure 8.3), we can classify a hybrid metaheuristic attending to its structure (hierarchical) or to the features of the algorithms involved in the hybrid (flat). Four classes are derived from the hierarchical taxonomy:

- *LRH (Low-level Relay Hybrid)*. This class of hybrids represents algorithms in which a given metaheuristic is embedded into a single-solution algorithm. We can find some examples of LRH in the literature [1] [19].
- *LTH (Low-level Teamwork Hybrid)*. This class comprises combinations of metaheuristics with strong exploring capabilities (like most EAs) with exploitation-oriented metaheuristics (most single-solution metaheuristics). Usually, exploitation-oriented methods replace or extend genetic operator such as mutation or crossover. There are numerous examples of this strategy, for example [17] [14] [10].
- *HRH (High-level Relay Hybrid)*. In this class of algorithms, self-contained metaheuristics are executed in a sequence. In HRH, an algorithm is used for improving the results obtained by another one. Many authors have used this idea [24] [18].
- *HTH (High-level Teamwork Hybrid)*. Self-contained algorithms perform a search in parallel, and cooperating to find an optimum. This model has been widely used in the literature [12] [25].

As to the flat classification, we can distinguish between:

- *Homogeneous/heterogeneous*. In homogeneous hybrids, all the combined algorithms use the same metaheuristic, while in heterogeneous algorithms different metaheuristics are used.
- *Global/partial*. In global hybrids, all the algorithms search in the whole search space. However, the search space is decomposed into subspaces in the partial hybrids.
- *Specialist/general*. In a general hybrid, all the algorithms solve the same problem, while specialist hybrids combine algorithms which solve different problems.

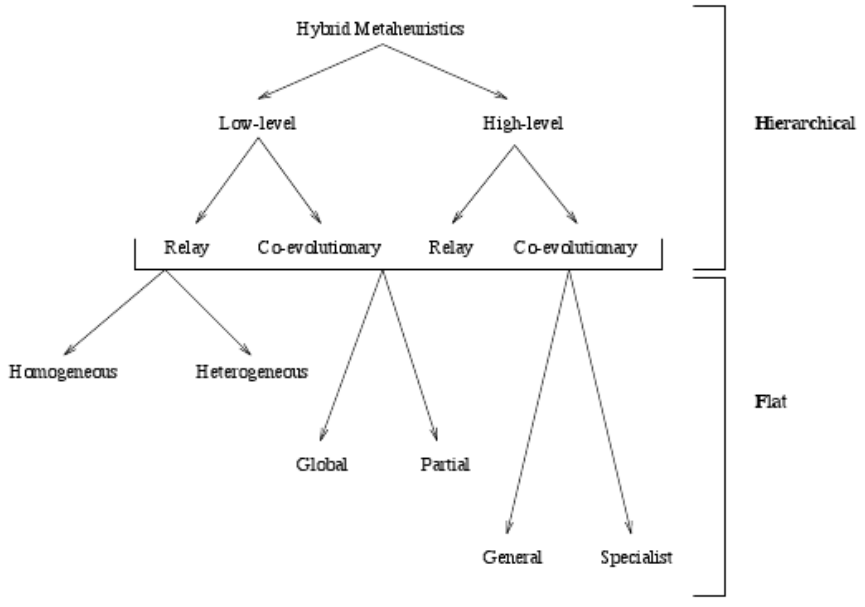


Fig. 8.3 Talbi's classification of hybrid metaheuristics

Attending to this taxonomy, our model can be classified as a High-level Teamwork Hybrid metaheuristic, while several self-contained algorithms cooperate in order to find a solution. HydroCM can be classified as well as heterogeneous, global and general, because two different metaheuristics search in the whole search space trying to solve the same problem.

8.3 Description of Our Proposal

In this section we present the particularities of HydroCM, as well as we briefly outline the algorithm that we have implemented in our tests, which has been called Ethane [13].

