Poznań University of Technology

Algorithm Portfolios
for Large Berth Allocation Problem Instances

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Algorithm Portfolios for Large Berth Allocation Problem Instances

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Abstract

In this report algorithm portfolios built as a solution to the algorithm selection problem (ASP) for large Berth Allocation Problem (BAP) are given.

Keywords: Algorithm selection problem, berth allocation problem, quality-runtime trade-off; scheduling; heuristics;

1 Introduction

Algorithm Selection Problem (ASP) consists in selecting a method most suitable to solve an instance of a certain problem. Algorithm portfolios are one of the ways of addressing the ASP. Algorithm portfolios are sets of algorithms which can be applied collectively to solve a certain problem. The algorithms can be, e.g., executed sequentially or in parallel, on a given instance of the considered problem and the best solution is chosen. Here we study algorithm portfolios for large instances of Berth Allocation Problem (BAP) [1]. The BAP must be solved as sub-problem in simulations of a port, and hence the execution time T of the portfolio is a key constraint.

The BAP considered in this paper is formulated as follows. A set of m berths of lengths λ_i, for $i = 1, \dots, m$, is given. There are n vessels defined by: arrival times r_j, lengths L_j, processing (unloading and loading) times p_j, and importance w_j, for $j = 1, \dots, n$. Vessel j can be moored at berth i only if $L_j \leq \lambda_i$. The quay is divided into discrete berths and each berth can accommodate at most two ships at the same time. The minimized objective is the mean weighted flow time $MWFT = \sum_{j=1}^{n}(c_j - r_j)w_j / \sum_{j=1}^{n} w_j$, where c_j is completion time of handling ship j.

Let $\mathcal{I}'$ be a set of training instances and let $\mathcal{A}$ be a set of algorithms. For each pair $(a, I) : a \in \mathcal{A}, I \in \mathcal{I}'$ a sequence of pairs $(t^1_{aI}, q^1_{aI}), (t^2_{aI}, q^2_{aI}), \dots,$ $(t^{K_{aI}}_{aI}, q^{K_{aI}}_{aI})$ representing solutions built by a for I over time is given. The t^j_{aI} are execution times and q^j_{aI} are mean weighted flow times. If some algorithm

a does not improve solution quality over time then only one pair (t^1_{aI}, q^1_{aI}) is given. Let $t(a, I, T)$ denote runtime of algorithm a on instance I with the time limit T. Let $y(a, I, T) = 1$ if $\exists j : t^j_{aI} \leq T, q^j_{aI} = q_{\min}(I, T)$, otherwise $y(a, I, T) = 0$.

In the following sections name *cover portfolio* refers to the algorithm portfolios obtained by solving the integer linear program (ILP) covering the test instances with minimum cost wins:

$$\min Cost \tag{1}$$

$$\sum_{a \in \mathcal{A}} y(a, I, T) x_a \geq 1 \quad \forall I \in \mathcal{I}' \tag{2}$$

$$\sum_{a \in \mathcal{A}} t(a, I, T) x_a \leq Cost \quad \forall I \in \mathcal{I}' \tag{3}$$

Name *regret portfolio* will refer to the algorithm portfolios obtained by solving the integer linear program covering the test instances by minimizing the greatest regret under limited computational $Cost$ (*Min-Max Regret (MaxReg)*:

$$\min G \tag{4}$$

$$\frac{q(a, I, T)}{q_{\min}(I, T)} u_{aI} \leq G \qquad \forall I \in \mathcal{I}' \quad \forall_{a \in \mathcal{A}} \tag{5}$$

$$\sum_{a \in \mathcal{A}} u_{aI} \geq 1 \qquad \forall I \in \mathcal{I}' \tag{6}$$

$$x_a \geq u_{aI} \qquad \forall I \in \mathcal{I}' \quad \forall_{a \in \mathcal{A}} \tag{7}$$

$$\sum_{a \in \mathcal{A}} t(a, I, T) x_{aI} \leq Cost \qquad \forall I \in \mathcal{I}' \tag{8}$$

Set $\mathcal{A}$ of evaluated algorithms has 72 members. In this, 60 algorithms are greedy, 12 are metaheuristics. The algorithms have been described in more detail in [2]. For the training and evaluation purposes set $\mathcal{I}'$ of random instances have been generated as follows: $n \sim U[1, 1000]$, $m \sim U[1, 100]$, $r_j \sim U[0, 1000]$, $p_j \sim U[1, 24]$, $w_j \sim U[1, 1000]$, $L_j, \lambda_i \sim U\{200, 215, 290, 305, 400\}$. By $\sim U[a, b]$ we denote that certain parameter is generated from discrete uniform distribution with integer values in range $[a, b]$. $\sim U\{x, \dots, y\}$ denotes that the parameter values are chosen with discrete uniform distribution from the set $\{x, \dots, y\}$. Unless stated to be otherwise, each configuration of the tests represents a population of 100 instances. In the tests a range of n values has been swept by visiting values $n \in \{2, 5, 10, 20, 50, 100, 200, 500, 1000, 2000, 5000, 10000\}$ one by one. This means that 100 instances have been generated with $n = 2$ while the remaining parameters have been randomly generated as described above. The set of 100 instances with $n = 2$ have been solved by all the algorithms to evaluate their performance. Next, values $n = 5, 10, \dots$ have been examined in the similar manner. This set of of instances will be referred to as *random instances* N. In the examination of the impact of m, the tested values were $m \in \{1, 2, 5, 10, 20, 50, 100\}$ while other parameters were generated as described above. These instances will be referred to as *random instances* M.

In the next dataset, referred to as *real* instances, a collection of ship arrival times (r_j), processing times (p_j), lengths L_j, has been obtained from Automatic Identification System (AIS), a global radio vessel tracking system, for 8 ports in 2016. The ports with the number of ships were: Gdynia – 465 ships, Long Beach – 995, Los Angeles – 1310, Le Havre – 2277, Hamburg – 3273, Rotterdam – 3997, Shanghai – 11197, Singapore – 18413. Quay lengths were obtained from the publicly available port authority data. Overall, the algorithm portfolios have been constructed for the following datasets:

dataset 1 all 1200 random instances N,

dataset 2 100 random instances N with $n = 10000$,

dataset 3 700 all random instances M,

dataset 4 100 random instances M with $m = 2$,

dataset 5 Real instances.

More on the considered problem, its application, and solution will be given in [3].

2 Cover algorithm portfolios

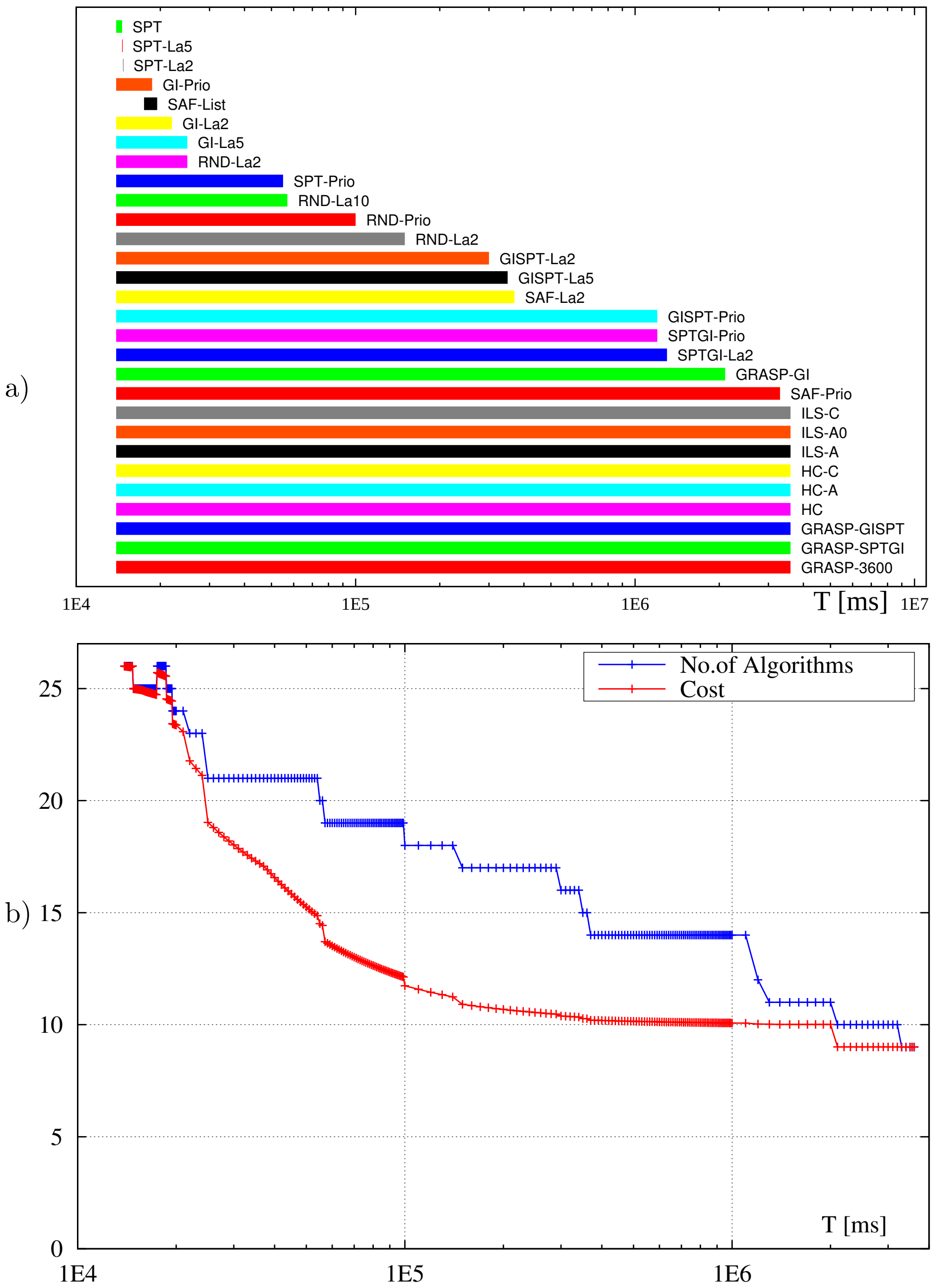


Figure 1: Cover portfolio built on all random instances N (dataset 1). a) portfolio evolution in time T, b) size and cost of portfolio (in T units), vs T.

a)

b)

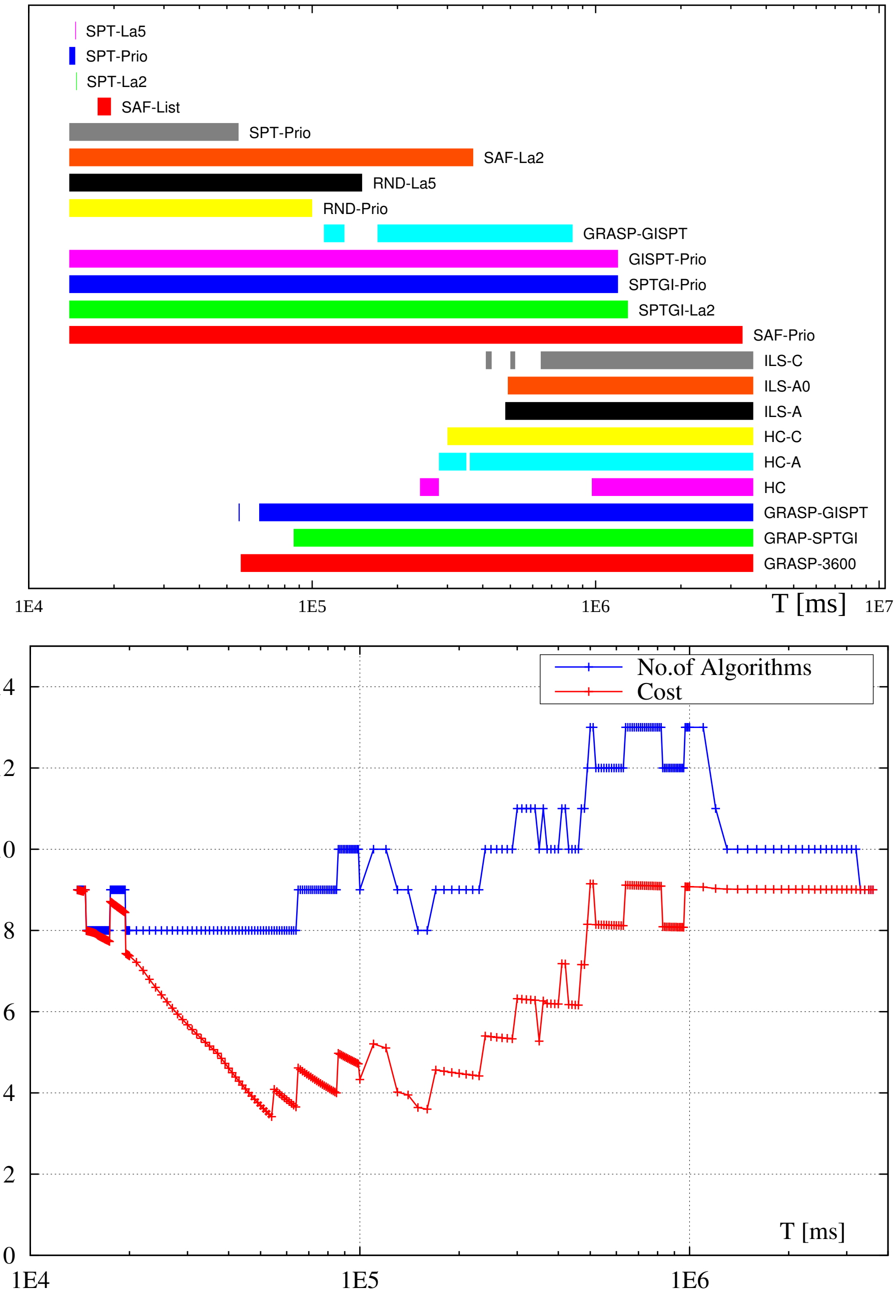


Figure 2: Cover portfolio built on random instances N for $n = 10000$ (dataset 2). a) portfolio evolution in time T, b) size and cost of portfolio (in T units), vs T.

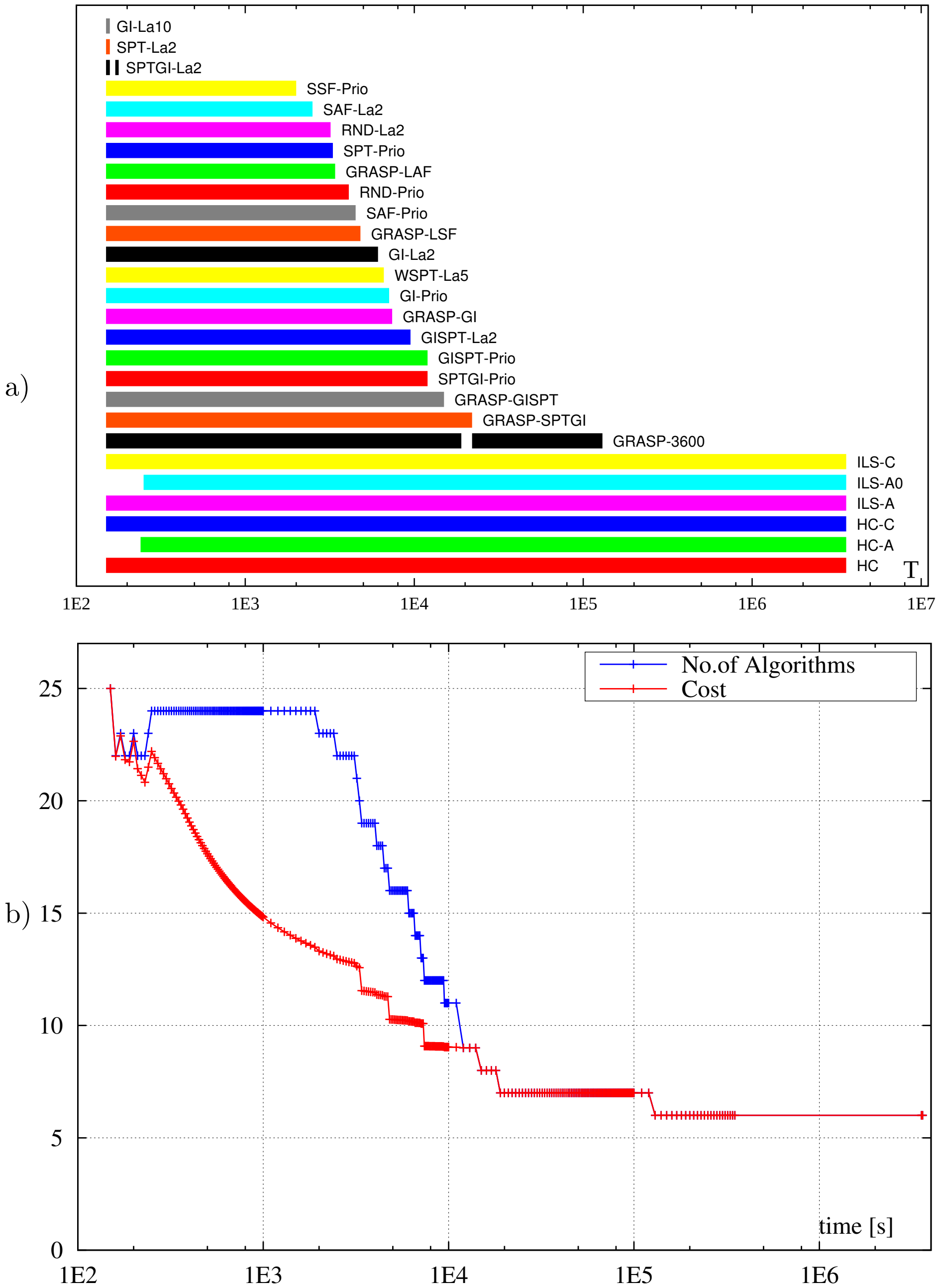


Figure 3: Cover portfolio built on all random instances M (dataset 3). a) portfolio evolution in time T, b) size and cost of portfolio (in T units), vs T.

