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The Master-Slave Paradigm with Heterogeneous Processors

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2 Problem statement and solutions on an heterogeneous platform:

- Without any communication cost
- With an initial scattering of data
- With initial and final communications
- With communications before each task
- With communications both before and after each task

3 Related work

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Master-slave tasking

Master-slave tasking Simple yet widely used technique.

Standard implementation Independent tasks executed by identical processors (the slave) under the centralized supervision of a control processor (the master).

Heterogeneous implementation Slave processors have different computation speeds.

Applications Any Monte Carlo simulation:

- ~> cellular microphysiology [SBSS98],
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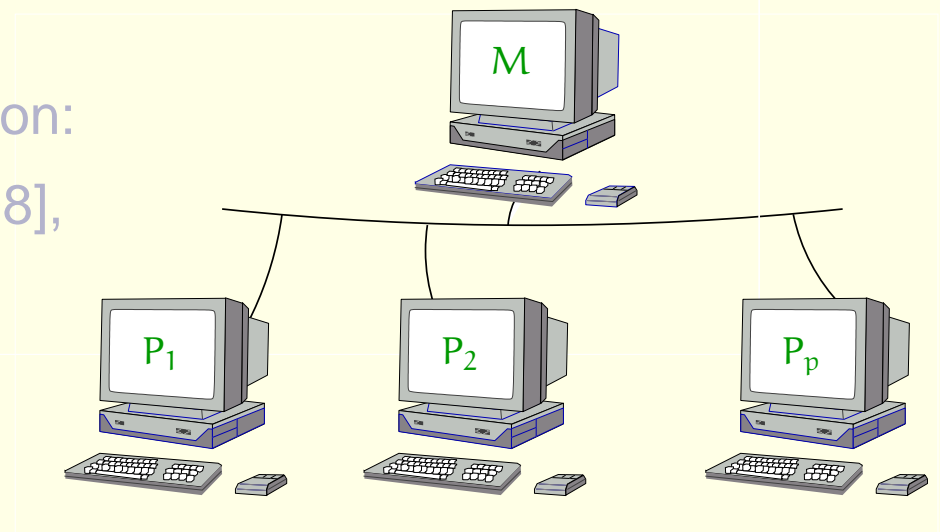
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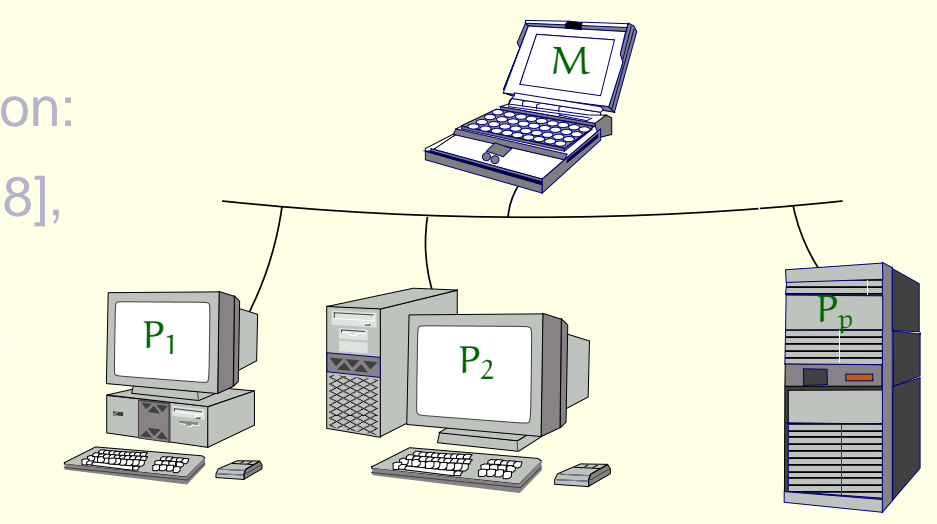
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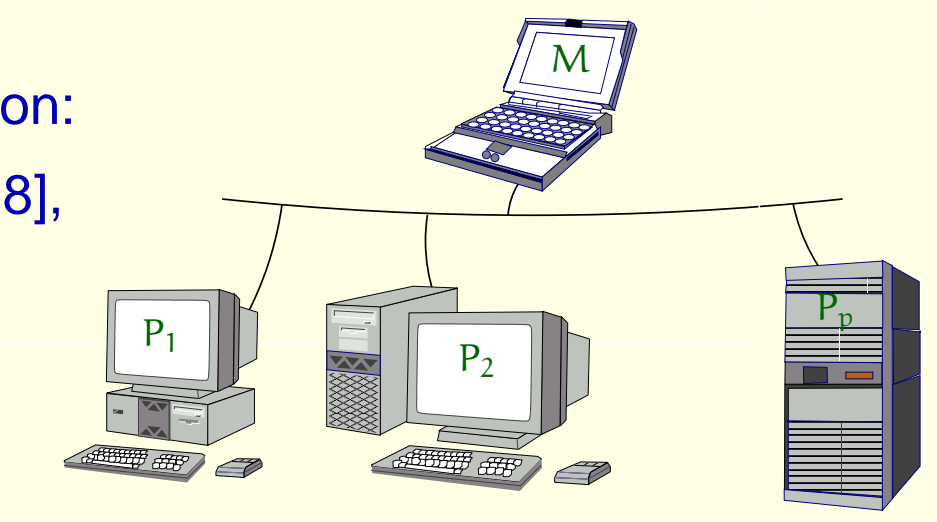
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- Pool of independent tasks to be processed by the p slaves.
- All tasks are of same-size, i.e. they represent the same amount of processing.
- Tasks are considered to be atomic (execution cannot be preempted once initiated).
- Communication through a shared medium, that can be accessed only in exclusive mode.