8.3.1 An Overview of HydroCM

In this work, we present a generic model for a complete family of parallel hybrid metaheuristics. The goal of the model is to provide a schema for the islands and communications of the parallel algorithm to efficiently perform a search over heterogeneous hardware architectures.

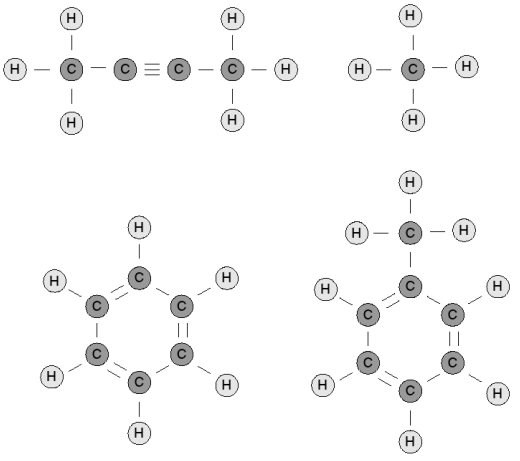


Fig. 8.4 Different hydrocarbon configurations that can be found in Nature; their structures are the basis of HydroCM

Our model is inspired in the structure of hydrocarbons as we can find them in the Nature (Figure 8.4). Hydrocarbons are based in only two different atoms, carbon and hydrogen, and each of them can keep a given number of bounds, being one for hydrogen and four for carbon.

In our model, we establish a resemblance between computers and atoms in the hydrocarbon. The bonds between atoms have a correspondence to communication channels, and double or triple bonds can be modeled as the amount of information being migrated (intensity of the interaction) or, in the case of non-population based algorithms, a higher migration rate. In our model, the fastest machines are associated with central carbon atoms (because of the higher computational effort caused by the migrations) and the slowest ones are associated with hydrogen atoms.

This model provides us with plenty of different schemes for designing a parallel heterogeneous algorithm because of the amount of hydrocarbons present in Nature and their different architectures: linear, ring, branches... obtaining a huge amount of different combinations depending on the number of fast and slow available computers and the topology of the network.

Ethane [13] can be viewed as an instance of HydroCM for an environment composed of eight nodes, where two of them are more powerful than the rest, and making use of ssGA and SA as the composing atoms. As well as Ethane is such an instance, we could instantiate many different algorithms depending on the underlying hardware architecture following the model proposed by HydroCM.

8.3.2 Ethane

With Ethane we propose an instance of HydroCM model, based in the chemical compound of the same name. The chemical compound called ethane consists of two carbon atoms and six hydrogen atoms, joined together with single chemical

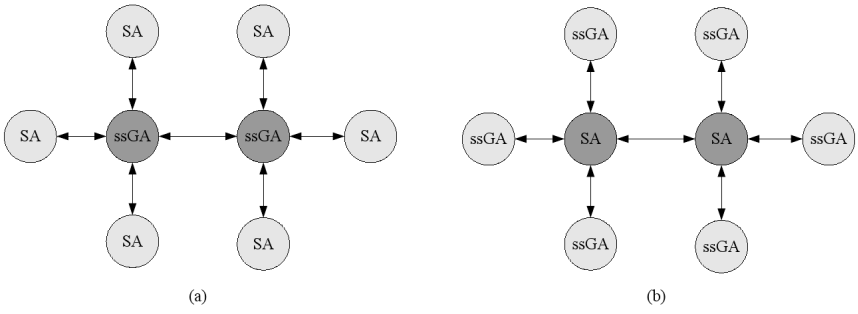


Fig. 8.5 Communication schema for Ethane G (a) and S (b)

bonds. In ethane, each carbon atom is bonded to three hydrogen atoms, and there is another bond between both carbon atoms. In our Ethane algorithm, we propose the same schema, using two basic algorithms resembling different atoms, and migration channels resembling bonds.