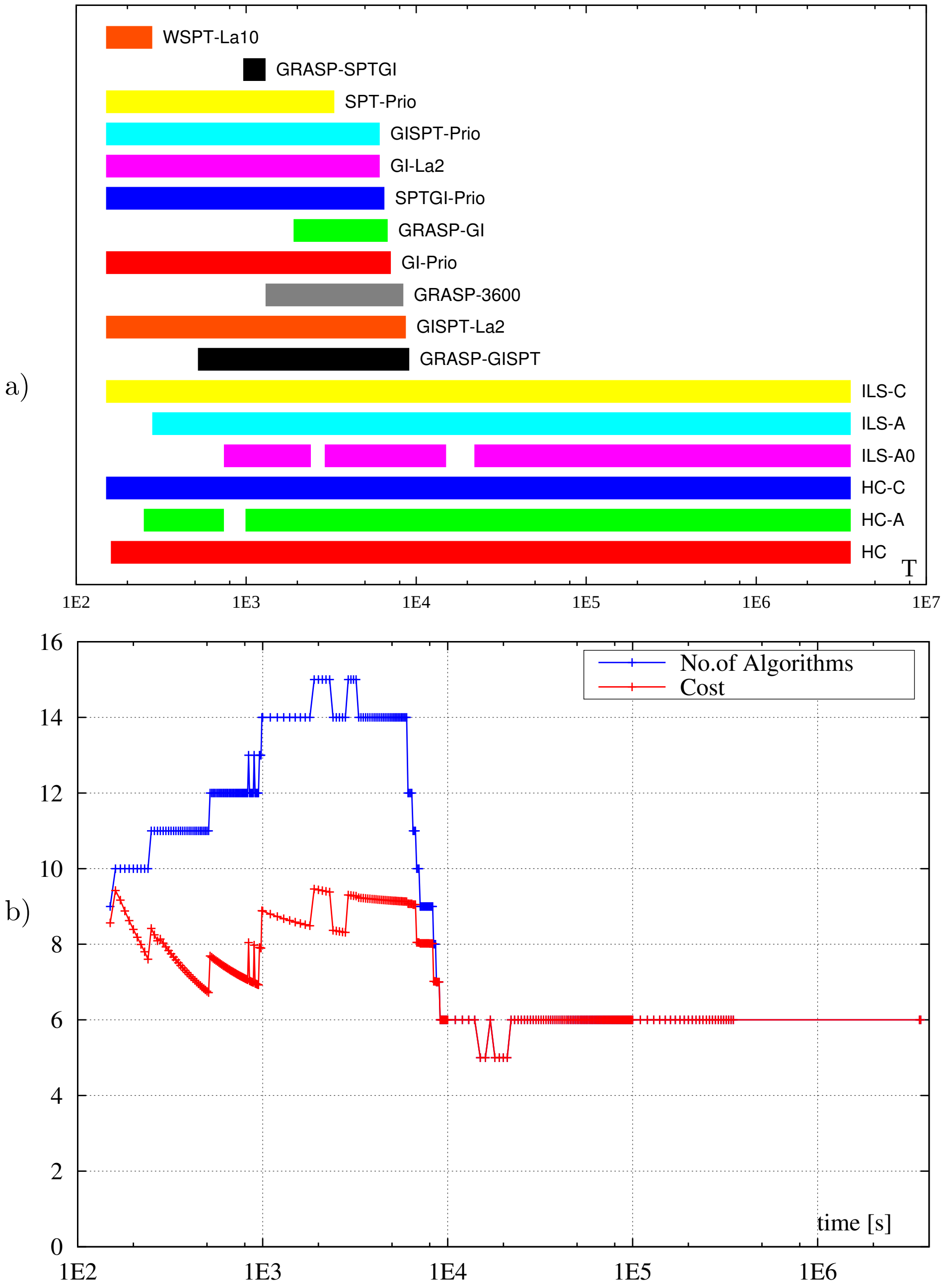


Figure 4: Cover portfolio built on random instances M with $m = 2$ (dataset 4). a) portfolio evolution in time T, b) size and cost of portfolio (in T units), vs T.

3 Regret portfolios for *all* random instances N (dataset 1)

Let us observe that regret portfolios for sufficiently large *Cost* limit comprise all algorithms (see Figs 9, 10, 15, 16, 21, 22, 27, 28).

a)

b)

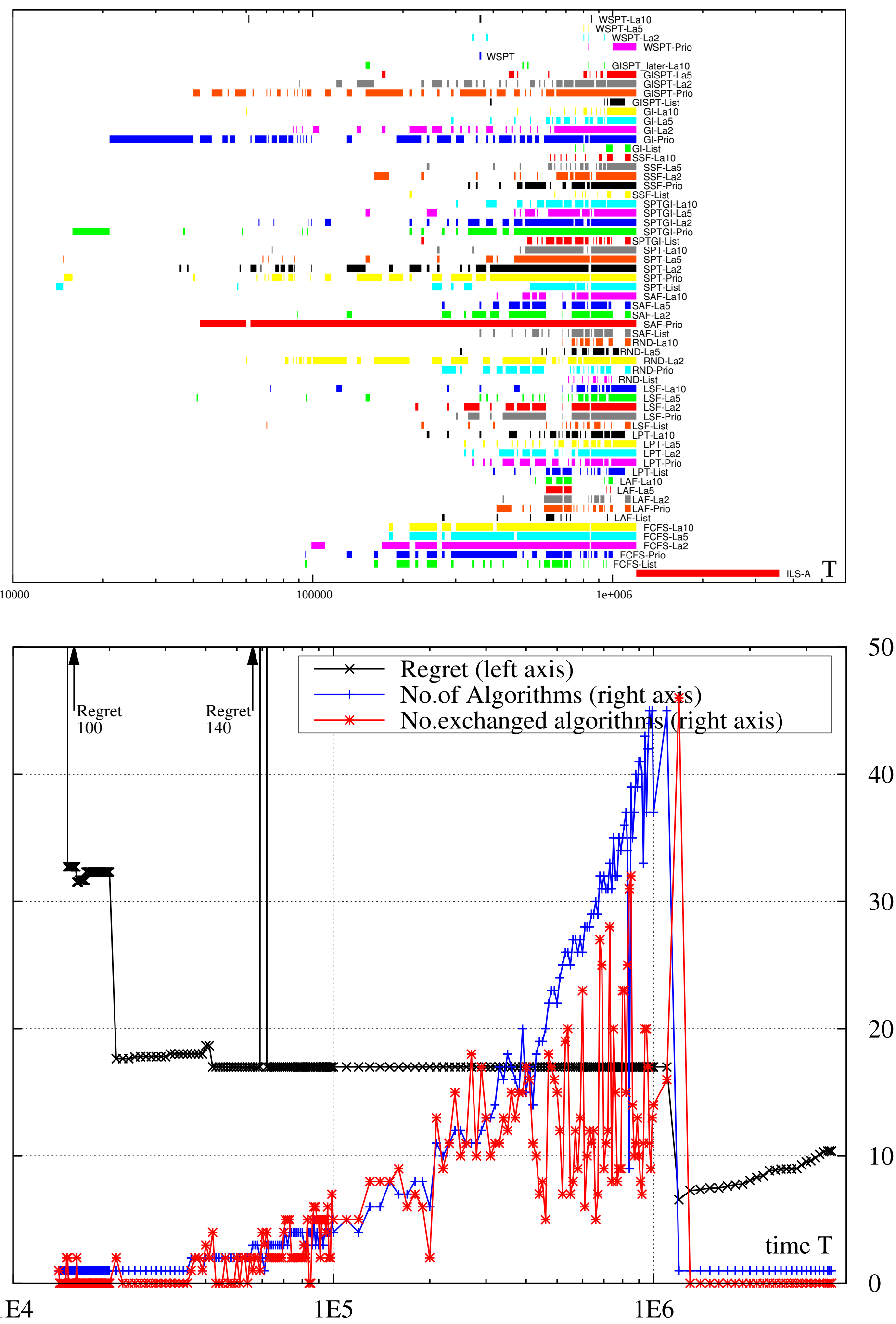


Figure 5: Algorithm portfolio built on all random instances N, (dataset 1) $Cost = 1T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

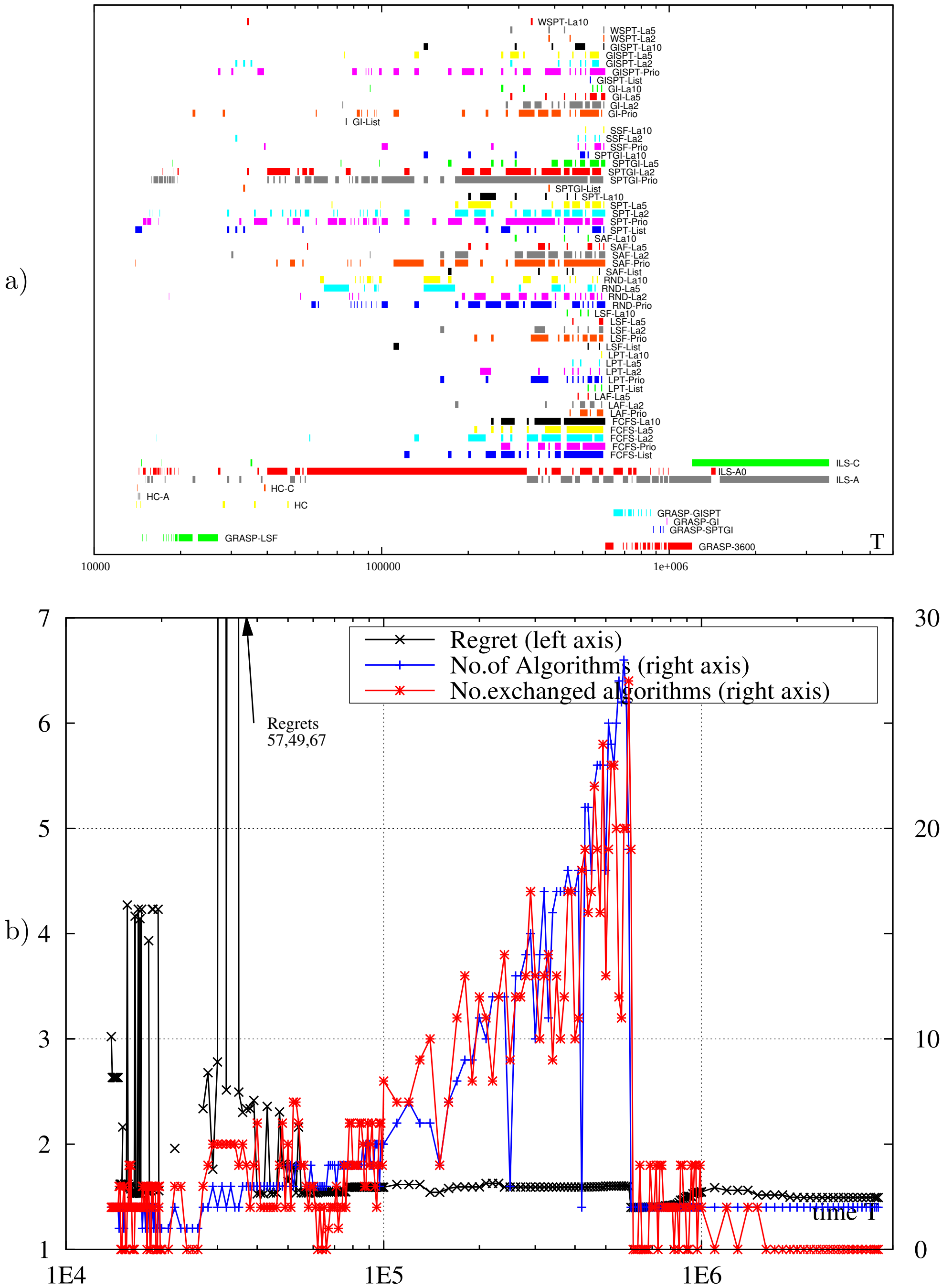


Figure 6: Algorithm portfolio built on all random instances N, (dataset 1) $Cost = 2T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a) b)

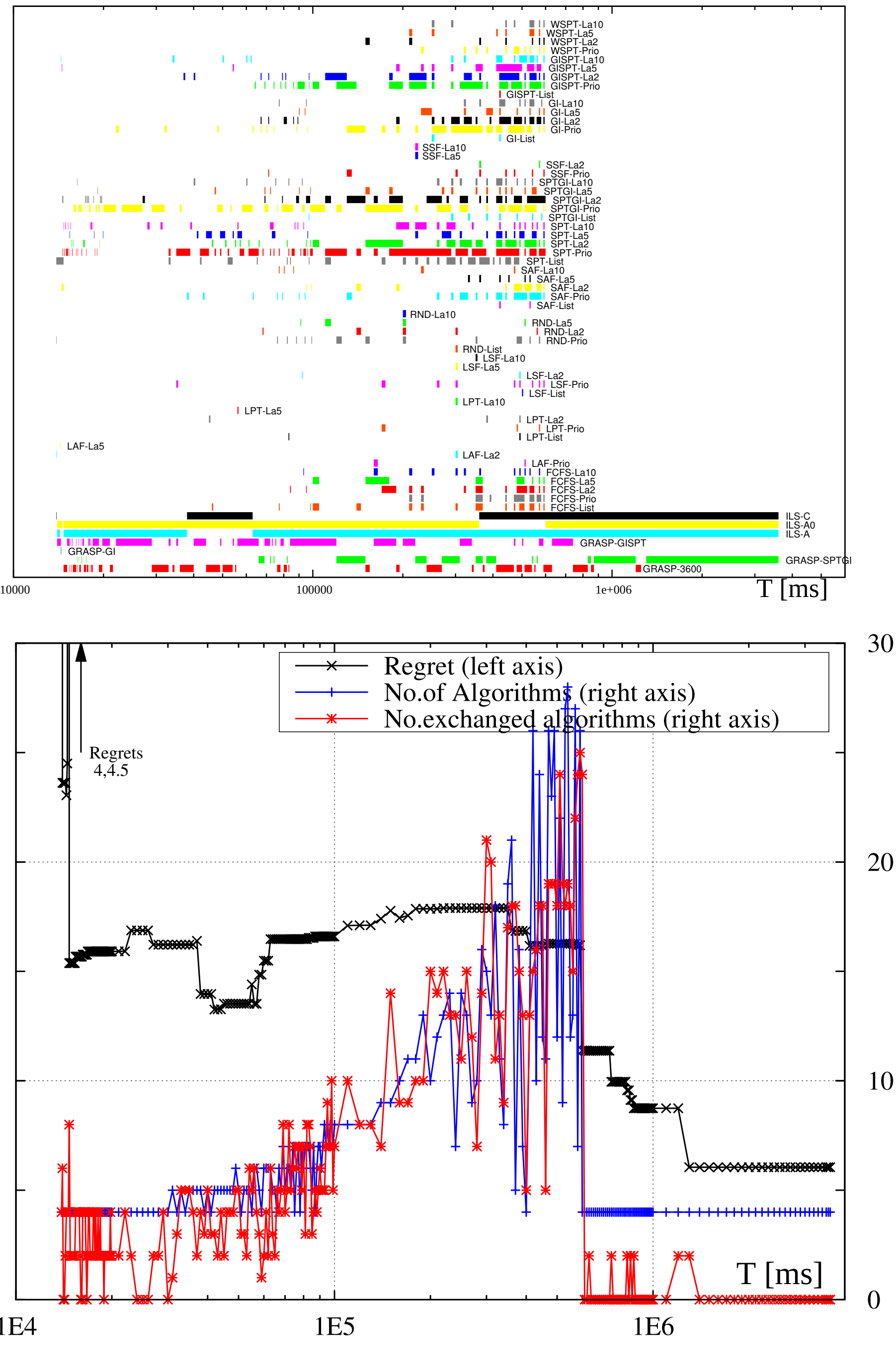


Figure 7: Algorithm portfolio built on all random instances N, (dataset 1) $Cost = 4T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

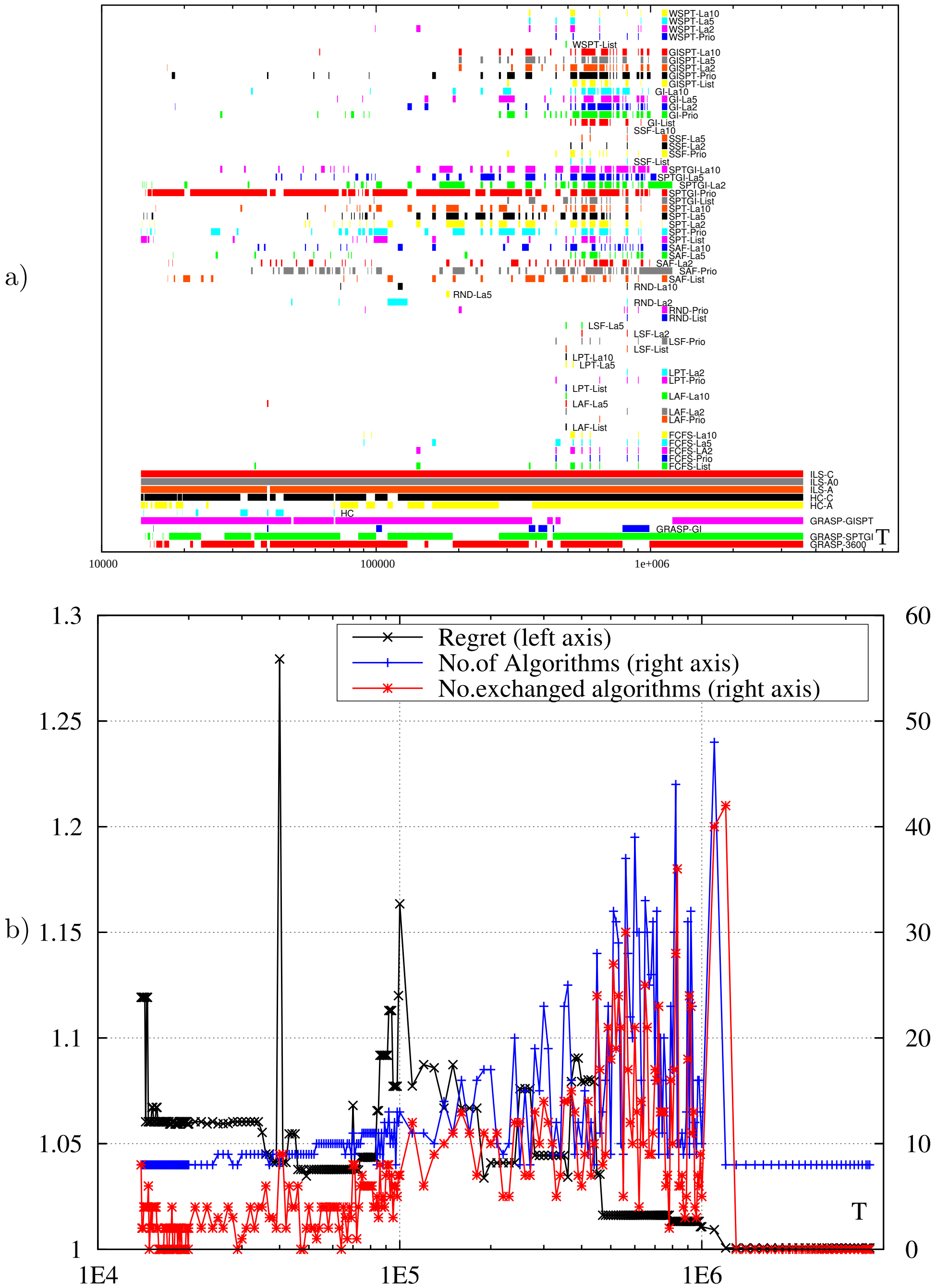
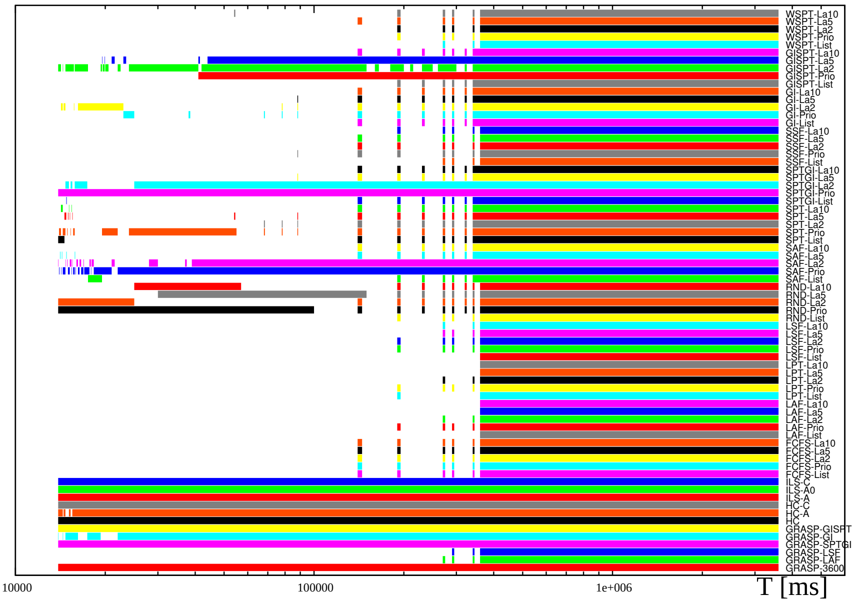


Figure 8: Algorithm portfolio built on all random instances N, (dataset 1) $Cost = 8T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a) 

