A novel cloud workflow scheduling algorithm based on stable matching game theory

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Scientific Workflows in Cloud Computing

- Many scientific applications (e.g., bioinformatics, astronomy, physics) are executed as **scientific workflows**.
- These workflows are commonly modeled as **Directed Acyclic Graphs (DAGs)**.
- Workflow tasks are executed on **heterogeneous cloud resources** (Virtual Machines).
- The assignment of DAG tasks to cloud VMs is known as **workflow scheduling**.
- Scheduling decisions strongly affect execution time and resource utilization.

$\Rightarrow$ **Workflow scheduling is a key challenge in cloud computing.**

Cloud Workflow Scheduling

1 Introduction

Cloud workflow scheduling is **challenging** due to:

- Resource heterogeneity;
- Task dependencies;
- Communication overhead;
- Conflicting optimization objectives.

Traditional scheduling lacks a balance between global goals and task-level equity.

The Challenge: Efficiency vs Task Fairness

Limitations of makespan-focused scheduling:

- Task-level fairness is frequently neglected.
- Imbalanced allocations may assign suboptimal resources to certain tasks.
- Ignoring individual task requirements can reduce overall user satisfaction.

Key Research Questions:

- How can *efficiency* and *fairness* be jointly optimized?
- Can game theory provide an effective solution?

Proposed Solution: SM-CPTD Algorithm

SM-CPTD = Stable Matching with Critical Path and Task Duplication.

Proposed in:

A novel cloud workflow scheduling algorithm based on stable matching game theory - Jia et al.

This innovative scheduling approach combines:

- **Stable Matching Game Theory** (SMGT) that models task-to-VM assignment as a two-sided matching problem.
- Critical-path optimization with Task Duplication.

$\Rightarrow$ **Balances workflow performance and task-level fairness.**

Project Objectives

This work aims to:

1. **Reproduce** the core algorithmic components of SM-CPTD following original specifications.
2. **Validate** reported performance improvements through independent experimentation.
3. **Evaluate** on standard scientific workflow benchmarks: *Montage*, *CyberShake*, *LIGO*, *Epigenomics*.
4. **Analyze** efficiency (SLR), utilization (AVU), and fairness (VF) of the scheduling.

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2 Problem Formulation

Workflow and Cloud Model

2 Problem Formulation

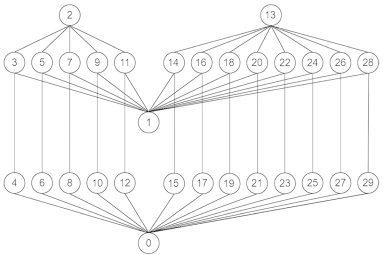

Figure: CyberShake Workflow (30 tasks).

A workflow is represented as **DAG** $= (T, E)$ where:

- $T = \{t_0, t_1, \ldots, t_{n-1}\}$: set of n tasks.
- E: directed edges encoding precedence constraints and data dependencies.
  - For each task t_i: pre(t_i) and succ(t_i) define the set of predecessor and successor tasks.
  - t_{entry}: tasks with no predecessors.
  - t_{exit}: tasks with no successors.
- Each task t_i has computational size s_i (MI).

The DAG structure defines execution order and communication requirements.

Data Transfer

2 Problem Formulation

Size of Data Transmission Matrix:

$$TT = \begin{bmatrix} 0 & TT_{0,1} & \cdots & TT_{0,n-1} \\ TT_{1,0} & 0 & \cdots & TT_{1,n-1} \\ \vdots & \vdots & \ddots & \vdots \\ TT_{n-1,0} & TT_{n-1,1} & \cdots & 0 \end{bmatrix} \in \mathbb{R}^{n \times n}$$

where

$$TT_{i,j} = \begin{cases} s_{t_i} \times \text{CCR} & \text{if } (t_i, t_j) \in E, \\ 0 & \text{otherwise.} \end{cases}$$

where **CCR** (Compute-to-Communication Ratio) is the ratio of the average communication cost to the average computation cost.

Cloud Infrastructure Model

2 Problem Formulation

Cloud Model: a set of m virtual machines (VMs)

$$V = \{VM_0, VM_1, \ldots, VM_{m-1}\}$$

- Each VM_k has a processing capacity of p_k (in MIPS).
- The VMs are generally heterogeneous: $p_i \neq p_j$ for $i \neq j$.
- Communication between VMs is represented by a bandwidth matrix B (in Mbps).