For our study, we have implemented two different versions of the algorithm. In Figure 8.5 we show the schema for the two instances of Ethane studied in this chapter. Ethane G (Figure 8.5a) assigns a ssGA sub-algorithm to the central nodes, and a SA sub-algorithm to the *slave* nodes. On the contrary, Ethane S (Figure 8.5b) allocates a SA sub-algorithm in each one of the central carbon nodes, and a ssGA sub-algorithm in the *slave* nodes. With this schema, the most of the communication load falls on the *master* nodes, which are provided with the best hardware, moving some of the load out of the slowest nodes.

8.4 Performance Measures and Speedup

In this section we present the performance measures used for assessing the performance of the studied algorithms. The measures that are going to be used are the numerical effort, the total run time, and the speedup.

A widely accepted way of measuring the performance of a parallel metaheuristic is to check the number of evaluations of the fitness function needed to locate an optimum. This performance measure is called numerical effort. Numerical effort is widely used in the field of metaheuristics because it removes the effects of the implementation and the platform, but it could be misleading in many cases for parallel methods. Furthermore, the goal of the parallelism is not the reduction of the number of evaluations (this is a goal for decentralized algorithms) but the reduction of the running time.

The most significant performance measure for a parallel algorithm is the total run time needed to locate a solution. In a non-parallel algorithm, the use of the *CPU time* is a common performance measure. While parallelizing an algorithm should

definitely include some overhead, for example for communications, we are not able to use only the *CPU time* as a performance measure. Since the goal of parallelism is to reduce the real time needed to solve the problem, for parallel algorithms it becomes necessary to measure the real run time (wall-clock time) to find a solution.

Because of the non-deterministic behavior of metaheuristics, average values for time and numerical effort are usually needed. Although 30 runs could provide us a good estimation, we have executed the tests 100 times in this chapter in order to perform a rigurous statistical analysis.

In our analysis we will also study the speedup. The speedup represents the ratio between sequential and parallel average execution times ($E[T_1]$ and $E[T_m]$ respectively).

$$s_m = \frac{E[T_1]}{E[T_m]} \tag{8.1}$$

For the speedup to be a meaningful metric, we have to take care of many aspects for its analysis. Because of the aforementioned non-deterministic behavior of metaheuristics it is necessary to use average times, being these times the wall-clock times. The algorithms run in the single and multiprocessor platform must be exactly the same, thus panmictic algorithms can not be used for the analysis. The algorithms have to be executed until they found the solution or a solution of the same quality [2]. Since in our study we are working over a heterogeneous platform, our reference point is the execution time of the program on the fastest single processor.

8.5 Problems, Parameters, and Platform

In this section we include the basic information necessary to reproduce the experiments that have been carried out for this work. First we will present the set of benchmark problems used for assessing the performance of our proposal. Second we will briefly explain the parameters used within the sub-algorithms, and then the underlying hardware and software platform.

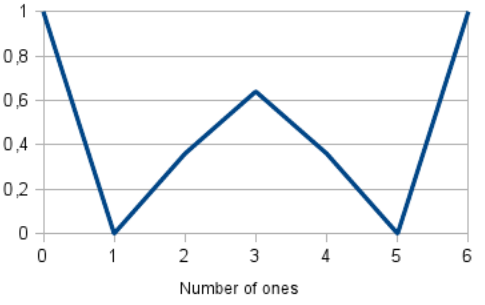
8.5.1 Benchmark Problems

In order to assess the performance of our algorithms, we have used two problems in the analysis: the Subset Sum Problem (SSP) [16] and the Massively Multimodal Deceptive Problem (MMDP) with 6 bits [15].

The SSP problem consists in finding a subset of values $V \subseteq W$ from a set of integers $W = \{w_1, w_2, ..., w_n\}$, such that the subset sum approaches a constant C without exceeding it. We have chosen an instance with 2048 random integer numbers in the

Table 8.1 Bipolar deception (6 bits) sub-function value

#ONES	sub-function value
0	1.000000
1	0.000000
2	0.360384
3	0.640576
4	0.360384
5	0.000000
6	1.000000



range $[0..10^4]$ following a Gaussian distribution, being the value of the sum for the optimum 3256234.