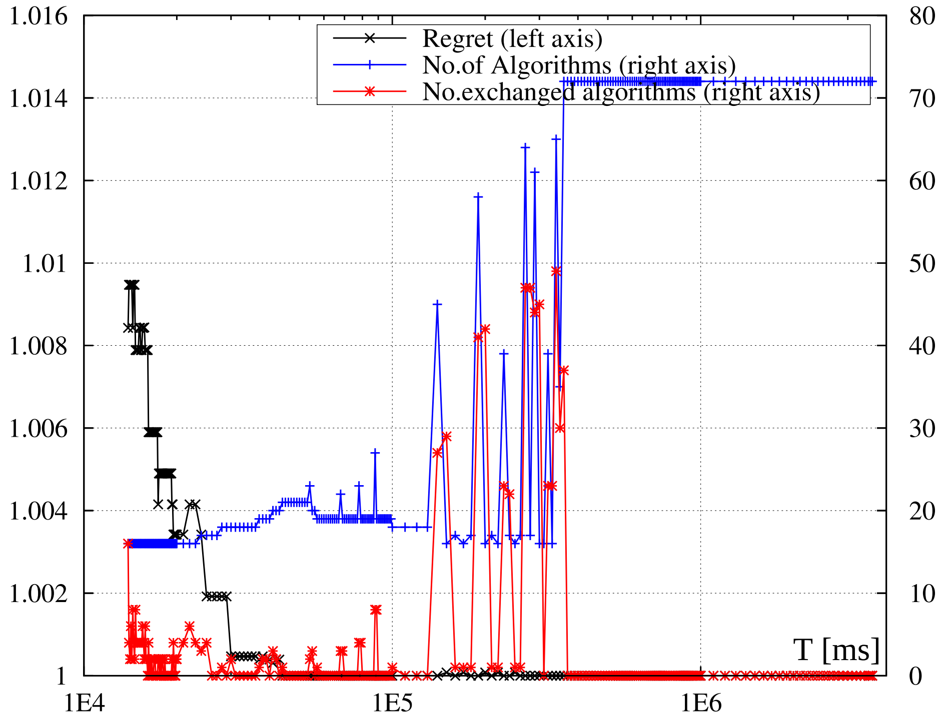
b) 

Figure 9: Algorithm portfolio built on all random instances N, (dataset 1) $Cost = 16T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)

b)

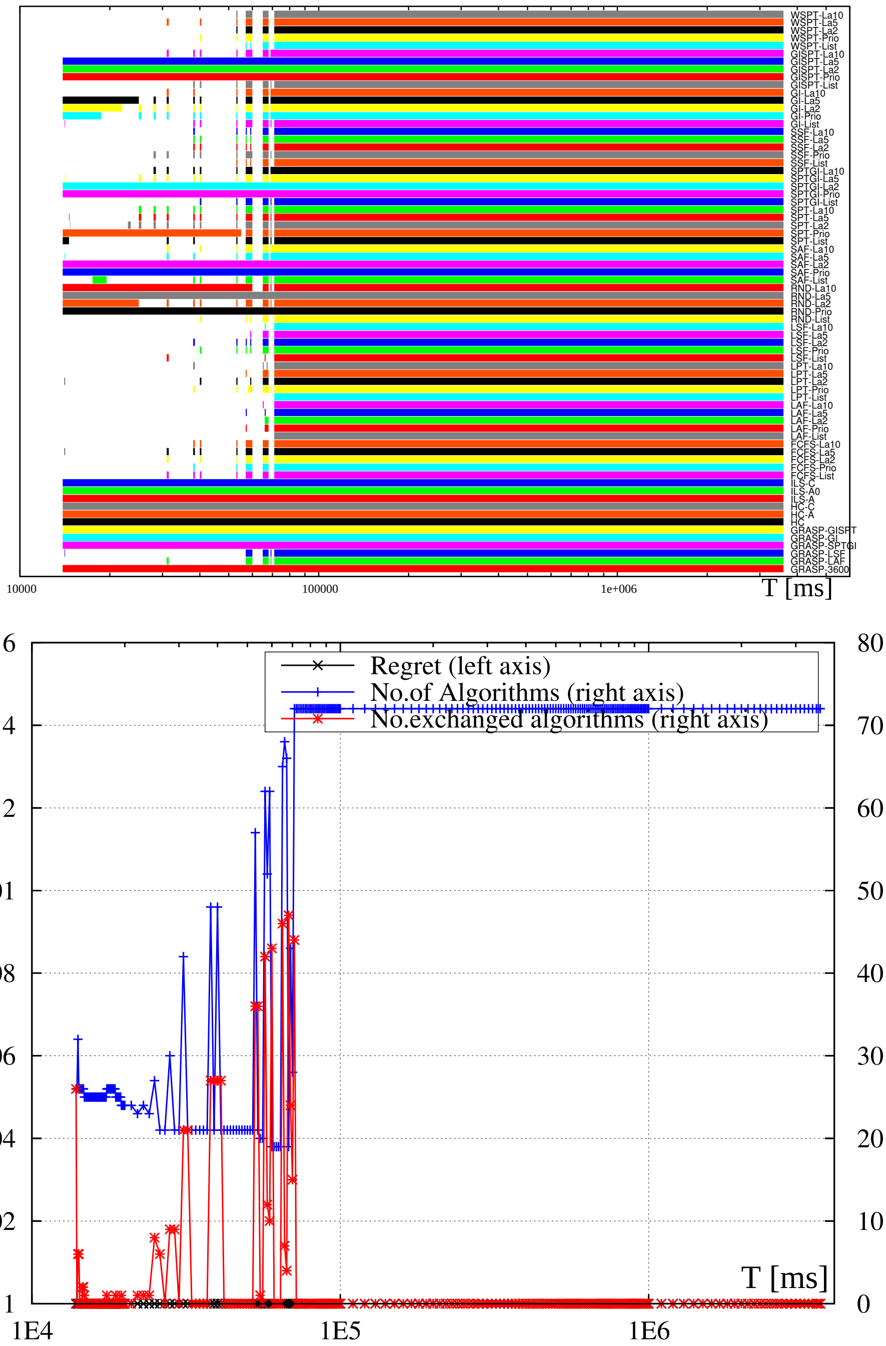


Figure 10: Algorithm portfolio built on all random instances N, (dataset 1) $Cost = 32T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

4 Regret portfolios for n=10000 random instances N (dataset 2)

a)

b)

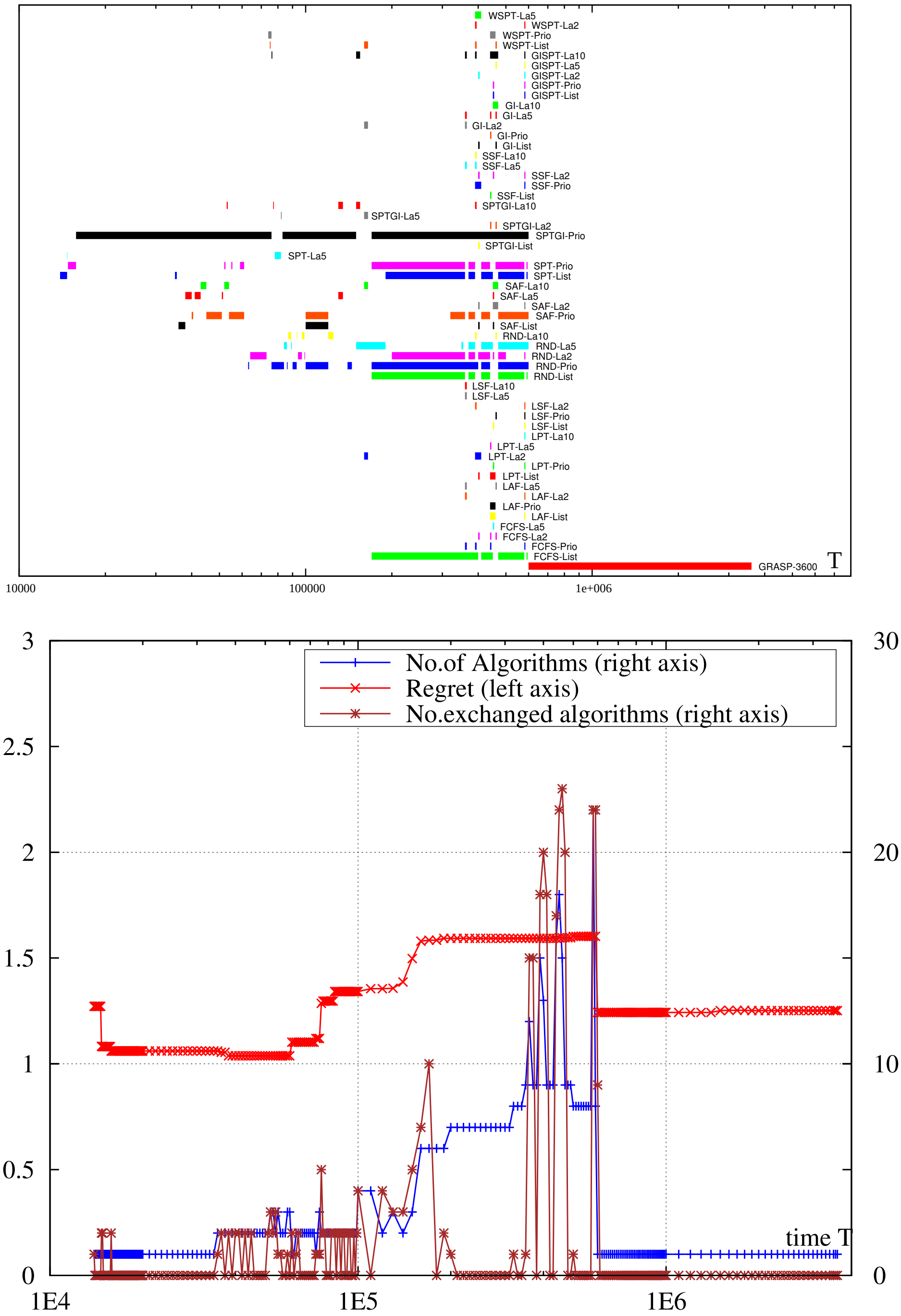


Figure 11: Algorithm portfolio built on random instances N with $n = 10000$, (dataset 2) $Cost = 1T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)

b)

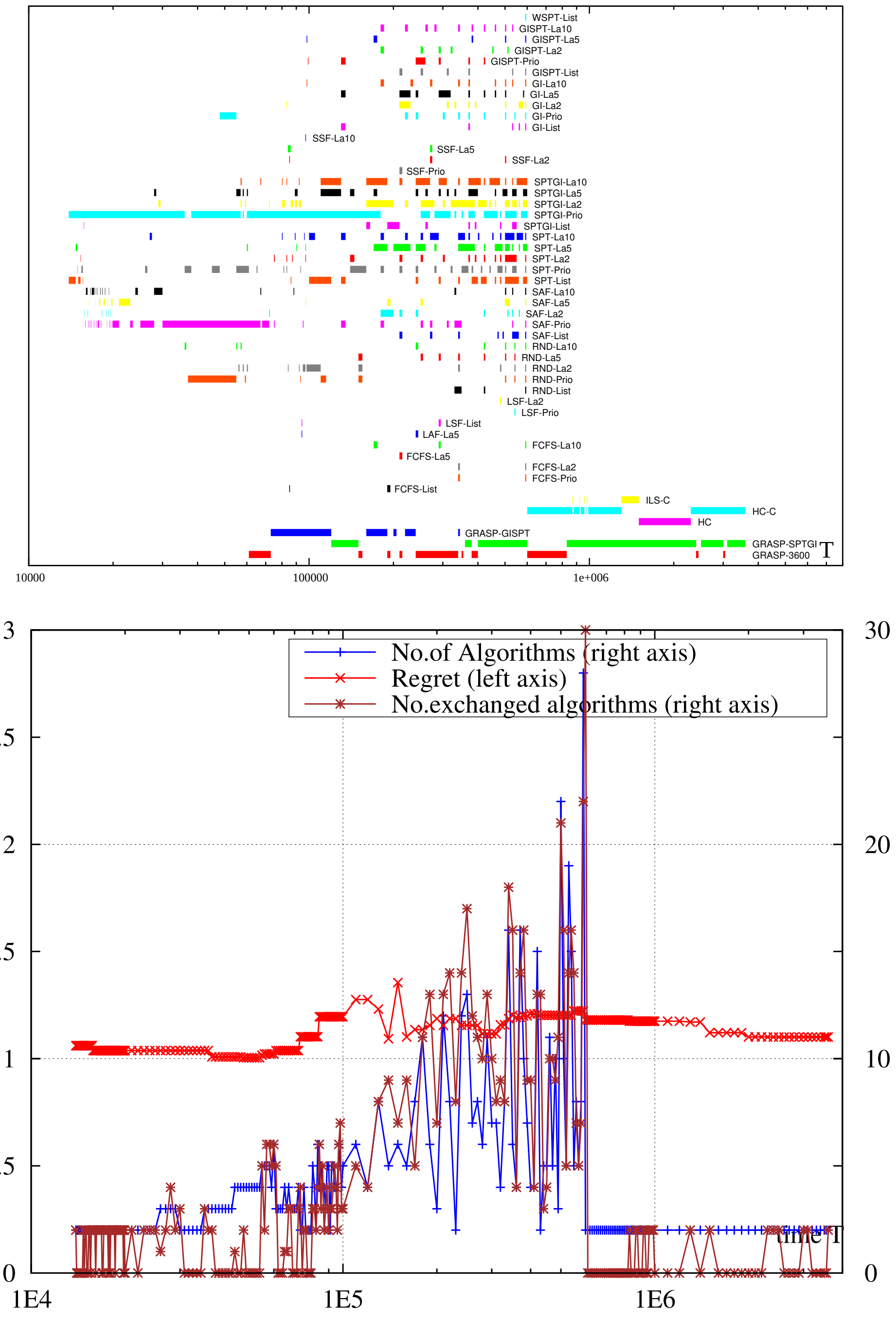


Figure 12: Algorithm portfolio built on random instances N with $n = 10000$, (dataset 2) $Cost = 2T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

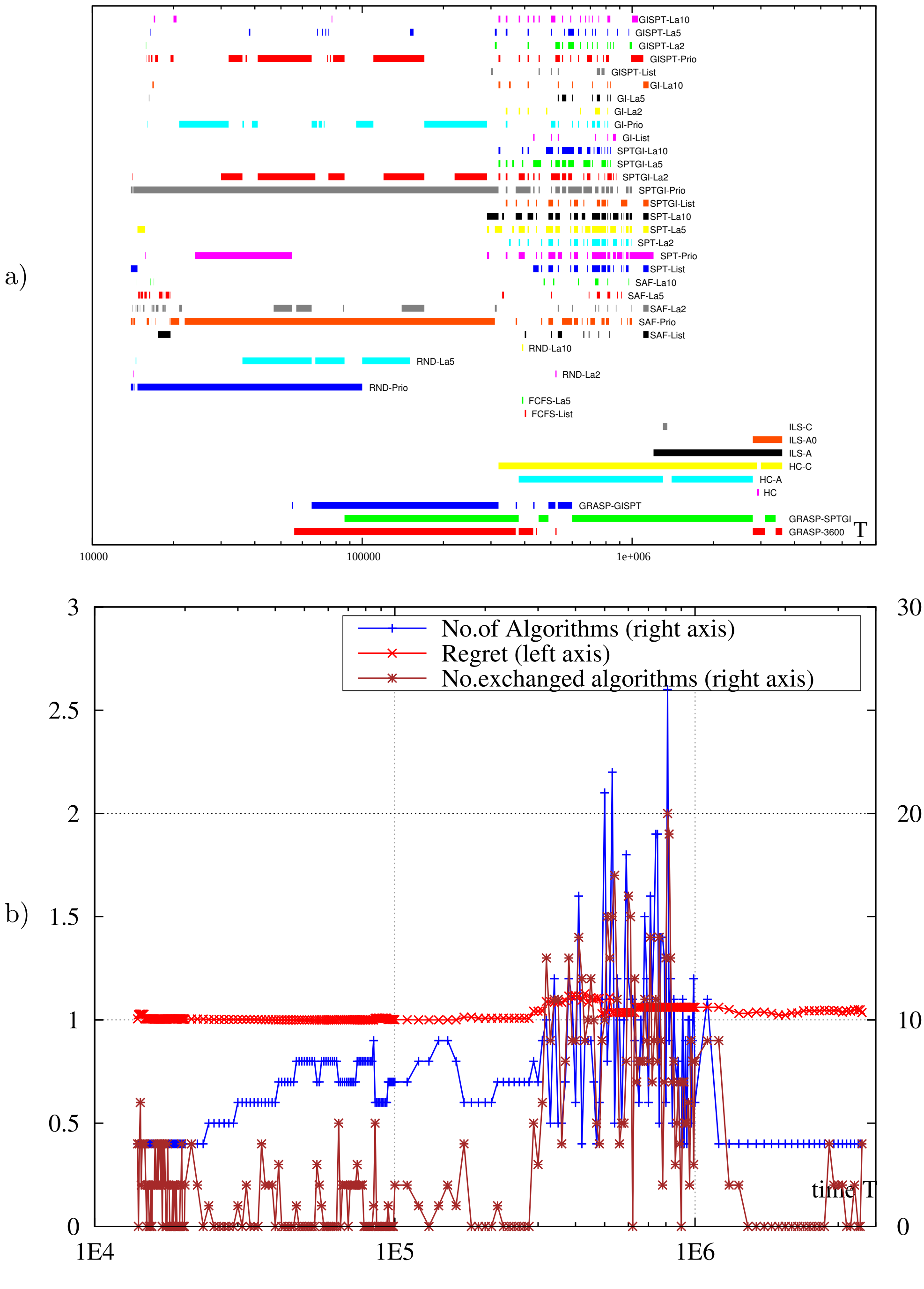


Figure 13: Algorithm portfolio built on random instances N with $n = 10000$, (dataset 2) $Cost = 4T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)

b)

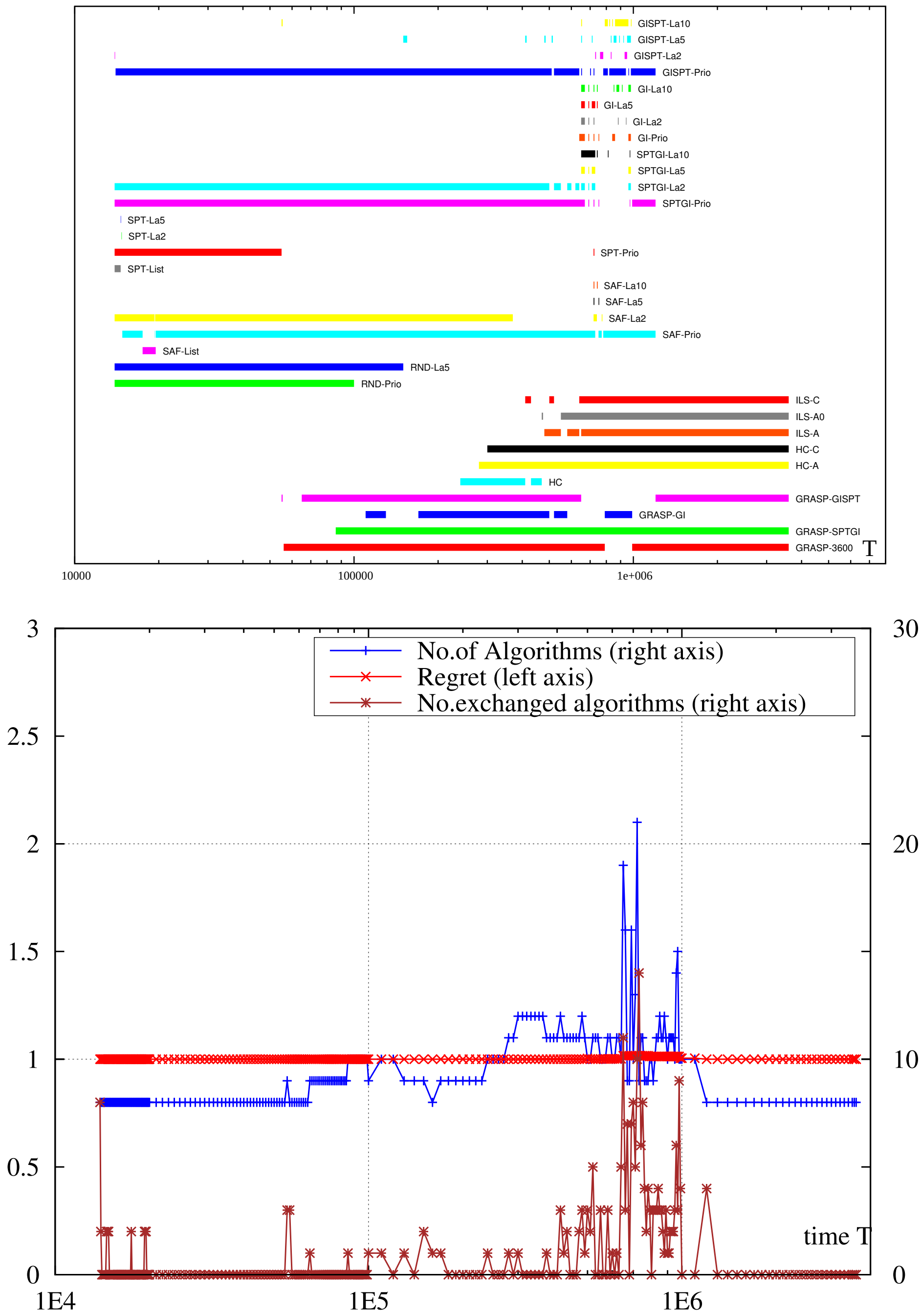


Figure 14: Algorithm portfolio built on random instances N with $n = 10000$, (dataset 2) $Cost = 8T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