The bandwidth matrix B is defined as:

$$B(\mathrm{VM}_k, \mathrm{VM}_l) = \begin{cases} 0, & \text{if } k = l, \\ b_{k,l}, & \text{if } k \neq l, \end{cases} \qquad \text{with } b_{k,l} \neq b_{l,k} \text{ in general.}$$

Execution and Communication Timing

Execution and Transmission Time:

$$ET(t_i, VM_k) = \frac{s_i}{p_k} \qquad T_{trans}(t_i, t_j) = \begin{cases} \frac{TT_{i,j}}{B(VM_k, VM_l)} & \text{if } k \neq l \\ 0 & \text{if } k = l \end{cases}$$

Start and Finish Time:

$$ST(t_i, \mathrm{VM}_k) = \begin{cases} 0 & t_i = t_{\text{entry}} \\ \max\limits_{t_j \in \mathrm{pre}(t_i)} \{FT(t_j) + T_{\text{trans}}(t_i, t_j)\} & \text{otherwise} \end{cases}$$

$$FT(t_i, \mathrm{VM}_k) = ST(t_i, \mathrm{VM}_k) + ET(t_i, \mathrm{VM}_k)$$

Timing models account for both computational work and data movement latency.

Problem Definition and Constraint

Goal : Find a mapping function $\sigma : T \rightarrow V$ that assigns each task to exactly one VM.

Constraint:

- **Precedence:** a task starts only after all predecessors complete.
- **VM availability:** one task per VM at a time.
- **No migration:** each task is assigned to exactly one VM.

Evaluation Metrics (1/3)

1. Makespan - Total execution time of the workflow:

$$\text{makespan} = \max_{k \in \{0,\ldots,m-1\}} \{MS(VM_k)\}$$

where $\text{MS}(\text{VM}_k)$ denotes the finish time of the last task assigned to VM_k

2. Scheduling Length Ratio (SLR) - Normalized metric comparing makespan to theoretical lower bound:

$$SLR = \frac{\text{makespan}}{\sum_{t_i \in CP} \min_{VM_j \in V} ET(t_i, VM_j)}$$

$SLR \geq 1$ **lower is better** — makespan closer to theoretical minimum.

Evaluation Metrics (2/3)

3. Average VM Utilization (AVU) - Effectiveness of resource usage:

$$VU(\mathrm{VM}_k) = \frac{\sum_{t_i \in \mathrm{VM}_k.\mathrm{waiting}} ET(t_i, \mathrm{VM}_k)}{\mathrm{makespan}}, \quad AVU = \frac{1}{m} \sum_{k=1}^{m} VU(\mathrm{VM}_k)$$

where VU is defined as the ratio between the total execution time of tasks assigned to it and the workflow makespan.

$AVU \leq 1$ **higher is better** — less idle time.

Evaluation Metrics (3/3)

4. Task Satisfaction - ratio between its actual execution time and its expected execution time (the execution time of the task on the fastest available virtual machine):

$$S_i = \frac{AET_i}{EET_i},$$

5. Variance of Fairness (VF) - Task satisfaction dispersion:

$$VF = \frac{1}{n}\sum_{i=1}^{n}(M - S_i)^2 \quad \text{where} \quad M \quad \text{is the mean satisfaction}$$

$VF \leq 1$ **lower is better** — more balanced allocation.

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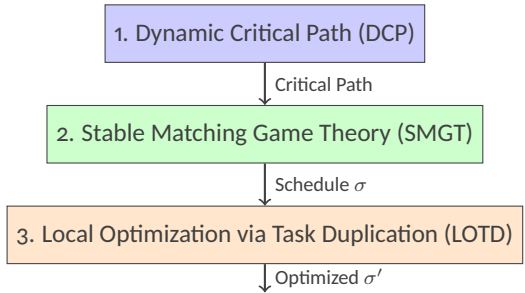
3 SM-CPTD Algorithm

Algorithm Overview

3 SM-CPTD Algorithm

Three-stage pipeline:

1. Identify critical tasks impacting makespan.
2. Fair and efficient task-VM matching.
3. Reduce communication delays and improve scheduling performance, via strategic duplication.



Phase 1: Dynamic Critical Path (DCP)

3 SM-CPTD Algorithm

Goal: Identify tasks that impact the makespan more.