MMDP is one of so called deceptive problems. Deceptive problems are specifically designed to make the algorithm converge to wrong regions of the search space, decorrelating the relationship between the fitness of a string and its genotype. In MMDP a binary string encodes k 6-bit sub-problems which contribute with a partial fitness depending on its number of 1's (unitation) following Table 8.1. We have used an instance with strings of 150 bits so that the global optimum is $k = 25$.

8.5.2 Parameters of the Algorithms and Platform

The parameters used in every ssGA sub-population are: a population size of 64 individuals, a crossover probability of 0.8 and a mutation probability of 4.0 divided by the chromosome length. The genetic operators are a single point crossover and a bit flip mutation. For the SA, we used the same mutation probability. For the SSP the chromosome length is 2048 an in the case of MMDP its length is 150 for both algorithms. In the case of the panmictic ssGA, the population size has been set to 64 individuals because larger populations have performed much worse than smaller ones for the proposed problems in our tests, and they have been not able to find the solution of the benchmark problems in a reasonable time.

We have chosen a migration frequency of 50 iterations for all the configurations after several initial preliminary experiments. The number of individuals migrated are 1 in all cases. For the ssGA, the emigrant is randomly selected and the immigrant always replaces the worst individual of the population. In the SA, the immigrant is treated as a new move.

The hardware infrastructure used in our analysis 8.6 consists of 8 different machines: 2 of them have an Intel Core 2 Quad Q9400 @ 2.66GHz processor and 4GB of RAM (namely Type A, fast), the other 6 computers have an Intel Pentium 4 @ 2.4GHz processor and 1GB of RAM (namely Type B, slow). All the computers are managed by a GNU/Linux distribution, being Debian 5.0 for Type A, and SuSE 8.1, Debian 3.1 and Ubuntu 6.10 for Type B. The computers are connected

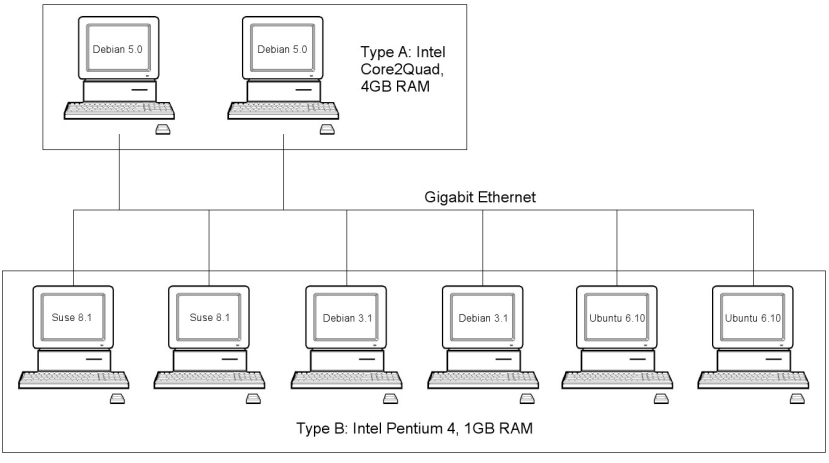


Fig. 8.6 Schema of the hardware infrastructure

by a Gigabit Ethernet Network. The algorithms have been implemented in Java in order to support both hardware and software heterogeneity. For the purpose of the analysis the version 1.6.0_01 of the Java Virtual Machine (JVM) is used in all the nodes.

8.6 Tests and Analysis

In this section we analyze the behavior of Ethane, and compare it with the well-known ssGA unidirectional ring. We have analyzed the aforementioned performance measures, being numerical effort, total run time and speedup, as well as the evolution of the fitness.