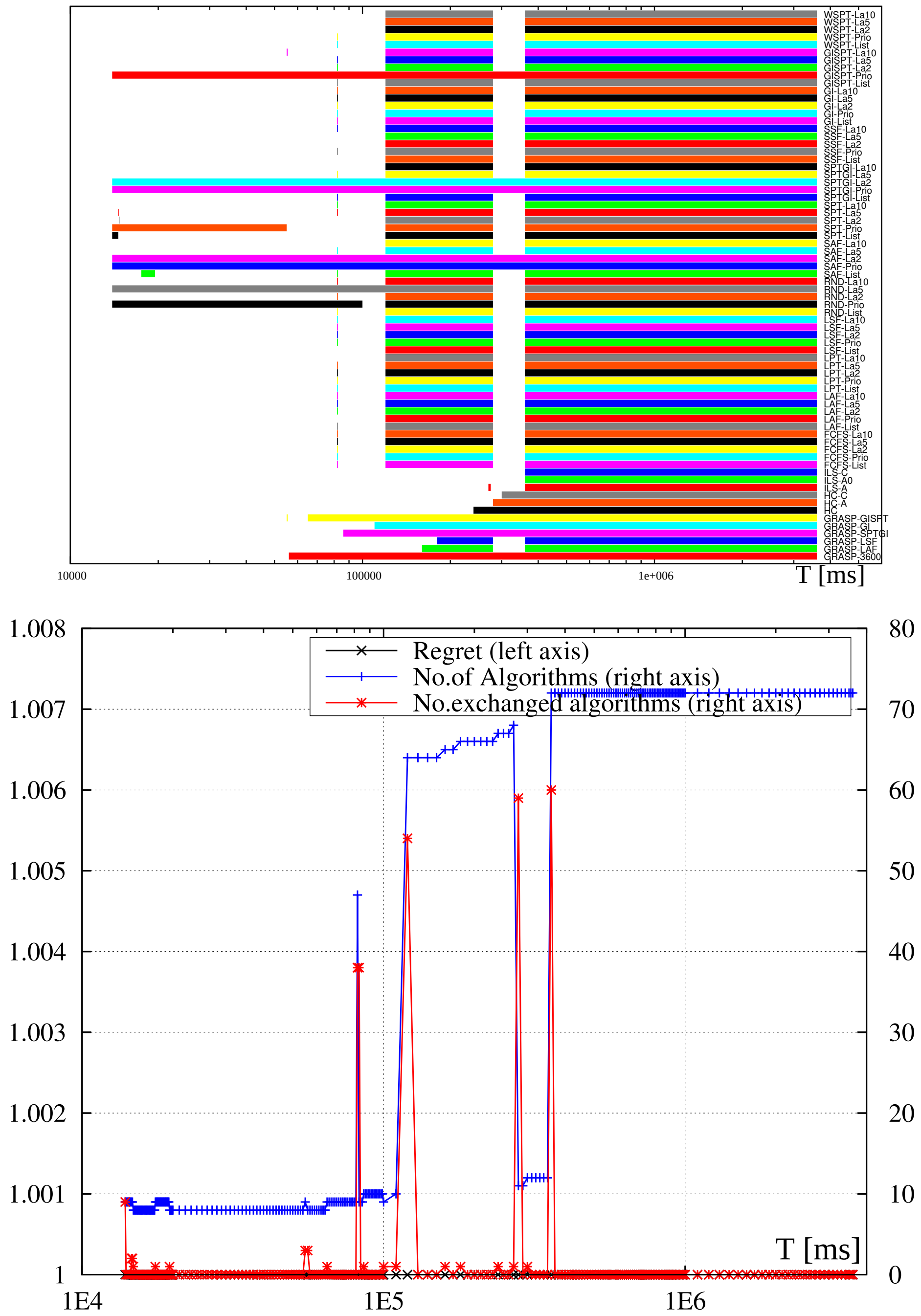
a)
b)


Figure 15: Algorithm portfolio built on random instances N with $n = 10000$, (dataset 2) $Cost = 16T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

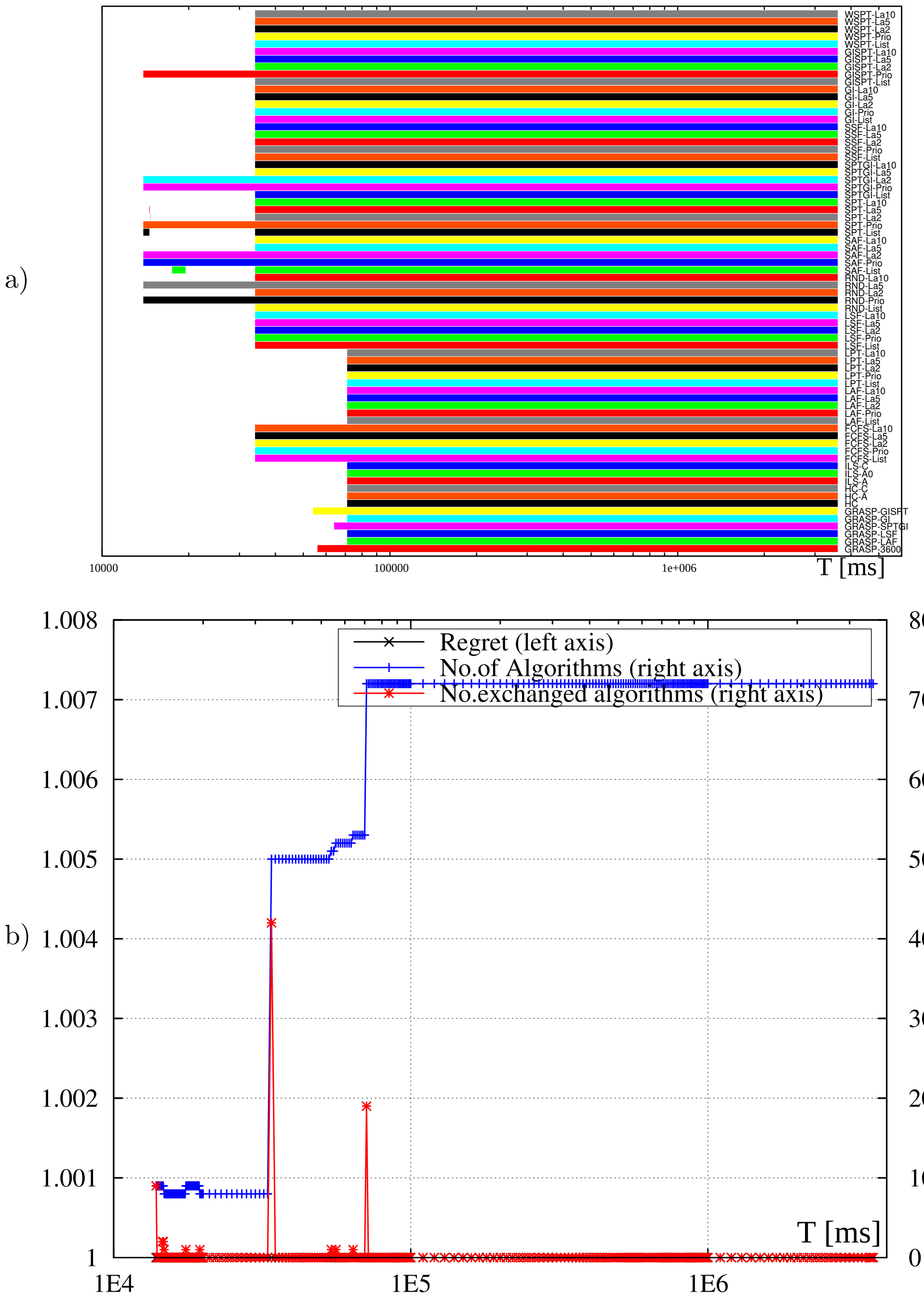


Figure 16: Algorithm portfolio built on random instances N with $n = 10000$, (dataset 2) $Cost = 32T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

5 Regret portfolios for *all* random instances M (dataset 3)

a)

b)

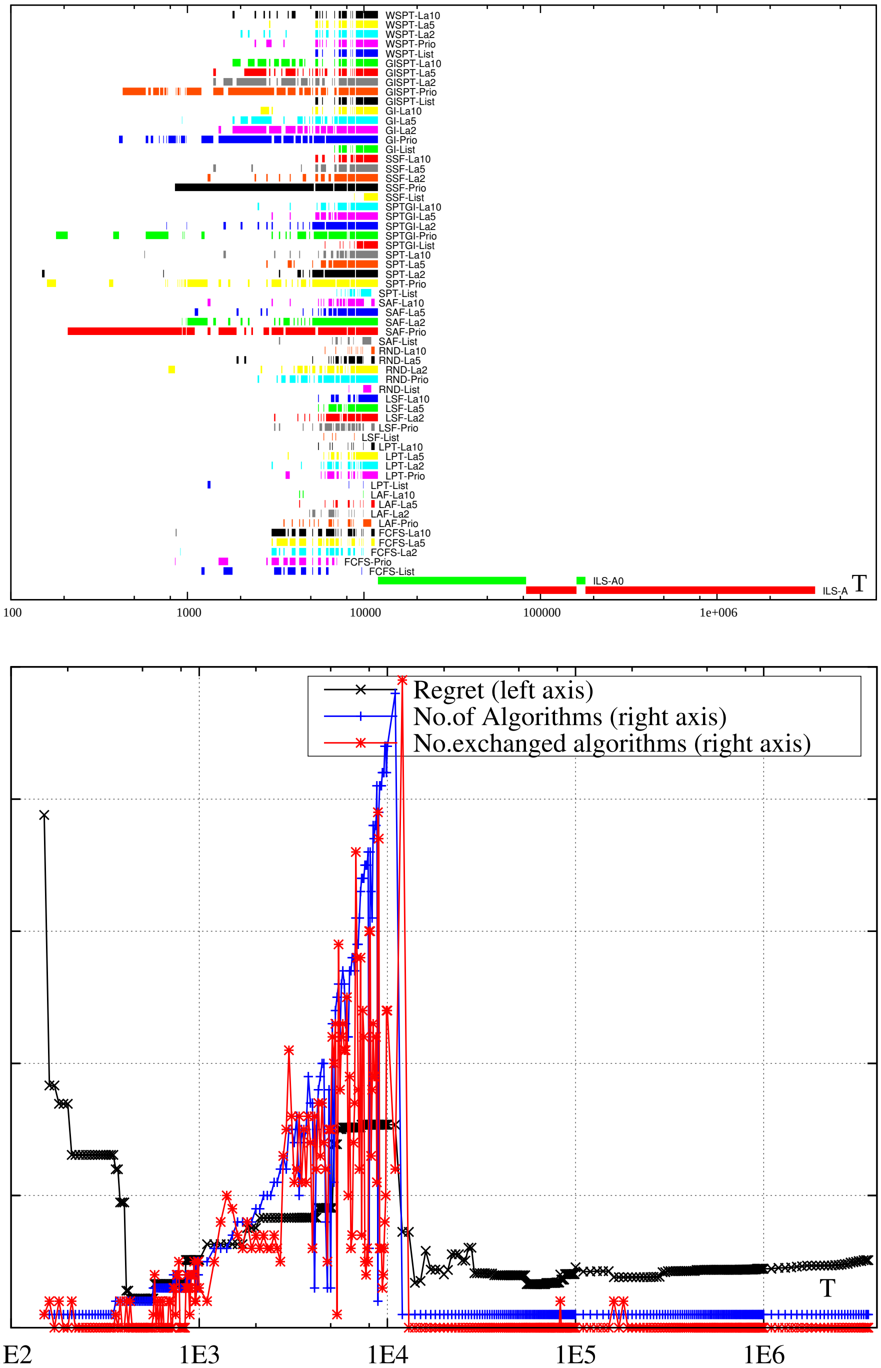


Figure 17: Algorithm portfolio built on all random instances M (dataset 3), $Cost = 1T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)

b)

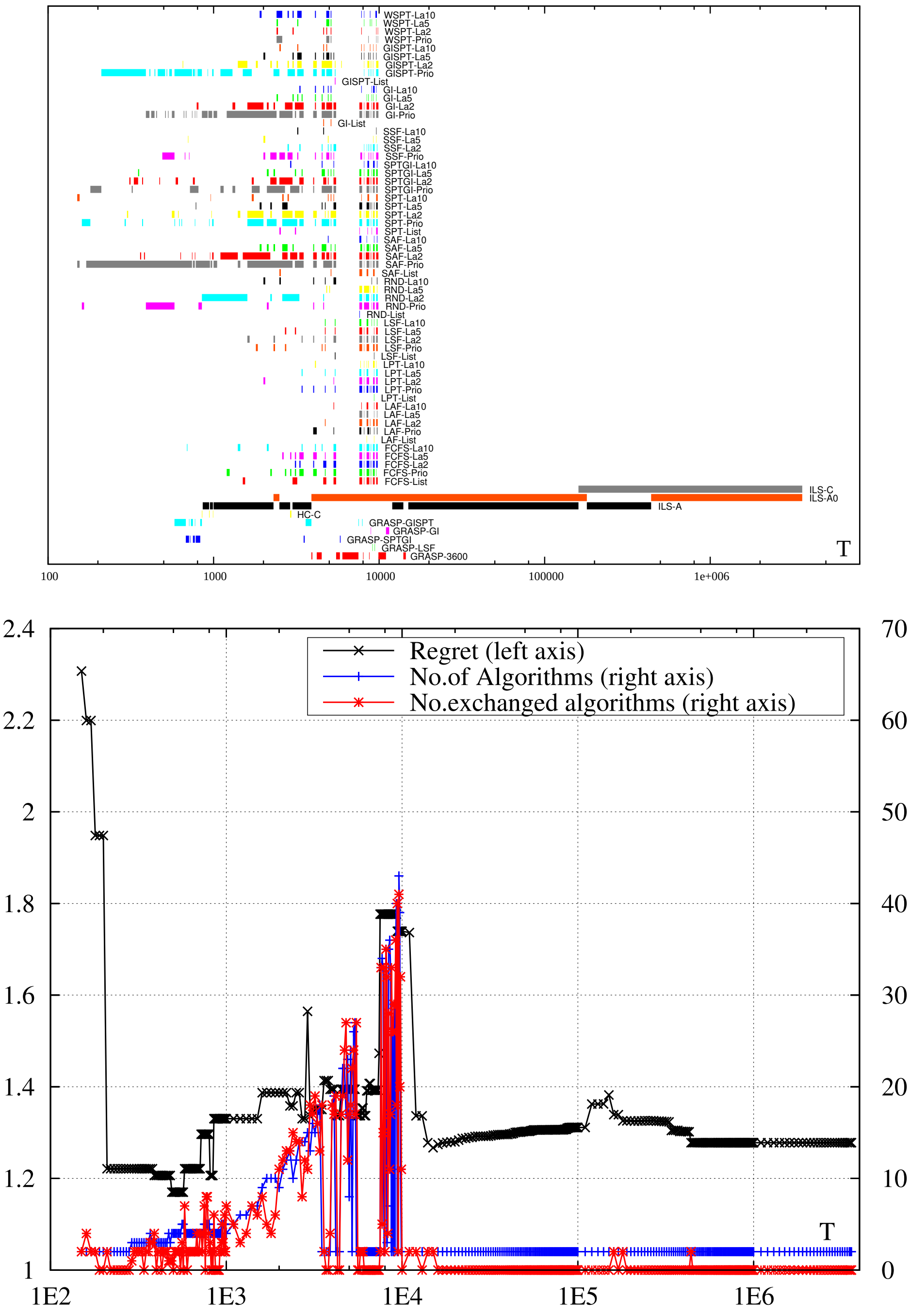


Figure 18: Algorithm portfolio built on all random instances M (dataset 3), $Cost = 2T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)

b)

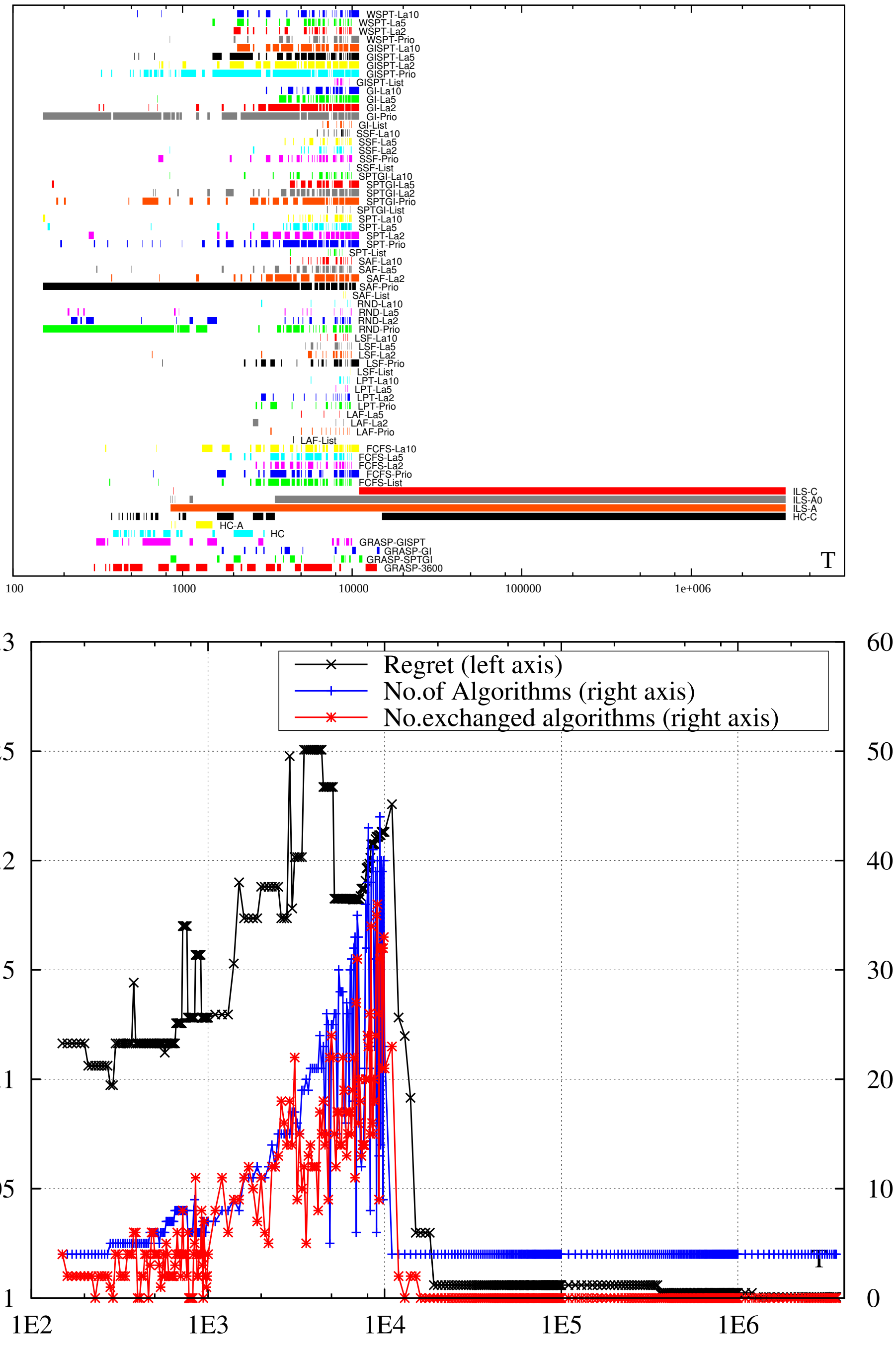


Figure 19: Algorithm portfolio built on all random instances M (dataset 3), $Cost = 4T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)

b)

