



A Genetic Algorithm with Communication Costs to Schedule Workflows on a SOA-Grid

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Workflow applications

- Combine several applications or application modules
- Precedence constraints (Files)
- Application domaine:
 Astronomy, Bioinformatics,
 Chemistry, Climate Modeling,
 Computer Science, Image
 Processing, etc.
- Batch processing
- Collection of workflows





SOA Grids



- Provides applications access
- Execution on clusters
- Simple acess for scientists
- Tools : DIET or NINF-G





Contents

- Context
- Q GA Scheduling
- Simulation
- General Dags
- 6 Identical Intrees



Framework model

Applicative framework

- Collection $\mathcal{B} = \{\mathcal{J}^j, 1 \leq j \leq N\}$ of N workflows to schedule
- ullet Workflow \mathcal{J}^j is represented by a DAG $\mathcal{J}^j = (\mathcal{T}^j, \mathcal{D}^j)$
 - lacksquare $\mathcal{T}^j = \{T_1^j, \dots, T_{n_i}^j\}$: the tasks
 - \mathcal{D}^j : the precedence constraints
 - $F_{k,i}^j$ is the file sent between T_k^j and T_i^j when $(T_k^j, T_i^j) \in \mathcal{D}^j$
- $\mathcal{T}=\cup_{j=1}^N\mathcal{T}^j=\{T^j_{i_j},1\leq i_j\leq n_j \text{ and }1\leq j\leq N\}$: set to schedule
- Typed tasks : t(i,j) as the type of task T_i^j .



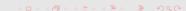




Framework model - 2

Target platform

- Platform PF : n machines modeled by an undirected graph $\mathcal{PF} = (\mathcal{P}, \mathcal{L})$
 - The vertices in $\mathcal{P} = \{p_1, \dots, p_n\}$ represent the machines
 - The edges of \mathcal{L} are the communication links
 - Each link (p_i, p_i) has a bandwidth $bw(p_i, p_i)$
- τ : set of task types available
 - Each machine p_i is able to perform a subset of τ .
 - $t \in \tau$ is available on the machine p_i , $w(t, p_i)$ is the time to perform a task of type t on p_i .
- a(i,j) is the machine on which T_i^j is assigned.







Framework model - 3

Communication model

- one-port model
 - one data transmitted / communication link
 - one reception and one transmission / node
- $lackbox{ } \mathcal{R}(p_k,p_i) = \{(p_i,p_{i'}) \in \mathcal{L}\} \text{ is a route from } p_k \text{ to } p_i.$

Problem definition

- Static scheduling
- Makespan optimization for the collection of worflows



Related works

Workflow Scheduling

- Makespan optimization : NP-Hard Problem
- List based heuristics: HEFT, Critical Path, etc.
- Difficult in heterogeneous contexts

Advanced algorithms

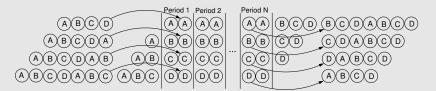
- GA for scheduling
 - GA give good results on complex systems
 - But still a heuristic, distance to optimal?
- Steady State :
 - flow optimization
 - identical intrees
 - optimal results





Steady-state Scheduling









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GA without communication costs

Classical GA for workflow:

- gene = task
- chromosome one row per processor
- phenotype = schedule
- fitness = 1/makespan
- population, generation, crossover, mutation ...

P0	Т0	T3	T4	P0	T0	T4
P1	Tl			P1	T3	Tl
P2	T2			P2	T2	

Do not take communication into account









With Communication Costs

Communications in the chromosome

- Communication task
- One row per communication link
- Dependencies to the source and target node -> inconsistent communications
- Poor efficiency

Evaluation function

- Communications depends upon tasks placement
- Fitness evaluation with comunication costs
- Used solution