We have implemented two different algorithms based on Ethane. For the first one, Ethane G, we have provided the Type A computers with a central ssGA island, and Type B computers with a SA island. For the second algorithm, Ethane S, the fastest machines run central SA islands and the slowest ones run ssGA. As we mentioned above, the migration scheme resembles a molecule of ethane as represented in Figure 8.5. In the parallel ssGA used as reference, the islands have been distributed over a unidirectional ring, placing the most powerful computers in the first and fourth place in a sort of MaxSumSort [9]. As we do not know the statistical distribution of the data, they have been statistically compared with Mann-Whitney U test.

Table 8.2 Number of evaluations for the tested models and panmictic algorithms

Algorithm	Subset Sum		MMDP6	
	Average	Std. Deviation	Average	Std. Deviation
Ethane G	**146418**	**174433**	1572735	919691
Ethane S	202815	198696	**708231**	**430353**
ssGA Ring	214824	239125	786583	805837
Panm. ssGA	179792	175177	*	*
Panm. SA	81737	93627	*	*

8.6.1 Numerical Effort

In Table 8.2 we show the numerical effort needed to find the optimum for each algorithm. It can be seen that our proposals performed better than the panmictic algorithms for both problems (in the case of MMPD, panmictic algorithms where not even able to find the optimum in a reasonable time). For the SSP, both Ethane versions performed numerically better than the reference ssGA ring, and one of the instances (Ethane S) performed better even for the MMDP.

From the point of view of numerical effort, all the differences are statistically significant according to the Mann-Whitney U test . Note that also the standard deviation is better in our algorithms, so that its behavior is more robust. We can see how the panmictic SA has reached the solution with less numerical effort because SA is a fast converging trajectory method, but as we will see in the forthcoming analysis of the run time, the time needed to find a solution is worse than for the studied parallel models.

Since the objective of our model is the reduction of the total execution time let us begin with the study of a more meaningful performance metric, the total run time.

8.6.2 Total Run Time

Table 8.3 shows the average execution time of each algorithm for each problem until global optimum is reached. As we can see, our proposals performed clearly better than the panmictic algorithms for both problems (remember that the panmictic algorithms where not able to find the optimum for the MMDP in a reasonable time) as well as better than the ssGA ring does.

As we can see in Table 8.3, Ethane G was the best performing algorithm for the SSP problem. The Mann-Whitney U test gives a p-value of 0.0412 for the Ethane G compared to the ssGA ring, so the difference is statistically significant. The average time needed for Ethane G to find a solution is more than 30% better than for ssGA ring.

Ethane S was the best algorithm solving the MMDP problem, with an average time slightly better than the ssGA ring, but with a much lower standard deviation, as Mann-Whitney U test confirms with a p-value of 0.007. The standard deviation

Table 8.3 Time - ms - for the tested models and panmictic algorithms

Algorithm	Subset Sum		MMDP6	
	Average	Std. Deviation	Average	Std. Deviation
Ethane G	**5318**	**6226**	9195	4942
Ethane S	7155	6922	**3052**	**1546**
ssGA Ring	7453	8107	3194	3380
Panm. ssGA	30008	29387	*	*
Panm. SA	13300	15443	*	*

of ssGA is more than twice the standard deviation of Ethane S. This means that the two representative instances of the Ethane family evaluated in this chapter can be both more efficient and more robust/stable than standard sequential and distributed popular algorithms.

8.6.3 Speedup

In Table 8.4, we can see a summary of the execution time of the studied algorithms within a single processor and its speedup with respect to the execution in the eight processors heterogeneous platform. As we can see, both versions of Ethane have obtained a better speedup than the ssGA for the SSP, but only Ethane S has achieved a better speedup for the MMDP.

As it is shown in Table 8.4, Ethane G has performed better than the reference ssGA ring even in a single processor in the case of SSP. Even when its performance over a single processor is still better, its speedup is the best of the three models. However, in general, the value for the speedup is not good for any of the algorithms for this problem, being the value for Ethane G a small $3\times$.

Ethane S still performed slightly better than the ssGA ring for a single processor for both problems. Even the speedup is better in both cases, being the best of the studied algorithms for the MMDP with a value of $6.76\times$. In the case of MMDP the speedup of the three algorithms was quite good although linear speedup was not reached.