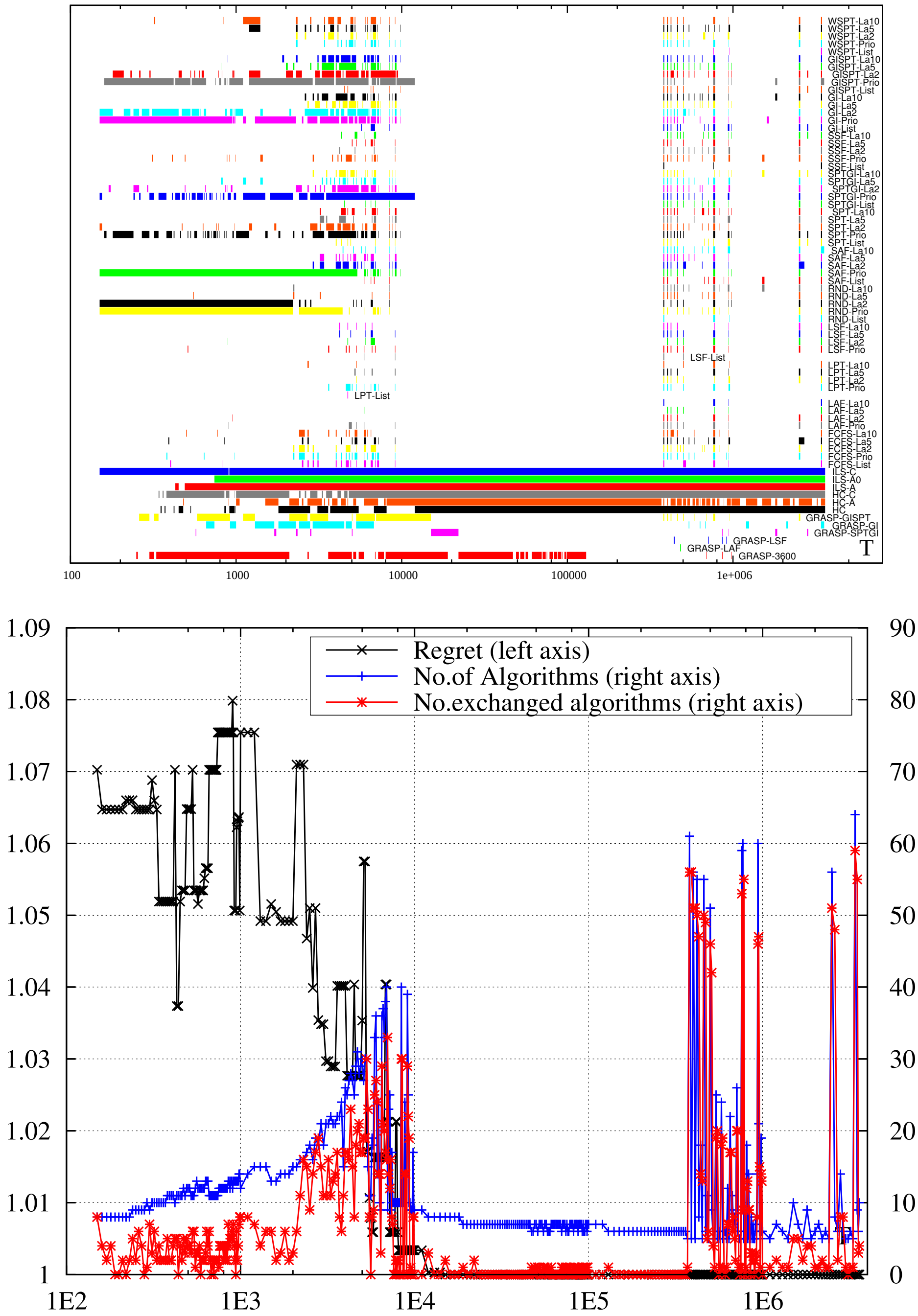


Figure 20: Algorithm portfolio built on all random instances M (dataset 3), $Cost = 8T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)

b)

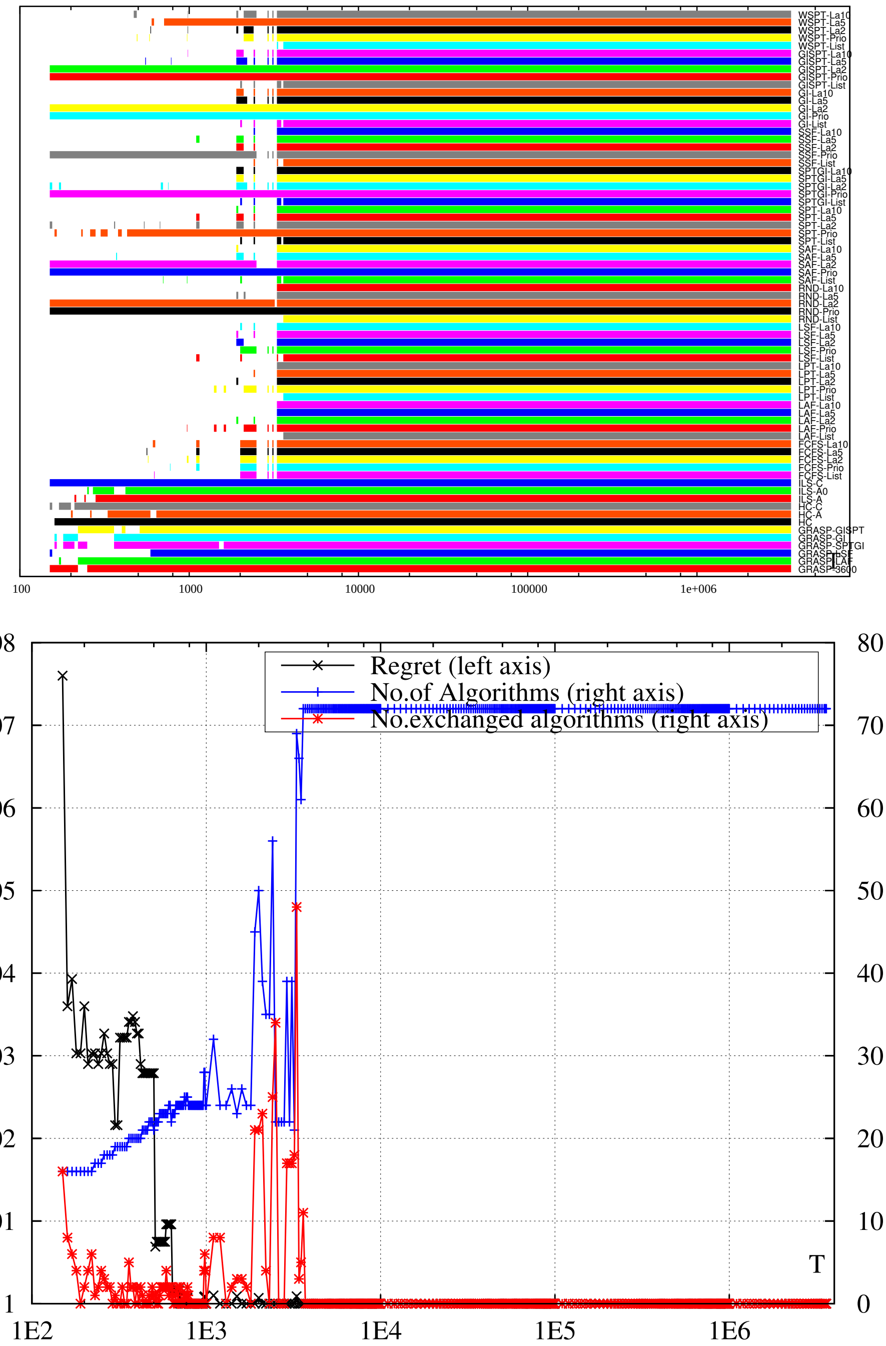


Figure 21: Algorithm portfolio built on all random instances M (dataset 3), $Cost = 16T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

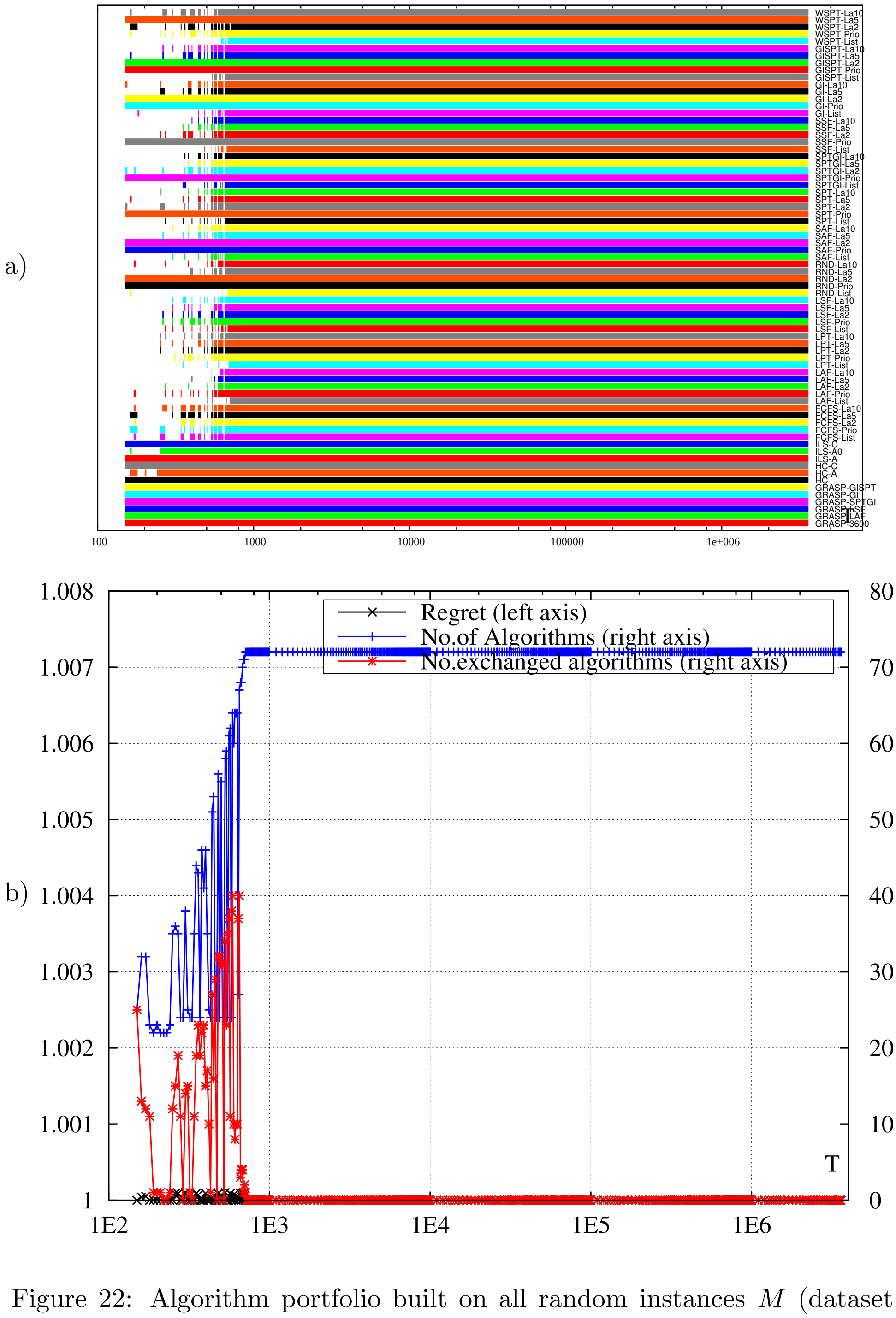


Figure 22: Algorithm portfolio built on all random instances M (dataset 3), $Cost = 32T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

6 Regret portfolios for $m = 2$ random instances M (dataset 4)

a)

b)

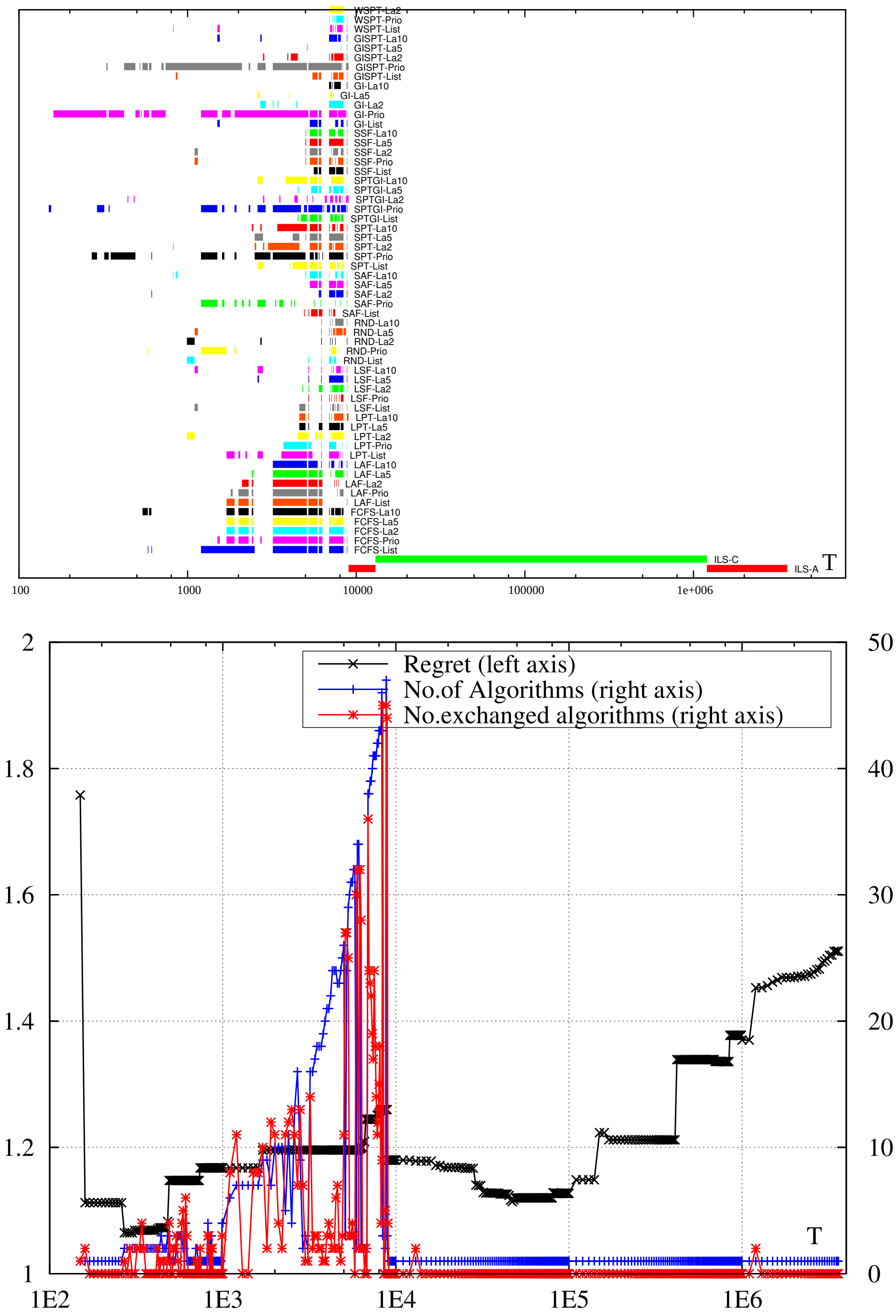
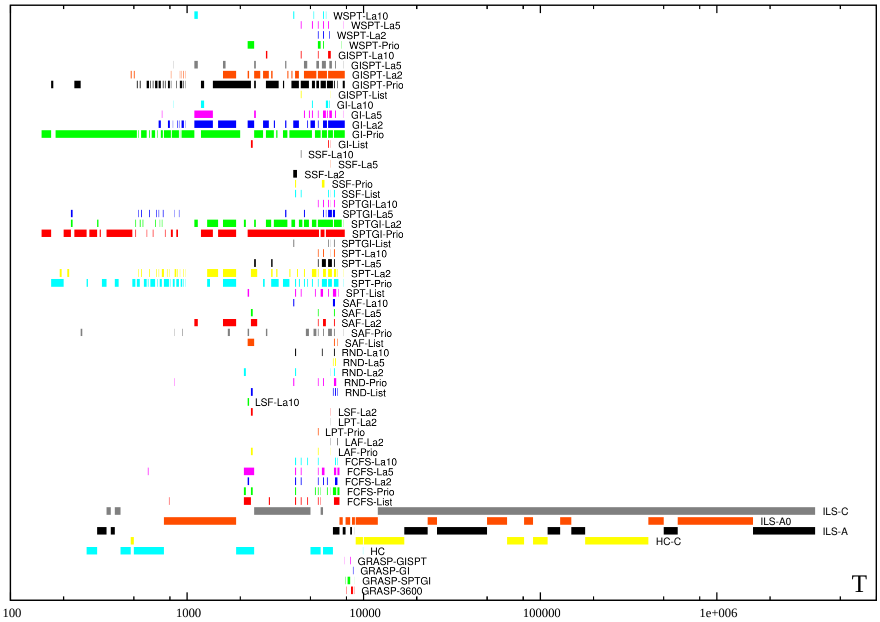


Figure 23: Algorithm portfolio built on random instances M, with $m = 2$ (dataset 4) $Cost = 1T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)



b)