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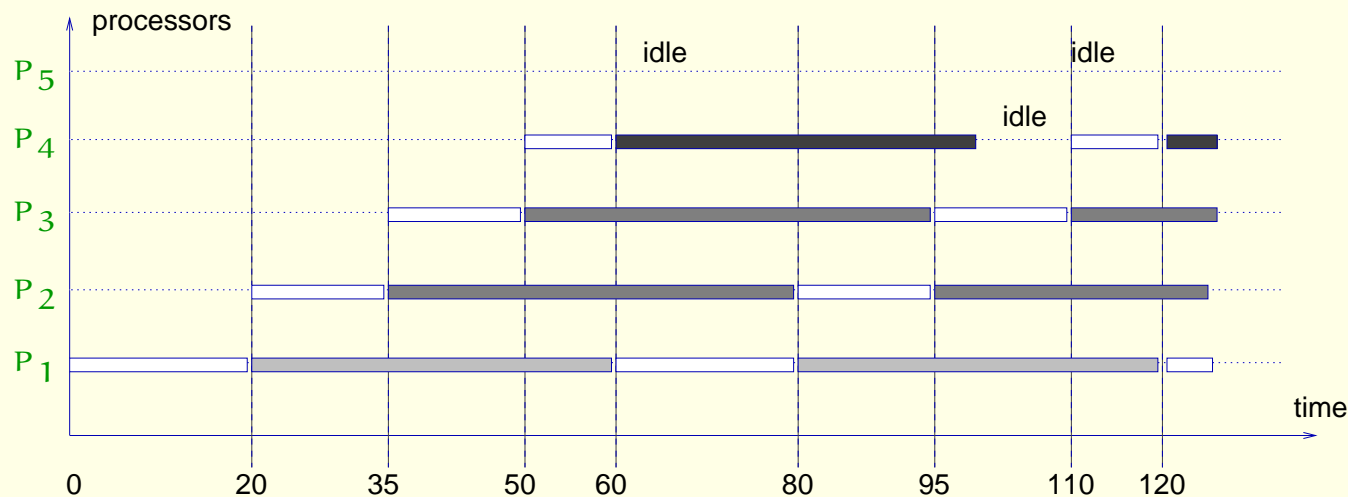
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Heterogeneous platform : Optimization problems

Processors are heterogeneous: slave P_i requires t_i units of time to process a single task. Each P_i will execute c_i tasks (where c_i is to be determined) from the pool.

MinTime(C) Given a total number of tasks C , determine the best allocation of tasks to slaves, i.e. the allocation $\mathcal{C} = \{c_1, c_2, \dots, c_p\}$ s.t. $\sum_{i=1}^p c_i = C$ and which minimizes the total execution time.

MaxTasks(T) Given a time bound T , determine the best allocation of tasks to slaves, i.e. the allocation $\mathcal{C} = \{c_1, c_2, \dots, c_p\}$ s.t. all processors complete their execution within T units of time and $\sum_{i=1}^p c_i = C$ is maximized.

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Without any communication cost

Assume first that there is no communication cost at all. It is not difficult to solve both previous problems using a greedy algorithm.

The solution of problem **MaxTasks(T)** is straightforward: we let $c_i = \left\lfloor \frac{T}{t_i} \right\rfloor$ for all i , $1 \leq i \leq p$, which obviously defines the optimal solution.

With an initial scattering of data

Problem statement

Formulation of this problem is taken from Andonie et al. [ACGG98] (implementation of distributed backpropagation neural networks on heterogeneous networks of workstations).

- each slave must receive some data file from the master processor
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What are we looking for?

- A permutation σ which determines the ordering of the messages from the host: the host sends data to slave P_i at time $\sigma(i)t_{\text{com}}$
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Solution from Andonie et al. [ACGG98]

They restrict the search to allocations where the fastest processors start computing first.

They use a dynamic programming algorithm to solve the optimization problem **MinTime(C)**.

With our setting for problem **MaxTasks1(T)**, this amounts to sort the cycle-times as $t_1 \leq t_2 \leq \dots \leq t_p$ and to let $\sigma(i) = i$ for $1 \leq i \leq p$.

The intuition is that fastest processors execute tasks more rapidly than the others, hence they should work longer.