Method: Compute rank values recursively:

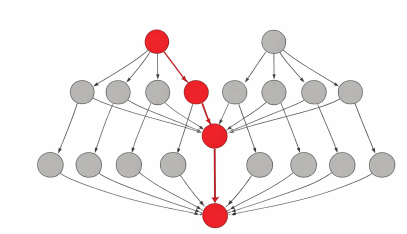
$$rank(t_i) = \overline{W}_i + \max_{t_j \in succ(t_i)} (\overline{c_{i,j}} + rank(t_j))$$

Where:

- $\overline{W}_i$: average computation time of task t_i.
- $\overline{c_{i,j}}$: average communication time between t_i and t_j.
- For exit task: $rank(t_{exit}) = \overline{W}_{exit}$.

Phase 1: Dynamic Critical Path (DCP)

3 SM-CPTD Algorithm



- **Critical Path** is defined by selecting task with maximum rank at each workflow level.
- Critical tasks are scheduled first on *fastest* VMs.

Reducing the execution time of the critical path is the most effective way to lower makespan.

Phase 2: Stable Matching (SMGT)

3 SM-CPTD Algorithm

Two-sided matching problem: Tasks $\leftrightarrow$ VMs

Preference Lists for both tasks and VMs are based on *earliest* estimated finish times.

Hierarchical Strategy:

1. Process workflow level-by-level.
2. Critical tasks assigned to fastest VMs first.
3. Other tasks matched using stable matching.
4. Capacity threshold prevents overloading:

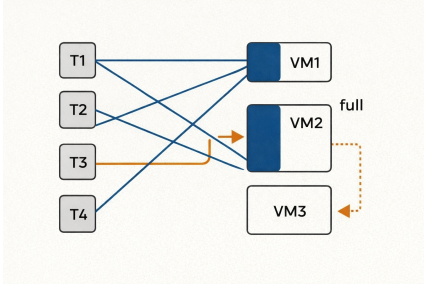
$$threshold(VM_k, l) = \left\lceil \frac{\sum_{v=0}^{l-1} n_v}{\sum_{j=0}^{m-1} p_j} \cdot p_k \right\rceil$$

Phase 2: Stable Matching (SMGT)

3 SM-CPTD Algorithm

Matching Process for each workflow level l of the non-critical tasks:

- Task proposes to most-preferred available VM.
- If VM below threshold: accept task.
- If VM at threshold: compare with worst current task.
- If task preferred: replace; otherwise try next VM.



Result: Fair allocation with balanced VM utilization.

Phase 3: Task Duplication (LOTD)

Goal: Reduce communication overhead by duplicating entry tasks.

Duplication Conditions: Task t_i can be duplicated on VM_k if:

1. At least one successor of t_i is on VM_k.
2. VM_k has sufficient idle time for t_i.
3. There is no increase in completion times of other tasks.

Why Only Entry Tasks?

- No predecessors $\Rightarrow$ no additional input communication.
- Avoids excessive resource waste.

Leverage unused VM capacity to reduce inter-VM communication.

Computational Complexity

3 SM-CPTD Algorithm

Phase	Best Case	Worst Case
Dynamic Critical Path	$O(n)$	$O(n^2)$
Stable Matching	$O(nml)$	$O(n^2 l)$
Task Duplication	$O(nm)$	$O(nm)$
Overall		$O(n^2 l)$

Where:

- n — number of tasks
- m — number of VMs
- l — number of workflow levels

Worst case scalability: quadratic in tasks, linear in levels.

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4 Experimental Setup

Implementation and Tools

4 Experimental Setup

Technology Stack:

- **Java 23.0.2** (OpenJDK): Core scheduling algorithms
- **Python 3**: Visualization and statistical analysis
- **Libraries:** NumPy, Pandas, Matplotlib, Seaborn, NetworkX

Design Principles:

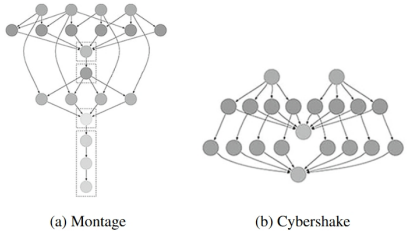
- Modular architecture.
- Clear separation of concerns.
- Reproducible experiments.

Workflow Structures

4 Experimental Setup

Scientific Workflow Considered:

- *Montage*: Astronomy image mosaics (parallel pipelines).
- *CyberShake*: Seismic hazard characterization (multi-level fork-join).
- *LIGO*: Gravitational wave detection (pipeline with synchronization).
- *Epigenomics*: Genomics data processing (parallel with aggregation).