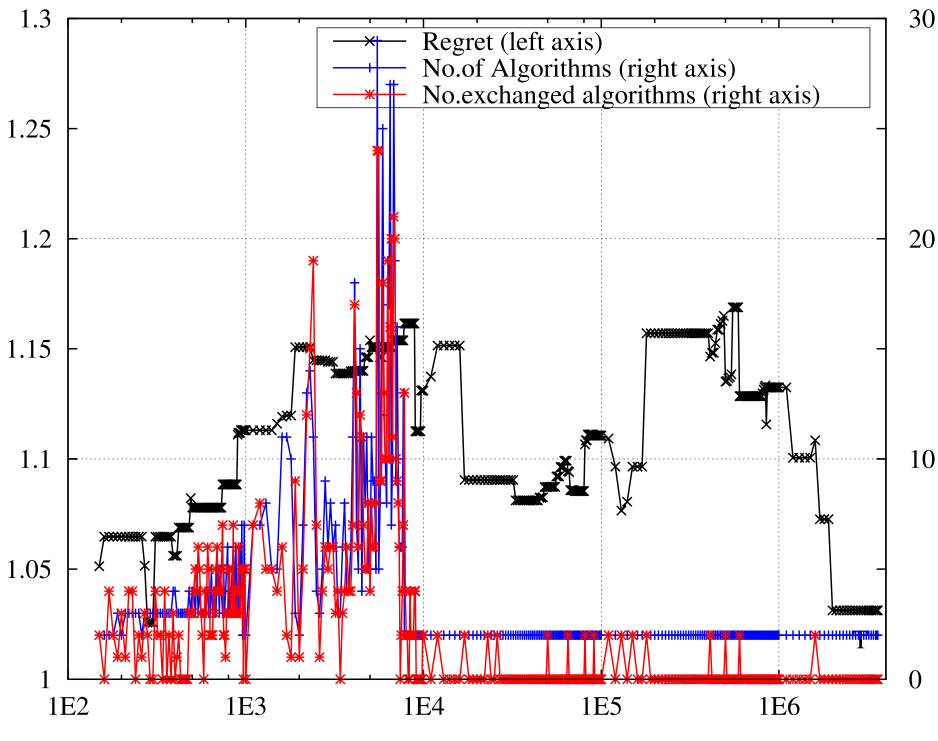


Figure 24: Algorithm portfolio built on random instances M, with $m = 2$ (dataset 4) $Cost = 2T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)

b)

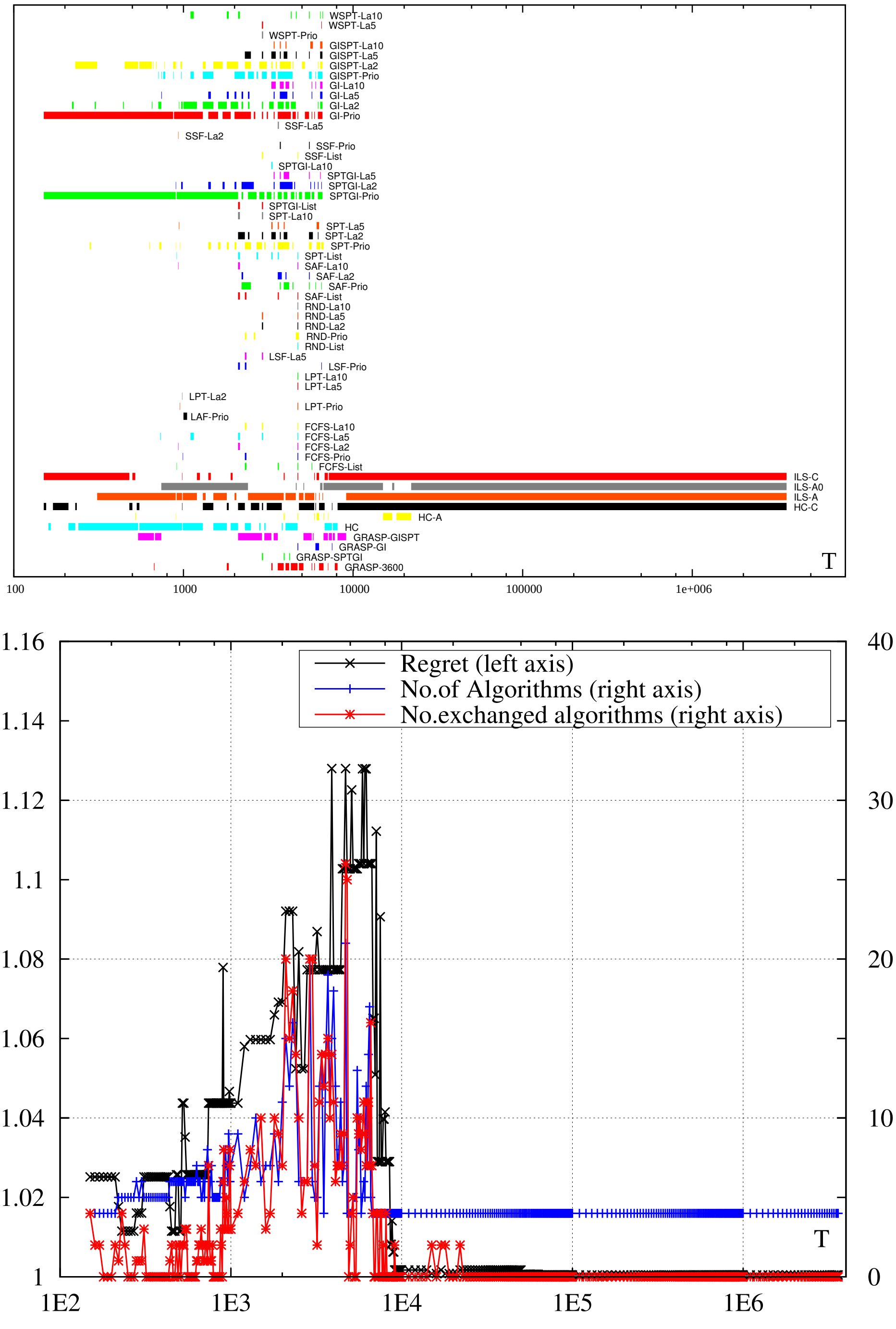


Figure 25: Algorithm portfolio built on random instances M, with $m = 2$ (dataset 4) $Cost = 4T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)
b)

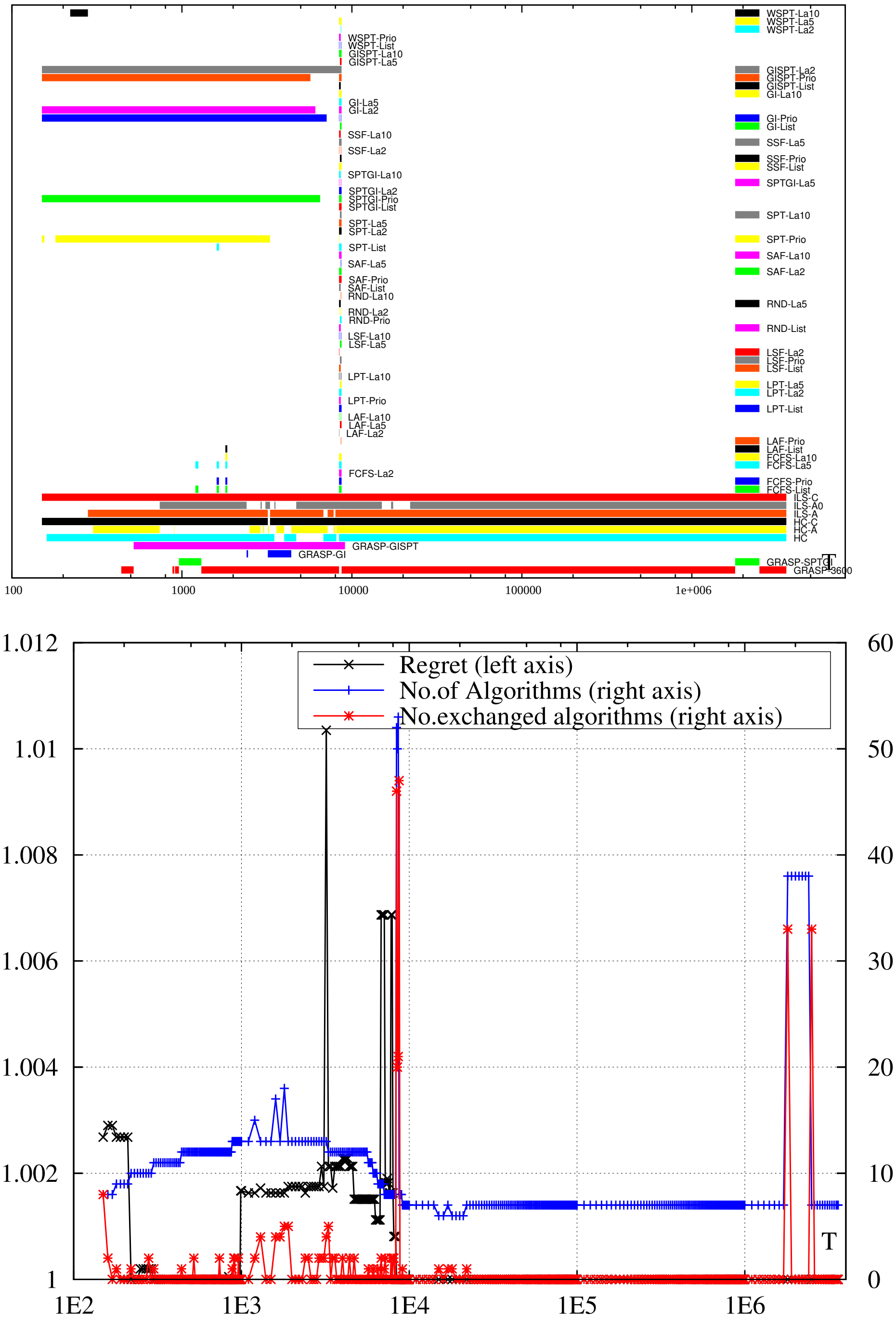


Figure 26: Algorithm portfolio built on random instances M, with $m = 2$ (dataset 4) $Cost = 8T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)

b)

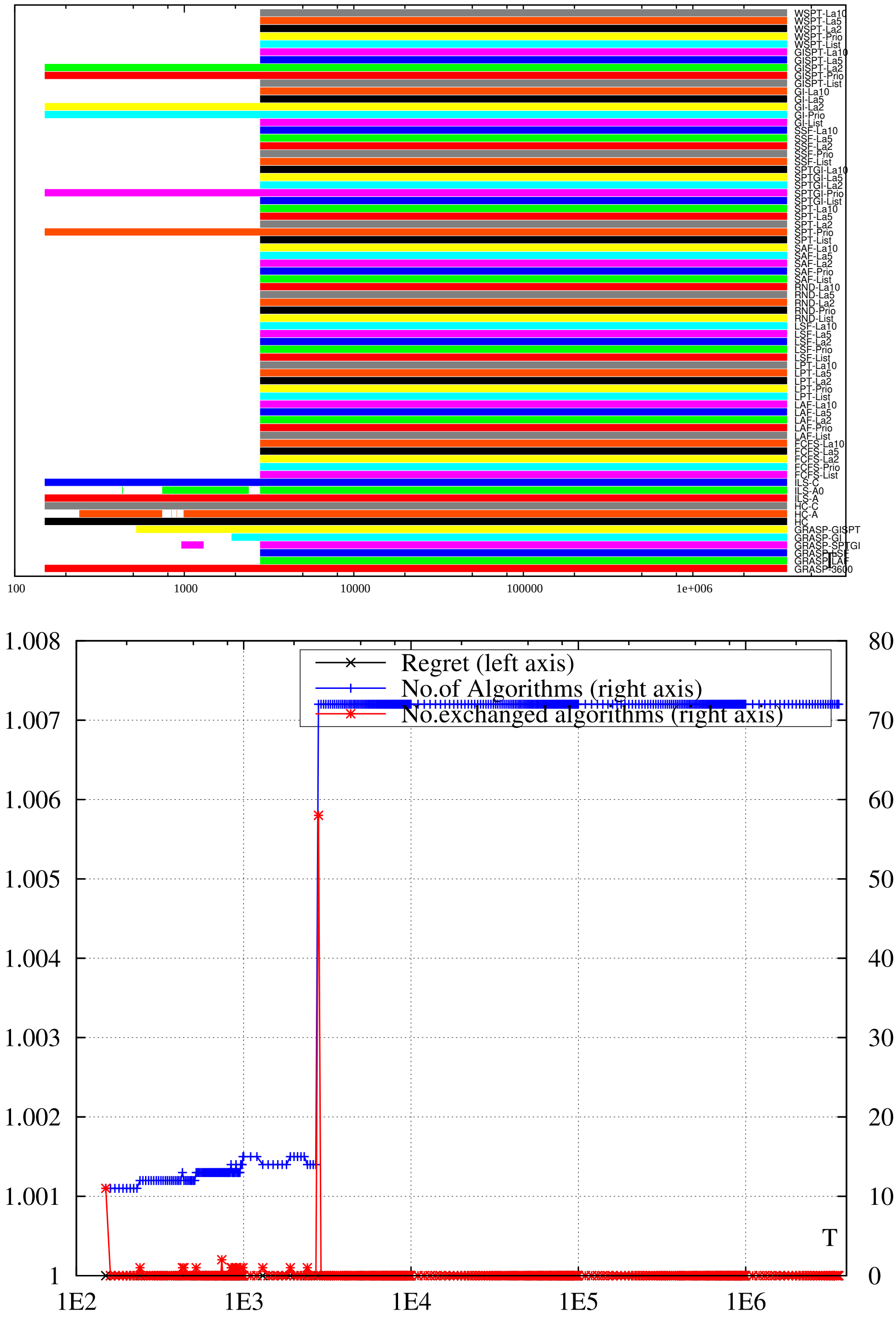


Figure 27: Algorithm portfolio built on random instances M, with $m = 2$ (dataset 4) $Cost = 16T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

a)

b)

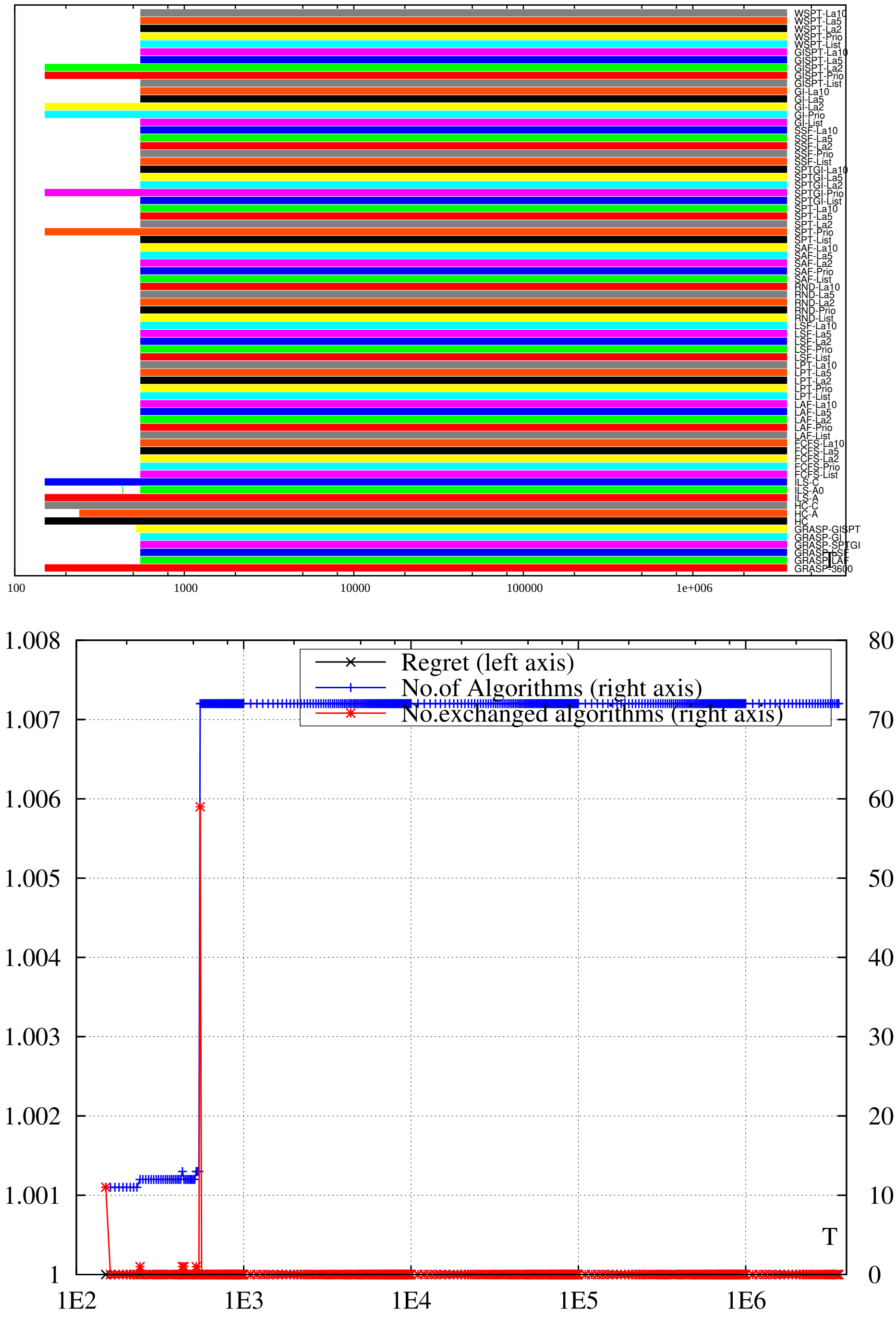


Figure 28: Algorithm portfolio built on random instances M, with $m = 2$ (dataset 4) $Cost = 32T$. a) portfolio evolution in time T, b) scores of the portfolio (regret, number of algorithms, number of algorithms exchanged), vs T.

7 Comparison of regret portfolio scores

In this section regret portfolios scores for $Cost = 1T, 2T, 4T, 8T$ are put together for an easier comparison.

a)

b)

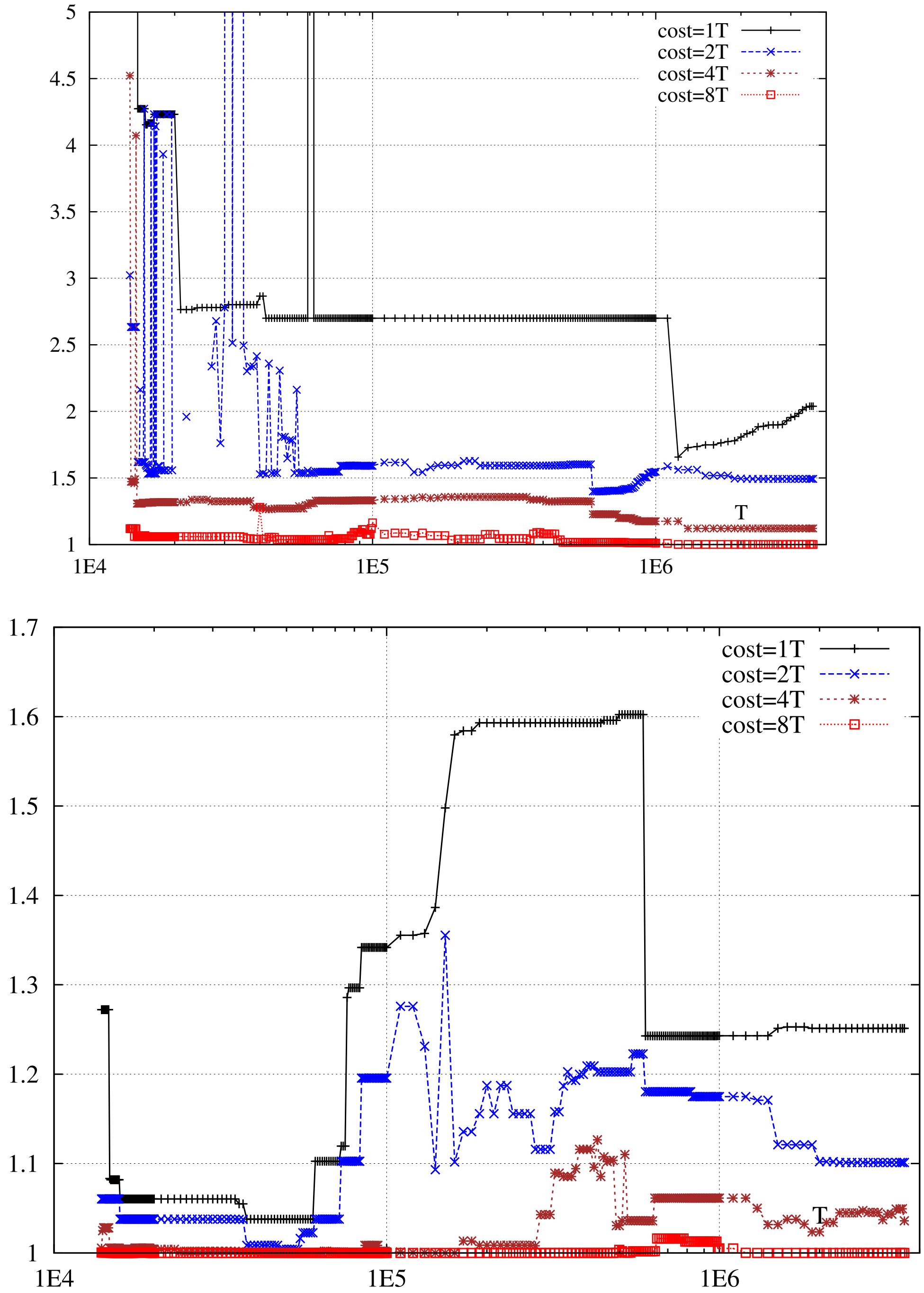


Figure 29: Comparison of regret portfolio regret scores built on random instances N. a) All random instances N (dataset 1), b) random instances N with $n = 10000$ (dataset 2).