The intuition is misleading in some cases:

$$t_1 = 5, t_2 = 9 \text{ and } t_{\text{com}} = 1.$$

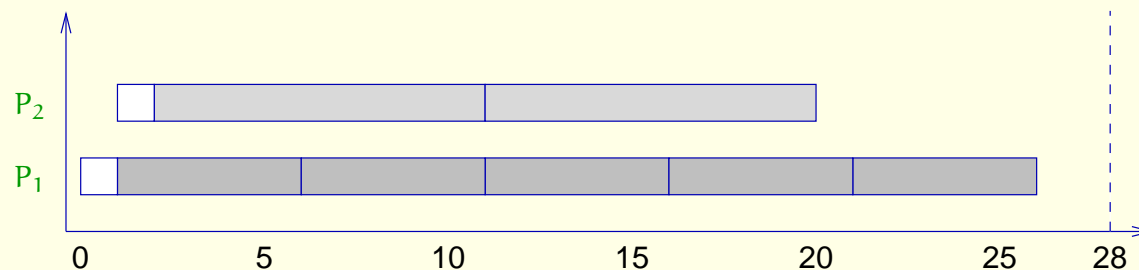
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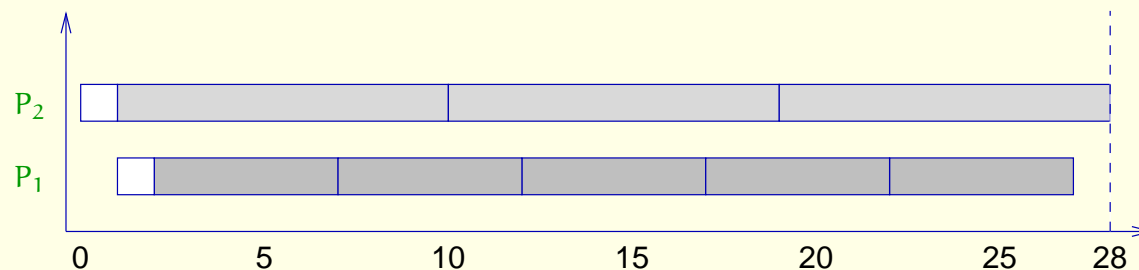
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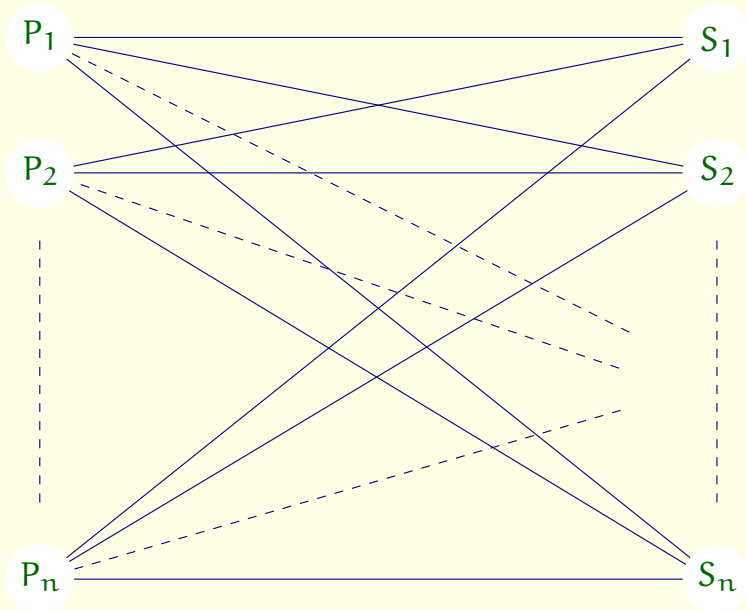
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Optimal solution



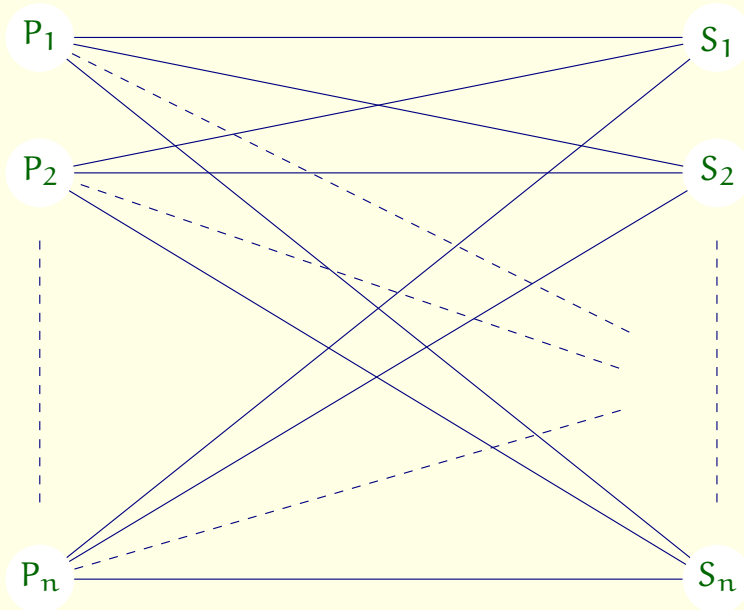
Bipartite graph for **MaxTasks1(T)**.

$$w(P_i, S_j) = \begin{cases} \text{maximum number of tasks} \\ \text{that } P_i \text{ can execute if } \sigma(i) = j \end{cases}$$
$$= \left\lfloor \frac{T - j t_{\text{com}}}{t_i} \right\rfloor$$

Solving **MaxTasks1(T)** reduces to finding the maximum weighted matching in the bipartite graph.