In the case of SSP, Ethane G and S have not showed a very good speedup, and ssGA has showed even a worse speedup. This fact could be explained by the huge difference among the computational power of the different hardware configurations

Table 8.4 Time - ms - for the tested models in a single processor and its speedup

Algorithm	Subset Sum		MMDP6	
	Avg. time	Speedup	Avg. time	Speedup
Ethane G	**15995**	**3.00**$\times$	41943	4.56$\times$
Ethane S	17817	2.49$\times$	**20627**	**6.76**$\times$
ssGA Ring	18137	2.43$\times$	21227	6.64$\times$

used (remember that the reference point for speedup is the best performing processor). Heterogeneous hardware might not be expected of very high speedup as homogeneous hardware.

8.6.4 Evolution of the Fitness

Figures 8.7 and 8.8 are showing, for each algorithm and each problem, the execution whose value for the run time is the median of the results.

In the case of SSP, the Figure shows that the two Ethane versions clearly outperform the ssGA ring, converging quite faster. We can see how Ethane G performs even better than Ethane S for this problem.

For the MMDP, Ethane S performed clearly better than Ethane G as we can see in Figure 8.8. Ethane S outperformed the ssGA ring, but the difference is not as large as with the SSP.

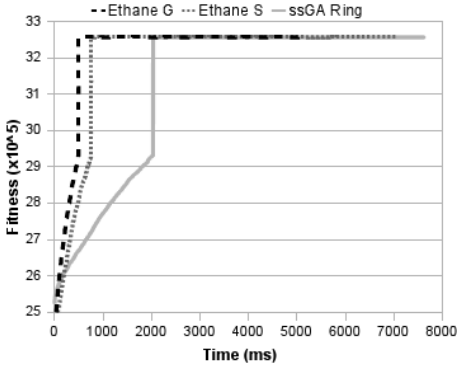


Fig. 8.7 Evolution of the fitness (time (ms) vs. fitness) for SSP

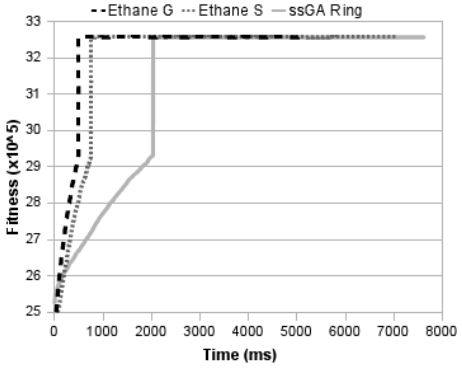


Fig. 8.8 Evolution of the fitness (time (ms) vs. fitness) for MMP

8.7 Conclusions

In this chapter we have presented a general model for designing hybrid algorithms depending on the underlying heterogeneous platform, inspired in the structures of the hydrocarbons present in Nature. We have also analyzed an instance of HydroCM: Ethane, a hybrid parallel search algorithm based on the structure of ethane.

We have performed a set of tests in order to assess the performance of our proposal, and compared it with a well-known state-of-the-art model, the ssGA unidirectional ring, and two well-known algorithms: SA and ssGA. Our tests have shown that the hybrid model can perform better in terms of time and numerical effort than the reference model, and Ethane is even able to find the solutions in a more robust/stable manner. Also the speedup of the proposed models is competitive with that of the reference model, obtaining quite good values even with the huge differences between the performance of the computers of the heterogeneous platform.

With HydroCM, our goal is to offer a hybrid general model for gracefully matching computers of different powers to run different algorithms for efficiently solve the same problem, in a way that an heterogeneous platform does not constitute a problem but, on the contrary, could be used as a target platform for specialized new parallel algorithms.

Acknowledgements. This work has been partially funded by the Spanish Ministry of Science and Innovation and FEDER under contract TIN2008-06491-C04-01 (the M* project). It has also been partially funded by the Andalusian Government under contract P07-TIC-03044 (DIRICOM project).

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