a)

b)

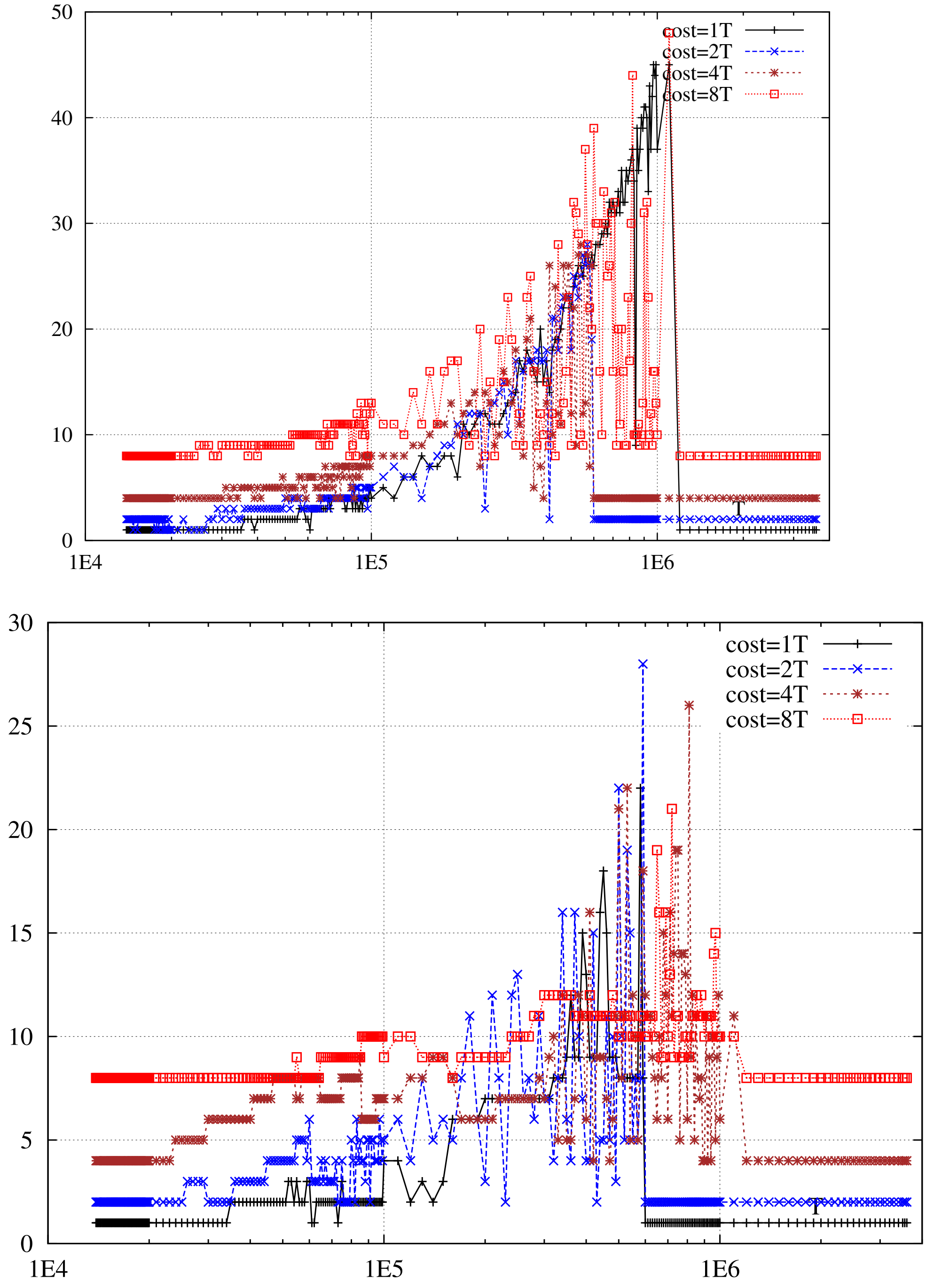
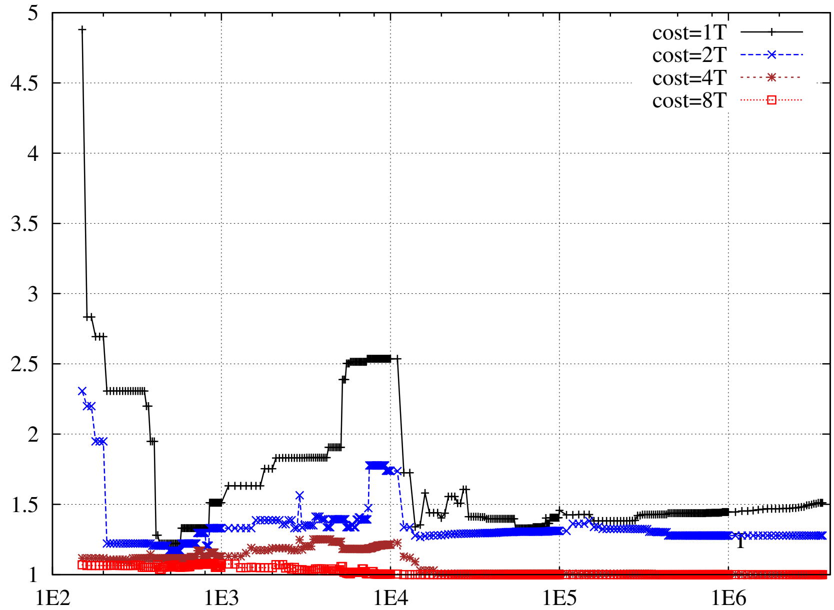


Figure 30: Comparison of the number of algorithms in the regret portfolios built on random instances N. a) All random instances N (dataset 1), b) random instances N with $n = 10000$ (dataset 2).

a)



b)

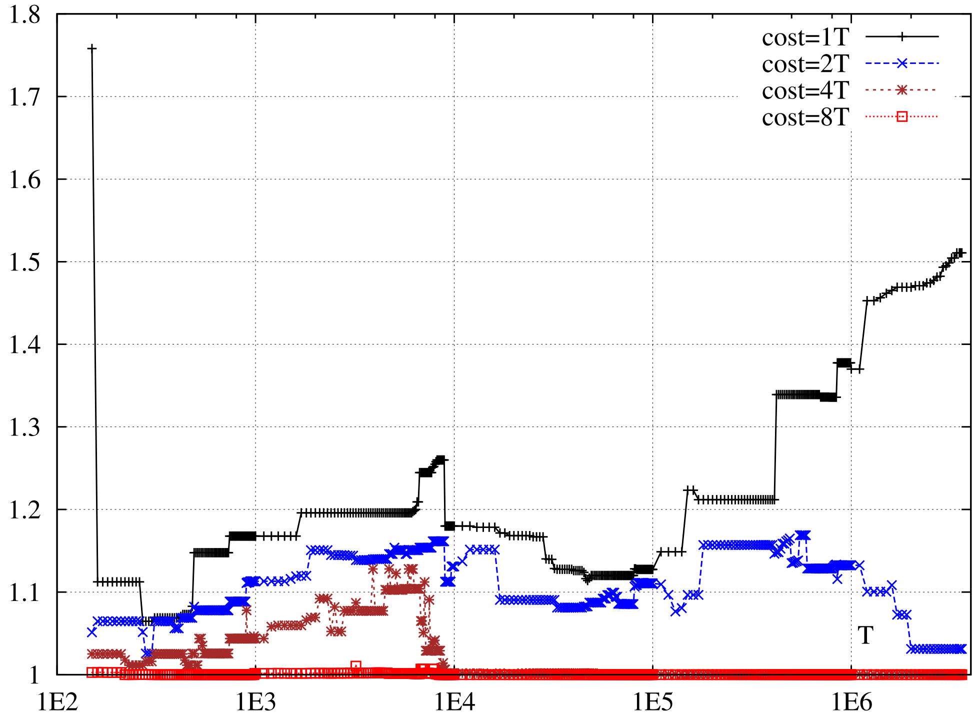


Figure 31: Comparison of regret portfolio regret scores built on random instances M. a) All random instances M (dataset 3), b) random M with $m = 2$ (dataset 4).

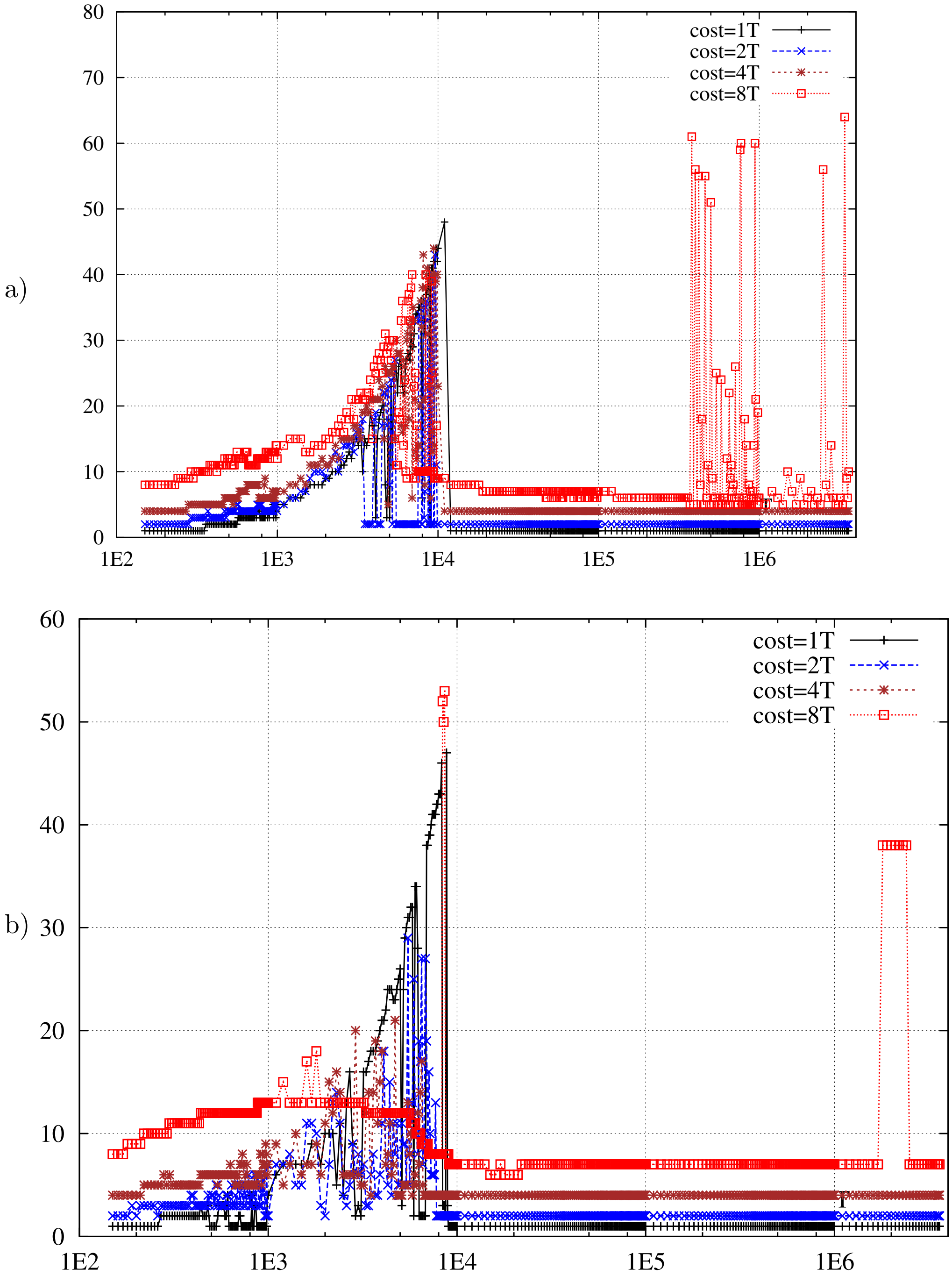


Figure 32: Comparison of the number of algorithms in the regret portfolios built on random instances M. a) All random instances M (dataset 3), b) random M with $m = 2$ (dataset 4).

8 Real Instance Portfolios (dataset 5)

In Fig.33b the lines of the cost (in T units) and the number of algorithms overlap. This means that the algorithms in the cover portfolio built for the real instances run in the whole time interval T.

It can be seen if Fig.38 and Fig.39 the cost limits $16T$ and $32T$ are not really binding for big T, and all algorithms are selected to the portfolio.

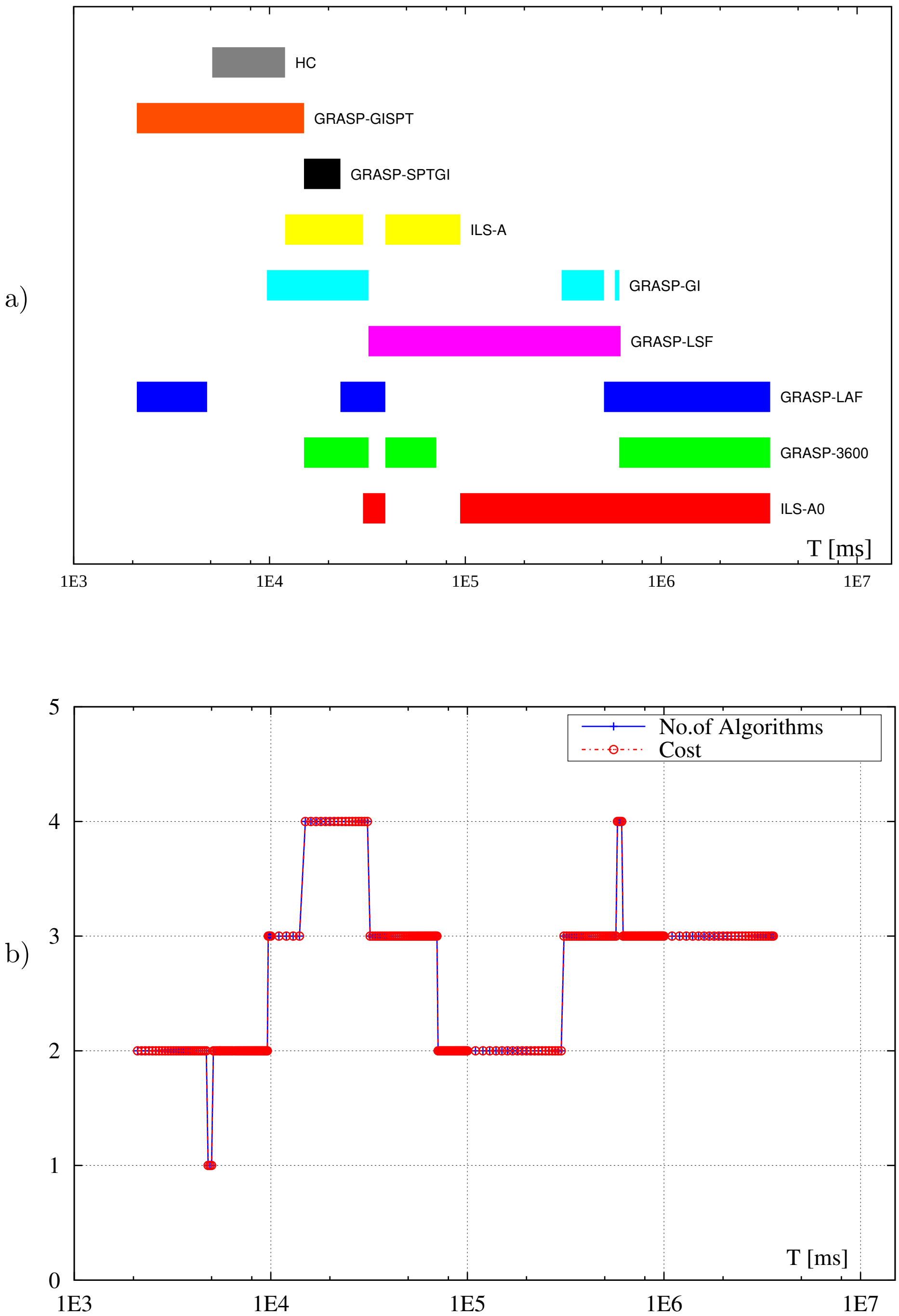
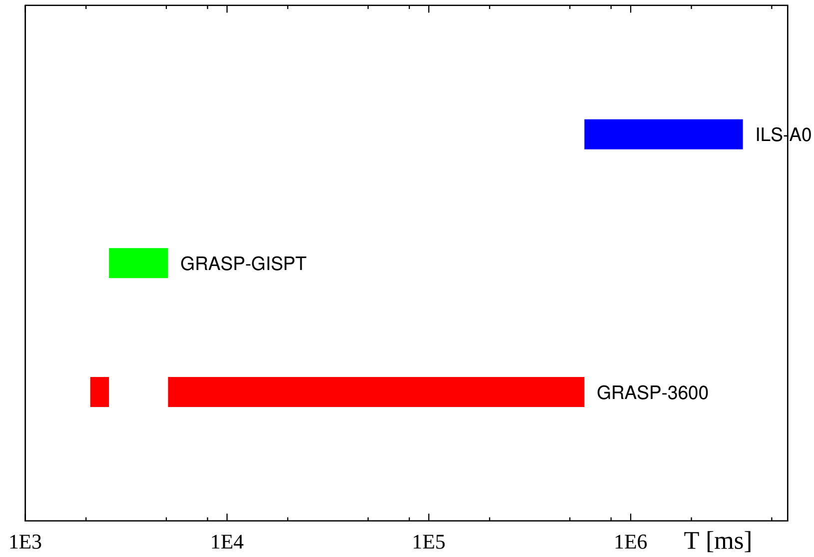


Figure 33: Cover portfolio built on real instances (dataset 5). a) portfolio evolution in time T, b) scores of the portfolio (number of algorithms, $Cost$ in T units, vs T.

a)



b)