Proposition 1. *The optimal solution to the **MaxTasks1(T)** problem with initial messages can be found in time of order $O(p^3)$ with p processors using some classical algorithm ([GM84, Wes96]) to find the maximum weighted matching in a bipartite graph*

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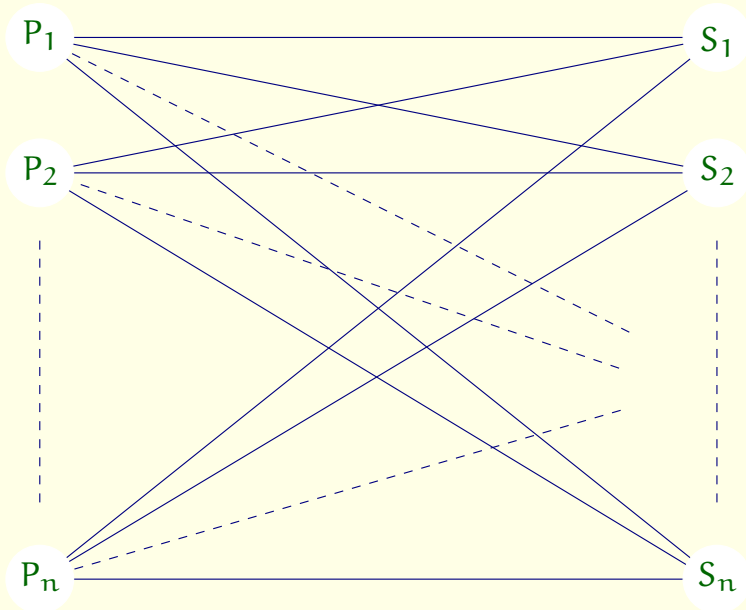
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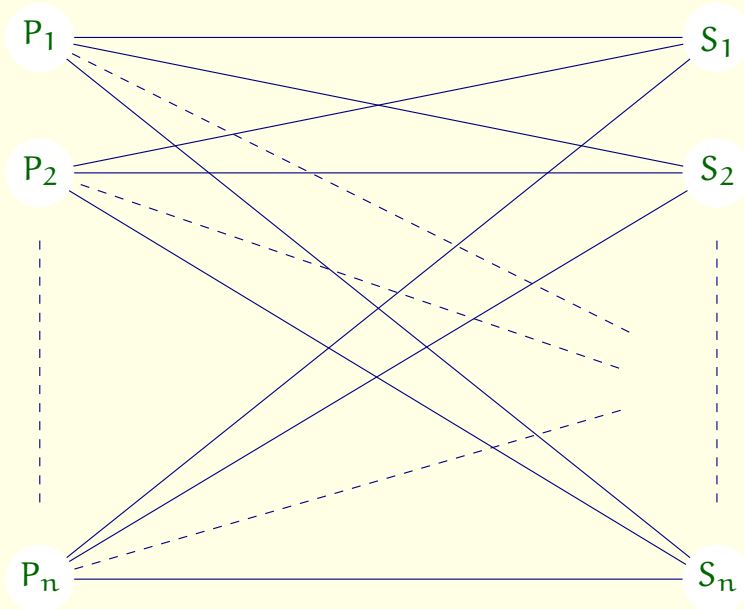
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With initial and final communications

Problem statement

Some results have been produced by the slaves or the master need some feedback on the computation:

- each slave must receive some data file from the master processor and send some results back after the processing \leadsto two communication costs: t_{com}^1 and t_{com}^2
- slave P_i process one task in t_i units of time

What are we looking for?

- A first permutation σ_1 which determines the ordering of the initial messages from the host: the host sends data to slave P_i at time $\sigma_1(i)t_{\text{com}}^1$
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MaxTasks2(T): Given a time bound T , determine the best allocation of tasks to slaves, i.e. two permutations σ_1 and σ_2 , and an allocation $\mathcal{C} = \{c_1, c_2, \dots, c_p\}$ s.t. all processors complete their execution within T units of time and the total number of tasks is maximized:

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- The solution to the MaxTasks2(T) problem with initial and final messages turns out to be surprisingly difficult.
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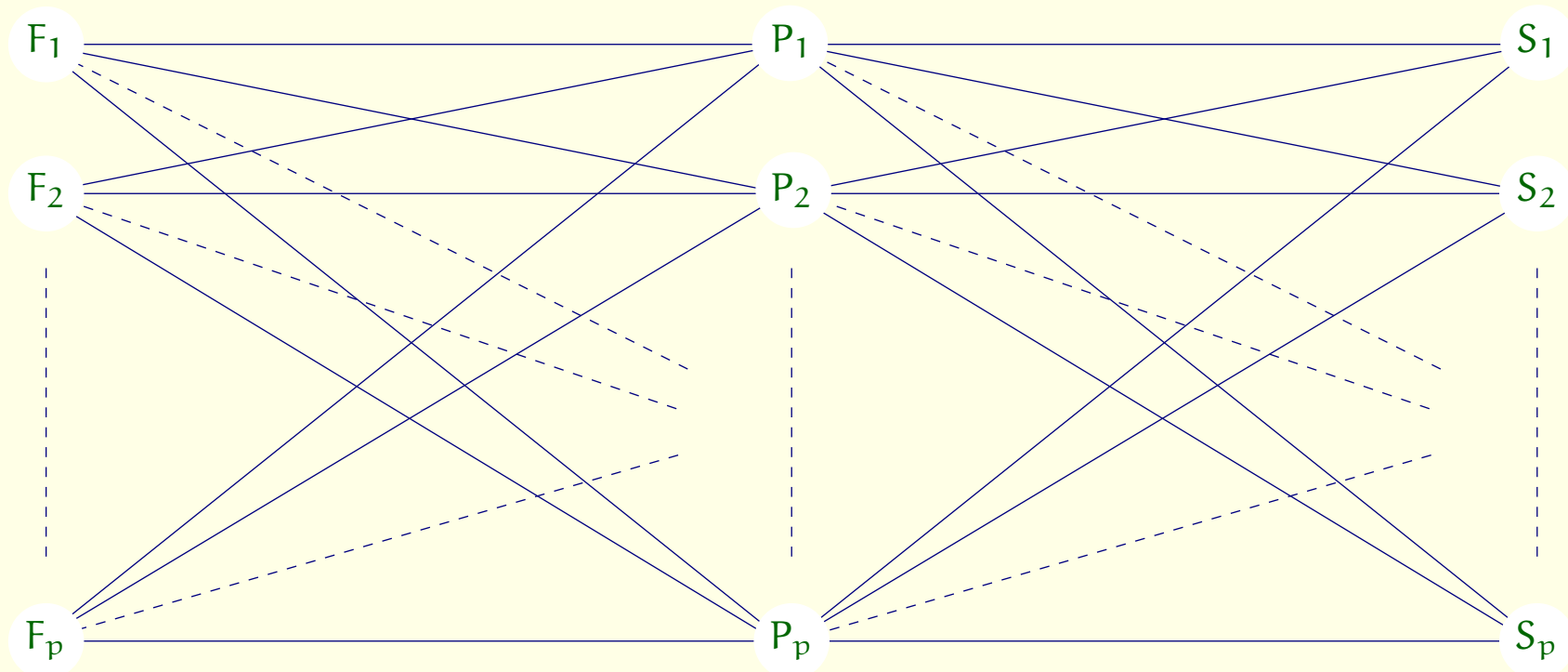
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- The solution to the MaxTasks2(T) problem with initial and final messages turns out to be surprisingly difficult.
- We do not know of any polynomial algorithm for the general case \leadsto efficient guaranteed approximation using matching techniques.

2-factor in a Tripartite graph



Tripartite graph with initial and final communications.

F_i 's correspond to σ_1 and S_i 's correspond to σ_2 . Rather than a matching, we extract a 2-factor from the graph. The complexity of extracting 2-factor from the graph with $3p$ vertices is of order $O(p^3)$ again.

Edge weights approximation

The problem is that edge weights cannot be determined fully accurately; the inequality $\sigma_1(i)t_{\text{com}}^1 + c_i t_i + \sigma_2(i)t_{\text{com}}^2 \leq T$ translates into

$$c_i \leq \left\lfloor \frac{T - \sigma_1(i)t_{\text{com}}^1 - \sigma_2(i)t_{\text{com}}^2}{t_i} \right\rfloor,$$

and we need to know both $\sigma_1(i)$ and $\sigma_2(i)$ to compute c_i . Instead, we use the approximation

$$\left\lfloor \frac{T/2 - \sigma_1(i)t_{\text{com}}^1}{t_i} \right\rfloor + \left\lfloor \frac{T/2 - \sigma_2(i)t_{\text{com}}^2}{t_i} \right\rfloor.$$

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A word on complexity

Is **MaxTasks2(T)** NP-complete?