(a) Montage (b) Cybershake

(c) LIGO (d) Epigenomics

Experimental Parameters

4 Experimental Setup

Simulation Setup and Parameters

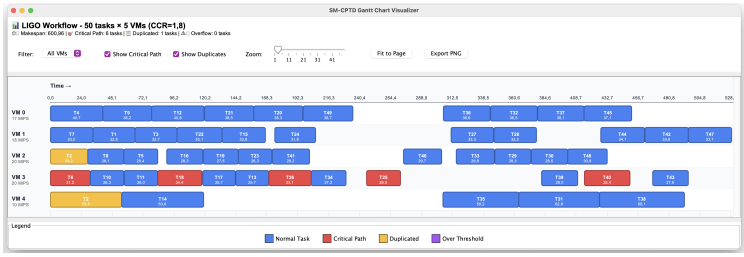
Parameter	Range	Distribution
Task size (MI)	500–700	$\mathcal{U}(500, 700)$
VM capacity (MIPS)	10–20	$\mathcal{U}(10, 20)$
Bandwidth (Mbps)	20–30	$\mathcal{U}(20, 30)$
CCR	0.4–2.0	fixed per experiment

Three **workflow scales** considered:

- **Small-scale**: 50 tasks executed on 5 VMs.
- **Medium-scale**: 100 tasks executed on 10 VMs.
- **Large-scale**: 1000 tasks executed on 50 VMs.

Statistical Reliability

4 Experimental Setup



Execution:

- 10 independent runs per scenario.
- Optional random seed for reproducibility.
- Gantt chart generation for visual inspection.

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5 Experimental Results

Communication Impact : SLR vs CCR

Experiment: CCR varies from 0.4 to 2.0 (step = 0.2) across small-, medium-, and large-scale workflow settings.

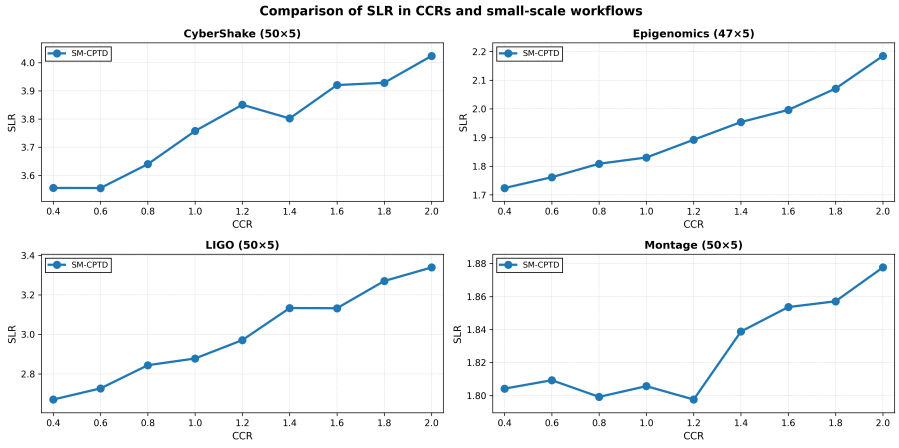
Question: How does increasing communication overhead affect scheduling efficiency?

Observation: SLR increases with higher CCR

- Higher CCR $\Rightarrow$ more communication overhead.
- Larger workflows show smoother trends (higher parallelism).
- Small workflows exhibit more variability.