Algorithm: fitness of a chromosome

```
Data: \mathcal{T}_{ToSched}: remaining tasks, C(T_i^j): completion time of T_i^j, \sigma(T_i^j): start
            time of T_i^j on p_{a(i,i)}, \delta(p_u): next time p_u is idle, w(t,p_i): the time to
            perform a task of type t on p_i, CT(F_{k,i}^j): the communication time to
           send F_{k,i}^{j} along route \mathcal{R}(p_{a(k,j)}, p_{a(i,j)})
\mathcal{T}_{ToSched} \leftarrow \mathcal{T}
while \mathcal{T}_{ToSched} \neq \emptyset do
       choose a free task T_i^l \in \mathcal{T}_{ToSched} (EFT heuristic)
       \mathcal{T}_{pred} \leftarrow \{ \mathcal{T}_{k}^{j} | (\mathcal{T}_{k}^{j}, \mathcal{T}_{i}^{j}) \in \mathcal{D}^{j} \} and \sigma(\mathcal{T}_{i}^{j}) \leftarrow 0
       foreach task T_k^j \in \mathcal{T}_{pred} do
        \sigma(T_i^j) \leftarrow \max(\sigma(T_i^j), C(T_k^j) + CT(F_{k,i}^j))
       \sigma(T_i^j) \leftarrow \max(\delta(p_{a(i,j)}), \sigma(T_i^j))
       C(T_i^j) \leftarrow \sigma(T_i^j) + w(t(i,j), p_{a(i,j)})
      \delta(p_{a(i,i)}) \leftarrow C(T_i^j) and \mathcal{T}_{ToSched} \leftarrow \mathcal{T}_{ToSched} \setminus \{T_i^j\}
return fitness(ch) = 1/C_{max} = 1/max_{T_i^j \in \mathcal{T}}(C(T_i^k))
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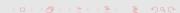
Experimental settings

Simulations

- SimGrid-MSG
- GA = 200 individuals

Platforms

- Random platform generation : uniform distribution
- Platform size : 4 to 10 nodes
- Homogeneous
- Heterogeneous
- CCR: communication to computation ratio









Experimental settings - 2

Applications

- Batch sizes from 1 to 10.000
- Applications: 4 to 12 tasks
- 1900 simulations of platform/application
- Heterogeneity :
 - Execution from 1 to 10
 - Communications from 1 to 4





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Communication Model

- No cost
- Static
- 1-route Bellman-Ford
- 3-route Bellman-Ford







Communication Model - Results

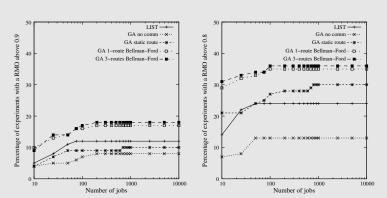


FIGURE: Comparing different algorithms to choose the route

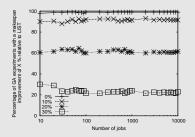




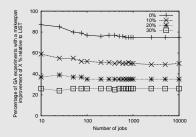




GA Improvement (3-Bellman-Ford)



a. Improvement for different DAGs



b. Improvement for identical DAGs



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Relative Measure to Optimal

Distance to optimal?

- Algorithm improves the quality of the results
- Case of collection of intrees: Steady state algorithm gives optimal flow
- Lower bound

Relative measure to Optimal (RMO)

- Optimal throughput ρ
- Lower bound $L_0 = \frac{N}{\rho}$, N number of intrees
- $RMO = \frac{\mathsf{L_o}}{makespan_s}$, $makespan_r$ result of the algorithm

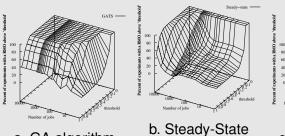






LIST -

Fully homogeneous platforms, $CCR \approx 0.01$



a. GA algorithm

Number of jobs

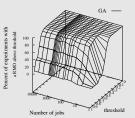
c. LIST algorithm

algorithm

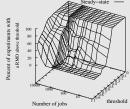




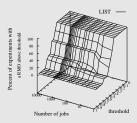
Fully homogeneous platforms, CCR ≈ 1



a. GA algorithm



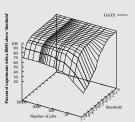
b. Steady-State algorithm



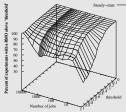
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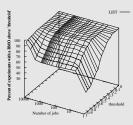
Fully heterogeneous platforms, CCR ≈ 0.01



a. GA algorithm



b. Steady-State algorithm

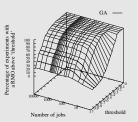


c. LIST algorithm

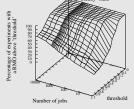




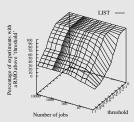
Fully heterogeneous platforms, CCR ≈ 1



a. GA algorithm



b. Steady-State algorithm



c. LIST algorithm



Conclusion and future works

Algorithm's performance:

- GA Scheduling for batches of workflows on SOA Grids with communication costs
- Collection of different workflows
- Identical intrees, comparison to optimal
- Complex implementation

Future Works

- Other communication models
- Other Genetic representation, network driven



Thank you!