It is as difficult as the following open (polynomial vs. NP-complete) problem in combinatorial optimization (see [Hed]):

Permutation Sums: Let $a_1 \leq a_2 \leq \dots \leq a_p$ be p positive integers satisfying $\sum_{i=1}^p a_i = p(p+1)$. Do there exist two permutations σ_1 and σ_2 of $\{1, 2, \dots, n\}$ such that

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With communications before each
task processing

Problem statement

Each task has its own description file:

- communications are required between the master and the slave before the processing of each task \rightsquigarrow each reception costs t_{com} units of time
- slave P_i process one task in t_i units of time

MaxTasks3(T): Given a time bound T , determine the best allocation of tasks to slaves, i.e. three functions $f_{\text{startcomm}}$, $f_{\text{startcomp}}$ and f_{proc} s.t. all processors complete their execution within T units of time and the total number of tasks is maximized:

$$\max (N \mid \forall i \leq N, f_{\text{startcomp}}(i) + t_{f_{\text{proc}}(i)} \leq T)$$

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Asymptotically optimal algorithm

Since MaxTasks3(T) is probably NP, we slightly change the problem and look for the maximum steady-state throughput of our platform.

- determining a pattern for communications and computations, that will be reproduced periodically throughout the execution
- two different cases whether the communication network is the limiting resource or not
- $\frac{t_{com}}{t_{com} + t_i}$ represent the ratio of the communication involved by processor P_i
- the value of $\sum_{i=1}^p \frac{t_{com}}{t_{com} + t_i}$ enable to know in which situation we are

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Network is not limiting: $\sum_{i=1}^p \frac{t_{\text{com}}}{t_{\text{com}} + t_i} \leq 1$

- All processors have to be fully used.
- $\tau_i = t_{\text{com}} + t_i$, for $1 \leq i \leq p$
- Let T^{pattern} be the least common multiple of these p values τ_i : T^{pattern} determines the length of the pattern.
- Let $\nu_i^{\text{pattern}} = \frac{T^{\text{pattern}}}{\tau_i}$

$$t_{\text{com}} = 1$$

$$t_1 = 2$$

$$t_2 = 3$$

$$t_3 = 5$$

$$t_4 = 5$$

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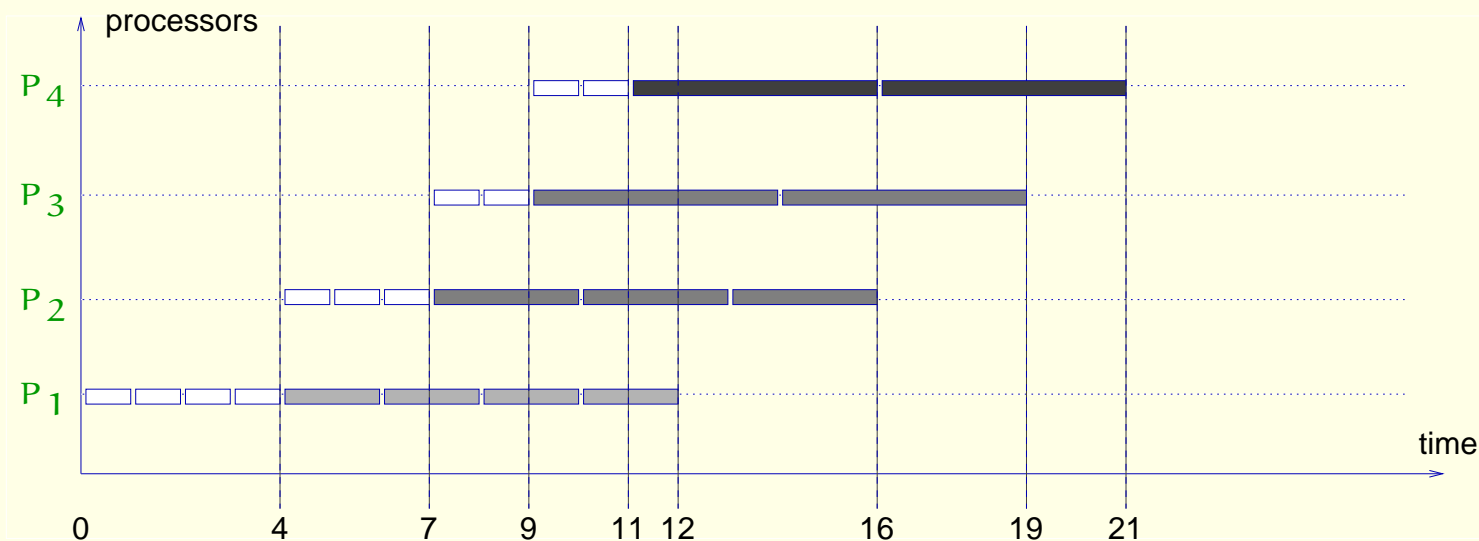
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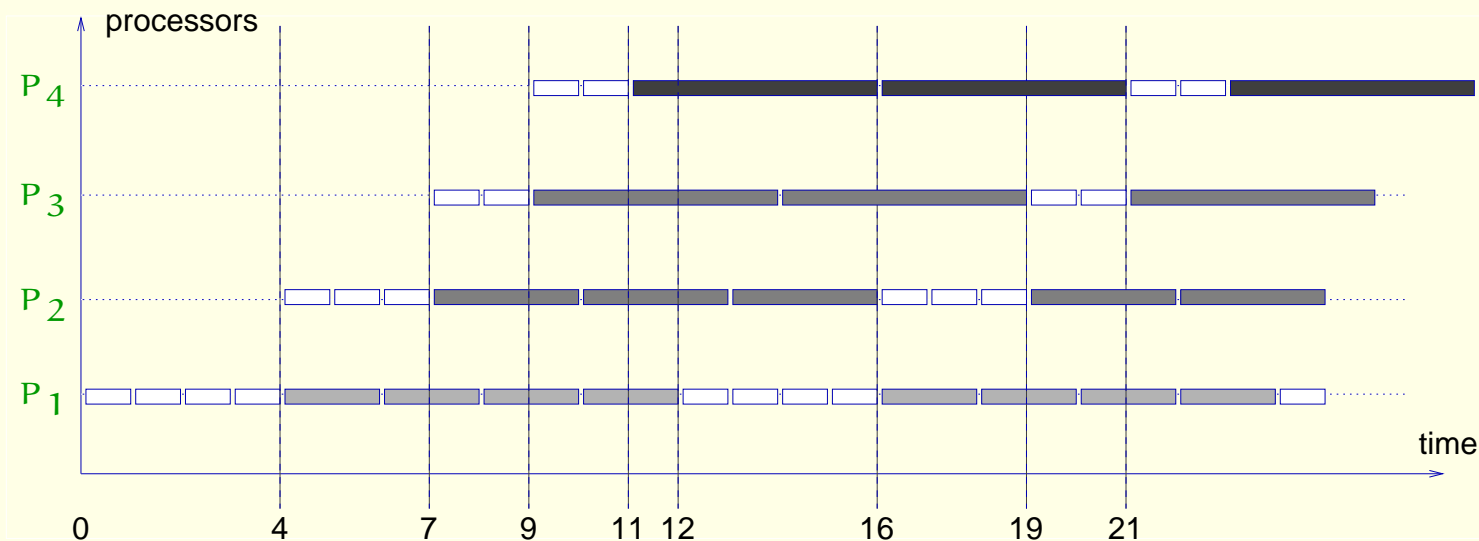
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Network is the limiting resource: $\sum_{i=1}^p \frac{t_{\text{com}}}{t_{\text{com}} + t_i} > 1$