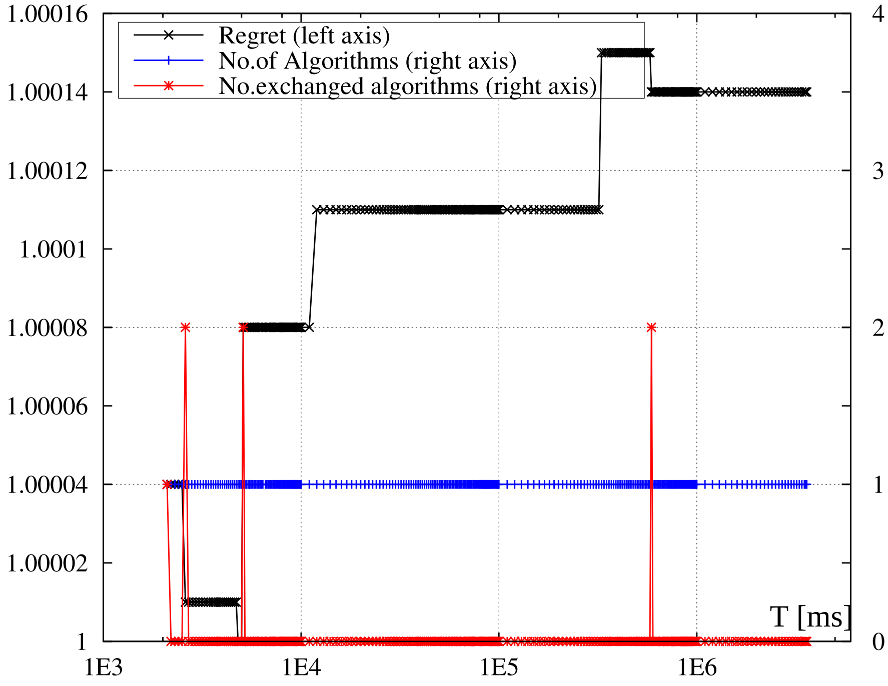
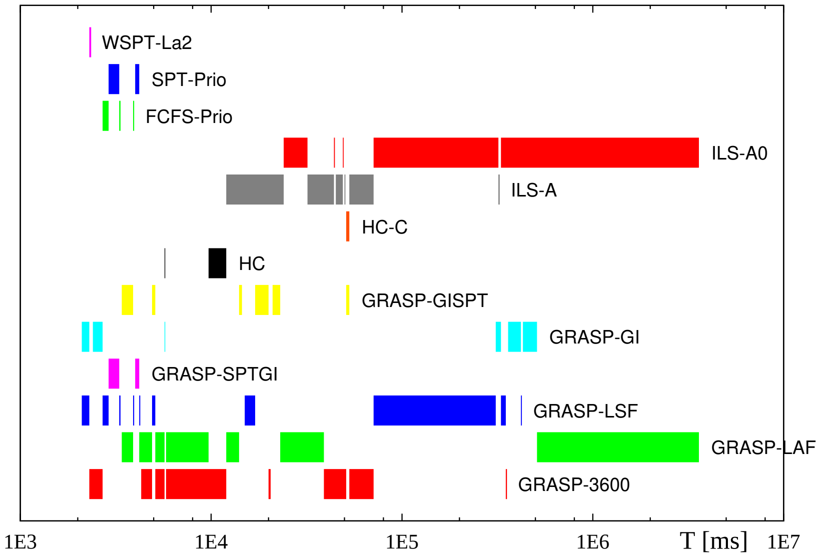


Figure 34: Regret portfolio built on real instances (dataset 5) $Cost = 1T$. a) portfolio evolution in time T, b) scores of the portfolio (number of algorithms, $Cost$ in T units, number of algorithms exchanged algorithms) vs T.

a)



b)

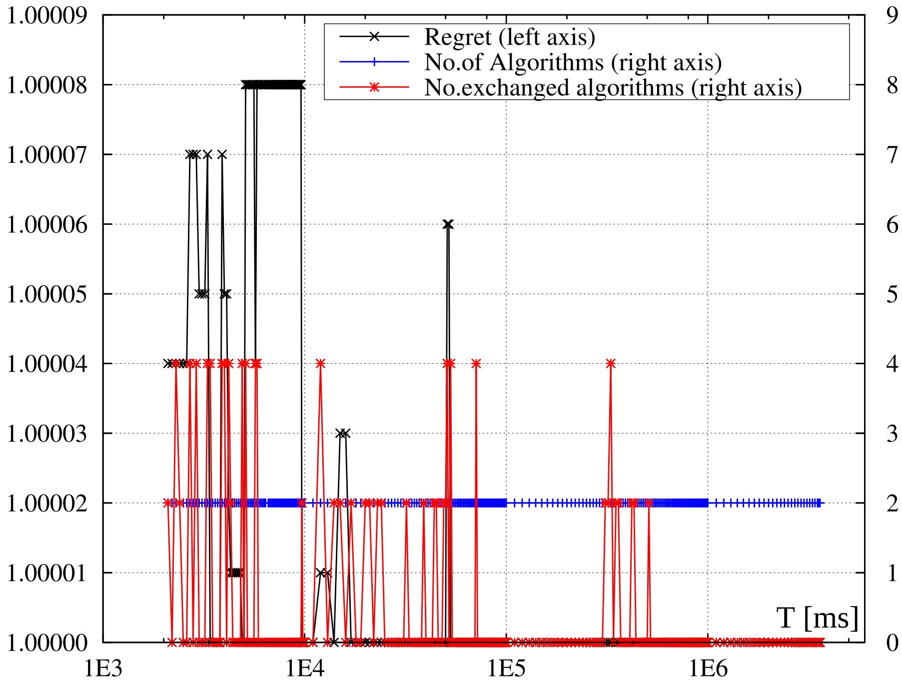


Figure 35: Regret portfolio built on real instances (dataset 5) $Cost = 2T$. a) portfolio evolution in time T, b) scores of the portfolio (number of algorithms, $Cost$ in T units, number of algorithms exchanged algorithms) vs T.

a)

b)

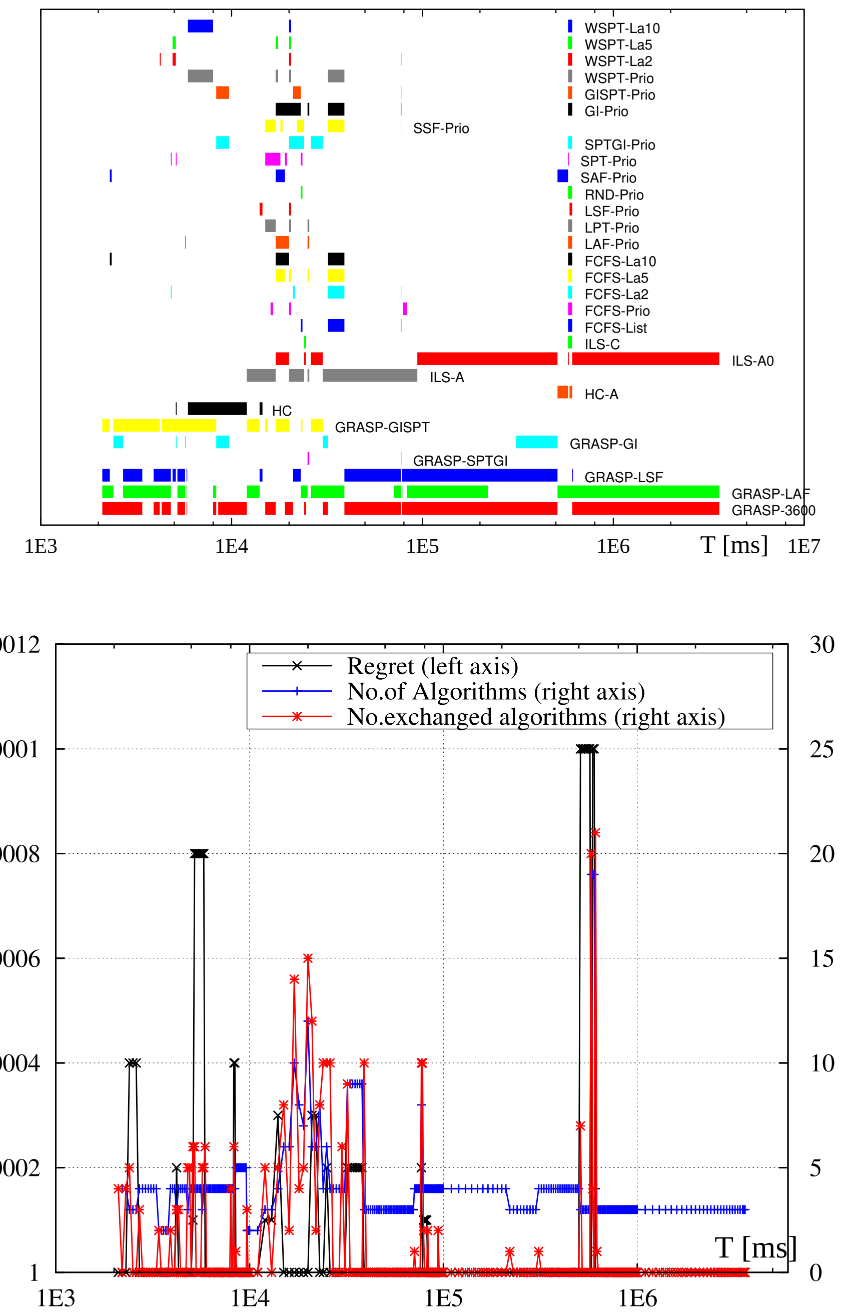
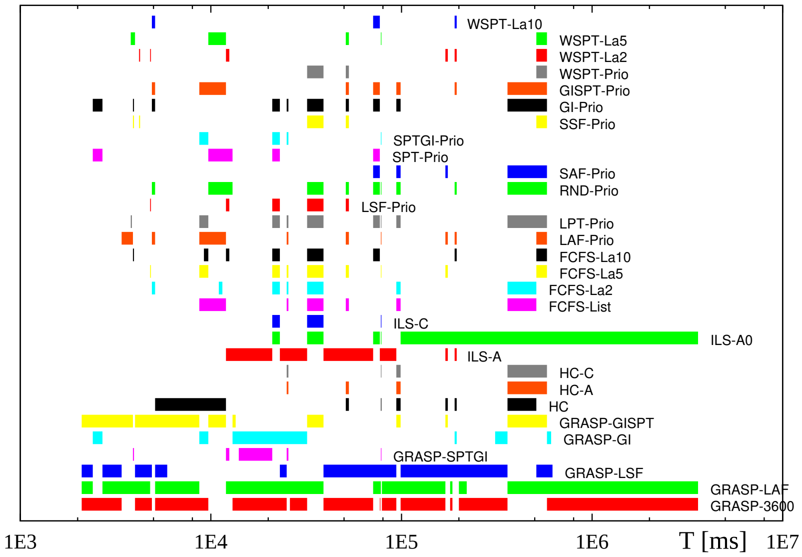


Figure 36: Regret portfolio built on real instances (dataset 5) $Cost = 4T$. a) portfolio evolution in time T, b) scores of the portfolio (number of algorithms, $Cost$ in T units, number of algorithms exchanged algorithms) vs T.

a)



b)

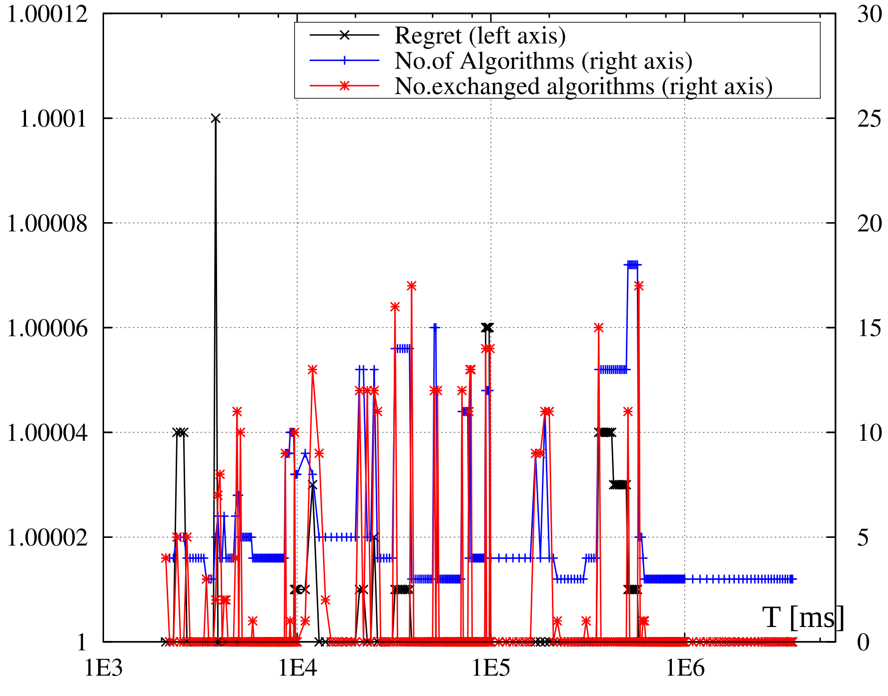


Figure 37: Regret portfolio built on real instances (dataset 5) $Cost = 8T$. a) portfolio evolution in time T, b) scores of the portfolio (number of algorithms, $Cost$ in T units, number of algorithms exchanged algorithms) vs T.

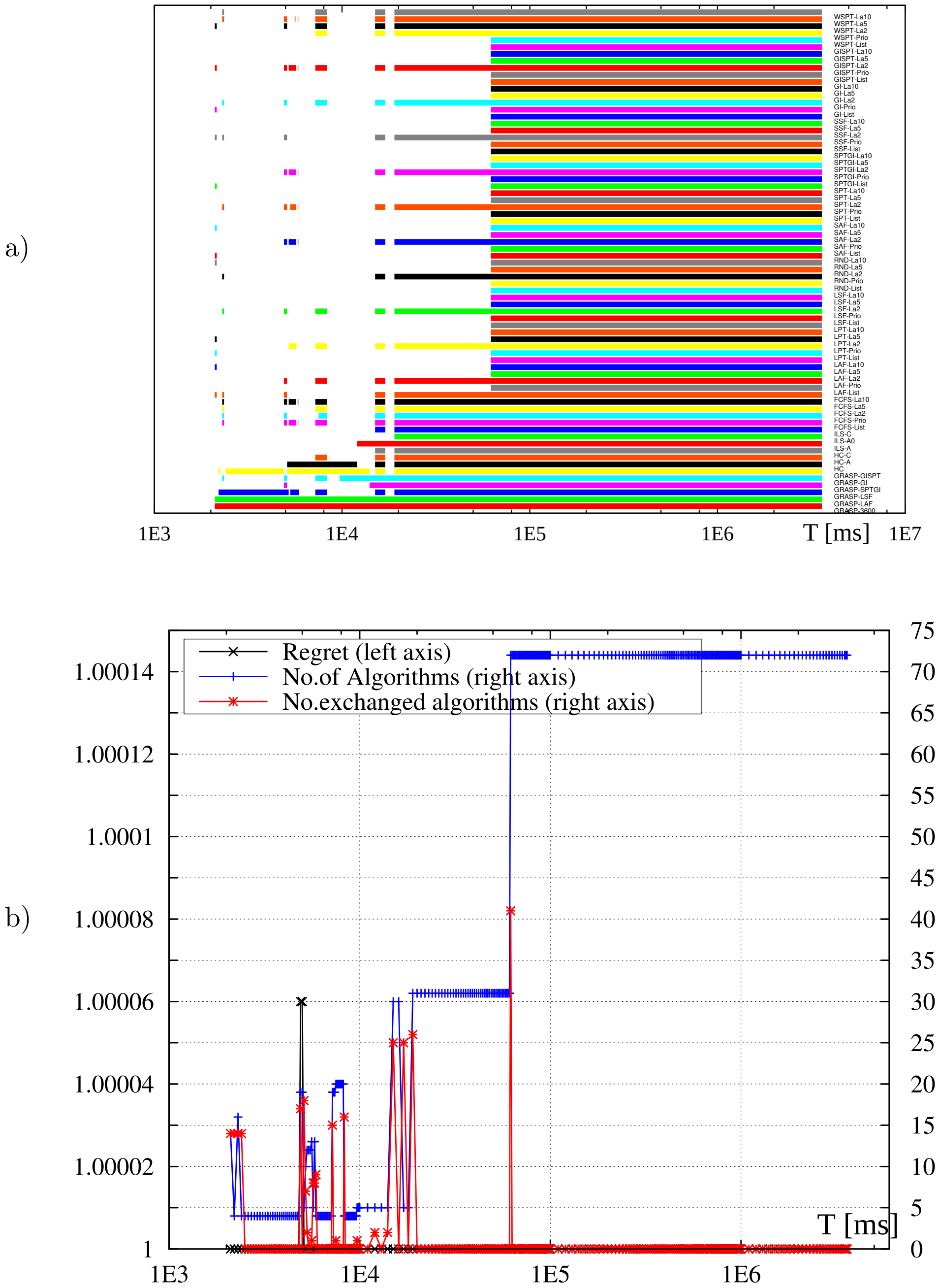
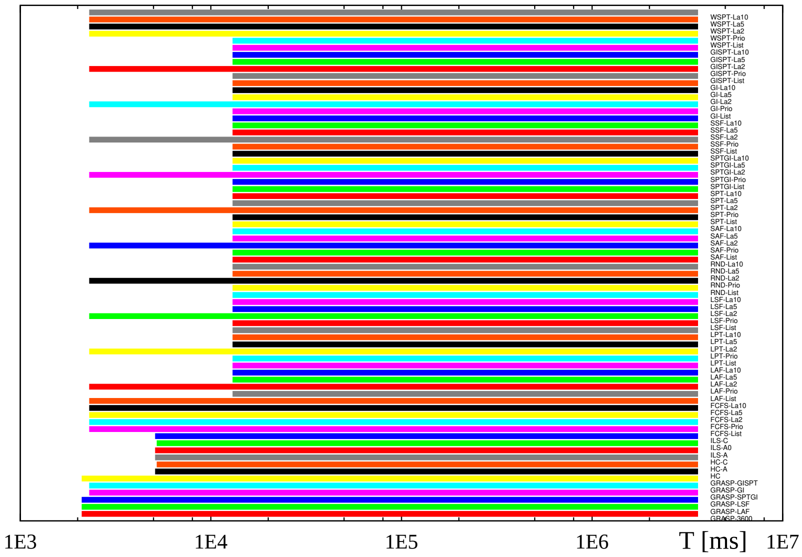


Figure 38: Regret portfolio built on real instances (dataset 5) $Cost = 16T$. a) portfolio evolution in time T, b) scores of the portfolio (number of algorithms, $Cost$ in T units, number of algorithms exchanged algorithms) vs T.

a) 

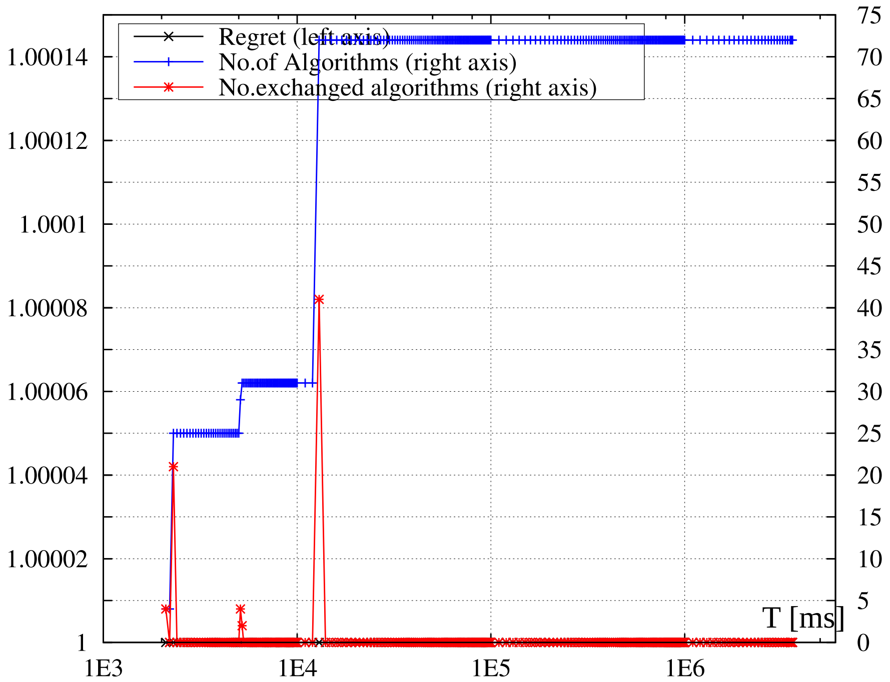
b) 

Figure 39: Regret portfolio built on real instances (dataset 5) $Cost = 32T$. a) portfolio evolution in time T, b) scores of the portfolio (number of algorithms, $Cost$ in T units, number of algorithms exchanged algorithms) vs T.

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