- The communication link has to always be in use: some nodes will be kept idle, some will be kept busy and one processor will be partly idle.
- Sort the cycle-times of the slave processors and assume that $t_1 \leq t_2 \leq \dots \leq t_p$. Define τ_i as before and let

$$p_{\max} = \max \left\{ k \mid \sum_{i=1}^k \frac{t_{\text{com}}}{t_{\text{com}} + t_i} \leq 1 \right\}.$$

- T^{pattern} and the v_i^{pattern} 's are defined in the same way as before

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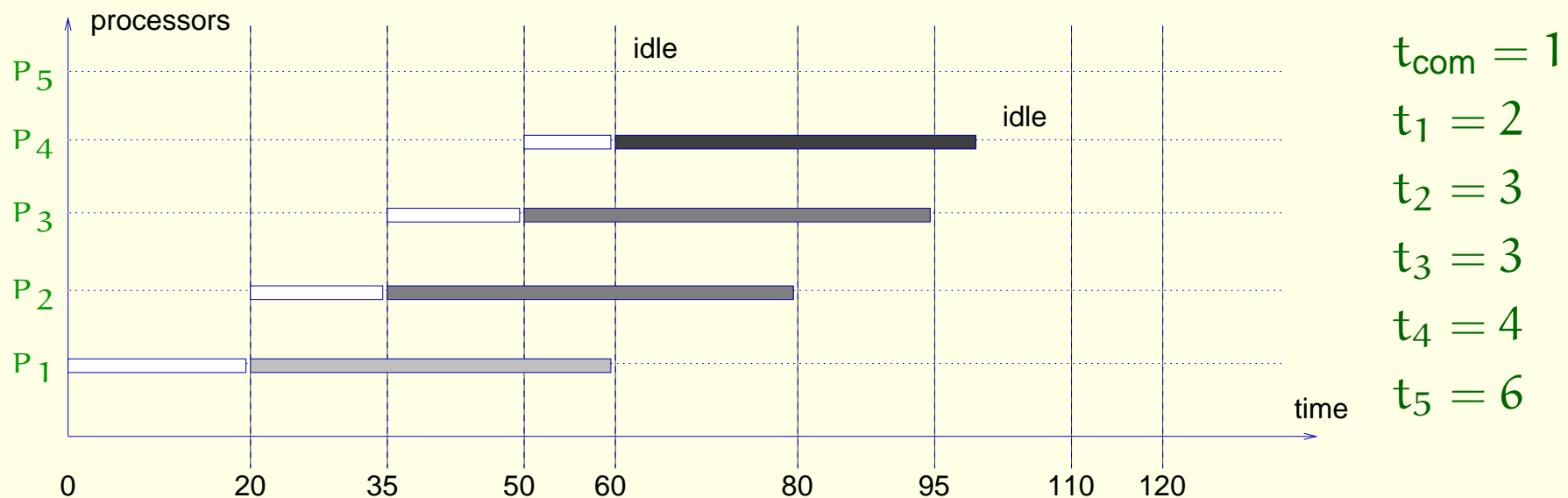
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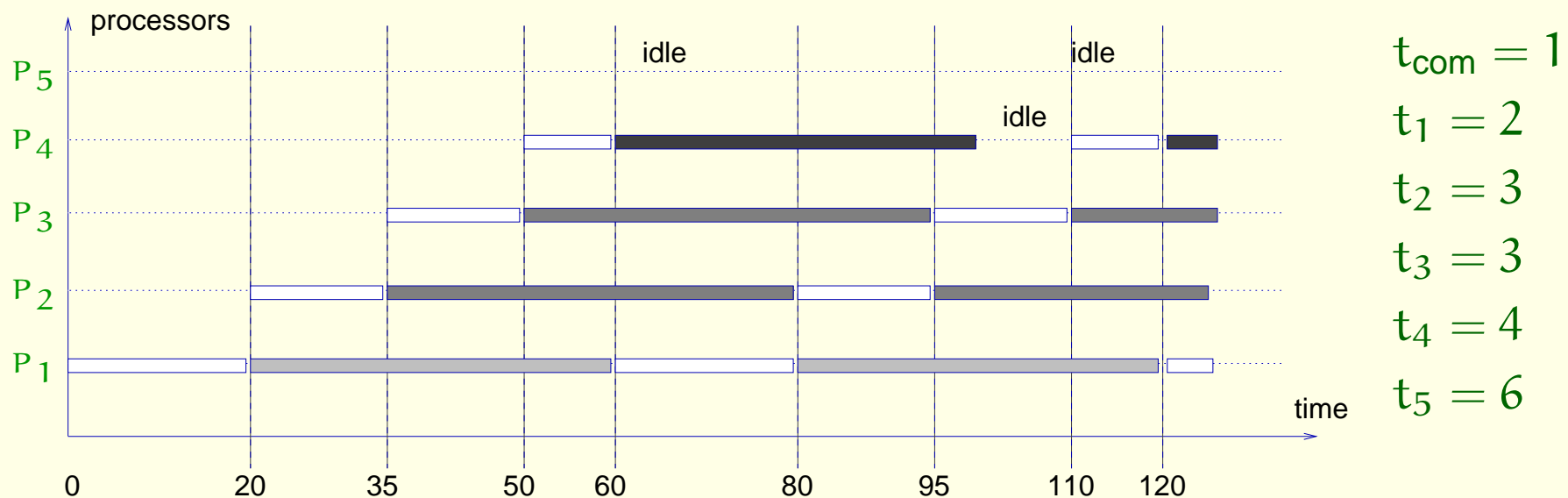


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Asymptotical optimality

Theorem 2 ([BLR01]). Let $N_{\text{opt}}(T)$ be the optimal number of tasks that can be executed within T time-steps. Let $N(T)$ be the number of tasks executed by the first algorithm if $\sum_{i=1}^p \frac{t_{\text{com}}}{t_{\text{com}} + t_i} \leq 1$, and by the second algorithm if $\sum_{i=1}^p \frac{t_{\text{com}}}{t_{\text{com}} + t_i} > 1$. Then

$$\lim_{T \rightarrow \infty} \frac{N(T)}{N_{\text{opt}}(T)} = 1.$$

With communications both before
and after each task processing

Problem statement

- communications are required between the master and the slave both before and after the processing of each task \rightsquigarrow two communication costs: t_{com}^1 and t_{com}^2
- slave P_i process one task in t_i units of time

Use the previous algorithm with $t_{\text{com}} = t_{\text{com}}^1 + t_{\text{com}}^2$

Theorem 3. *Let $N_{\text{opt}}(T)$ be the optimal number of tasks that can be executed within T time-steps, and let $N(T)$ be the number of tasks executed by our algorithm. Then*

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Related Work

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- parallel machine problems with a server : several complexity (NP-completeness) results [HPS00, KW97, BDFK⁺00] and providing guaranteed approximations [LG96] **MaxTasks1(T)** is a very special instance of this class of server problems
- **MaxTasks2(T)** is a special instance of the job-shop scheduling problem (see problem SS18 in [GJ91]). Because this instance is very specific, we do not know its complexity (polynomial versus NP-complete).
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Related Work

Our four problems differ from those studied in the literature with a server and start-up times in that

- all tasks are identical and independent,
- communication times (the counterpart of the set-up times) are identical too.

The difficulty lies solely in the heterogeneity of the computing resources.

Conclusion

- Deriving efficient algorithms for the simple master-slave paradigm, in the framework of heterogeneous computing resources, turns out to be surprisingly difficult.
- Optimal polynomial algorithm in the case of an initial scattering of data.
- Guaranteed polynomial approximation algorithm in the case of initial and final communications. We conjecture this problem to be intrinsically difficult even on (intuitively) simple instances.
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