Communication Impact : SLR vs CCR

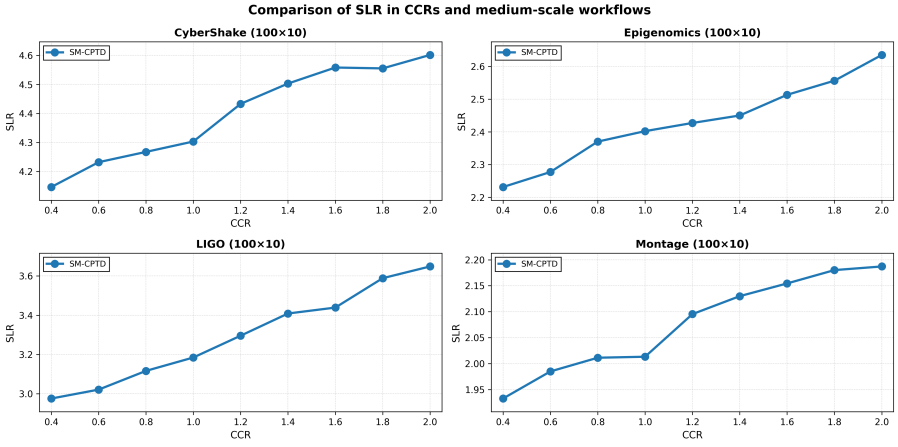
5 Experimental Results



SLR increases with CCR

Communication Impact : SLR vs CCR

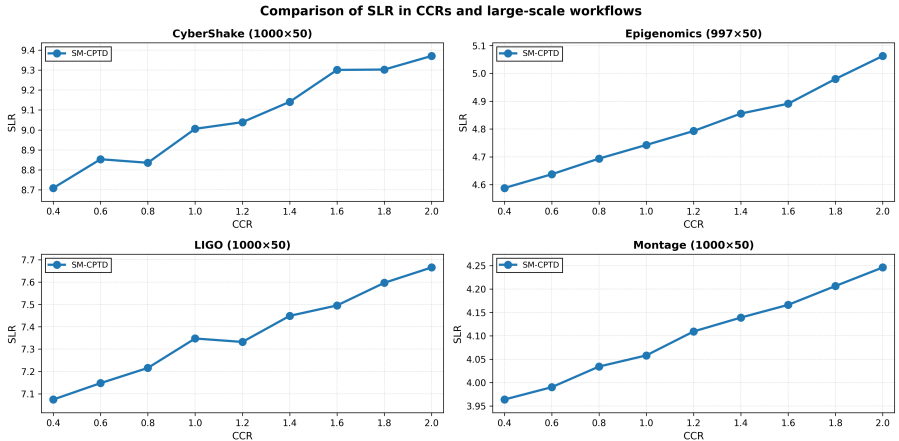
5 Experimental Results



As problem size increases, communication costs have greater impact on performance

Communication Impact : SLR vs CCR

5 Experimental Results



Wide parallel structures suffer most from communication overhead

Key finding

Question: Why do different DAG structures react differently to communication costs?

- **Wide DAGs** (*CyberShake*, *LIGO*): multiple synchronization points, high CCR amplifies delays where parallel branches converge.
- **Sequential DAGs** (*Montage*): overhead affects tasks more uniformly.
- Pipeline structures keep SLR growth more modest.

Workflows with wide parallel structures are more vulnerable to communication bottlenecks.

Scalability: SLR vs Number of VMs

Experiment: Fixed CCR = 1.0, vary number of VMs (from 30 to 70).

Question: Can additional computational resources improve the SLR?

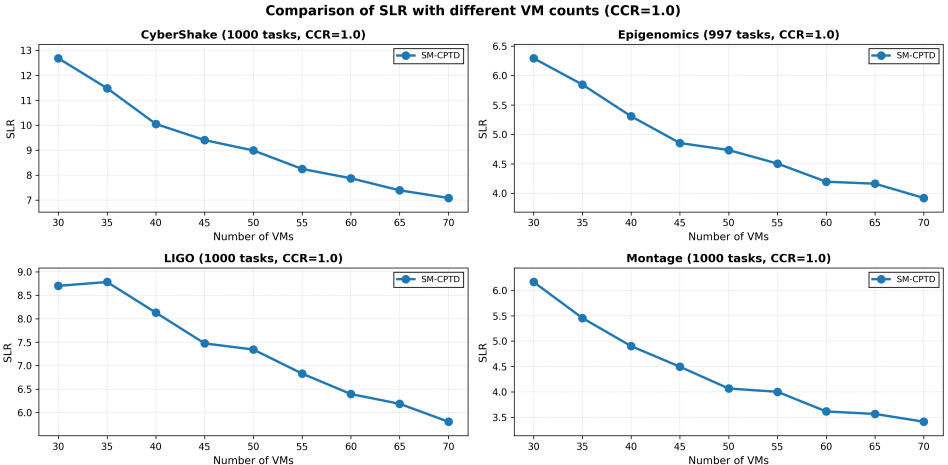
Observation: SLR decreases as VMs increase

- More VMs $\Rightarrow$ better parallelism $\Rightarrow$ lower SLR.
- Plateau reached when parallelism is limited by workflow structure.
- Diminishing returns after certain threshold.

SM-CPTD effectively exploits additional parallelism to approach the critical path bound.

Scalability: SLR vs Number of VMs

5 Experimental Results



VM Utilization Analysis: AVU vs CCR

Experiment: CCR varies from 0.4 to 2.0 (step = 0.2) across small-, medium-, and large-scale workflow settings.

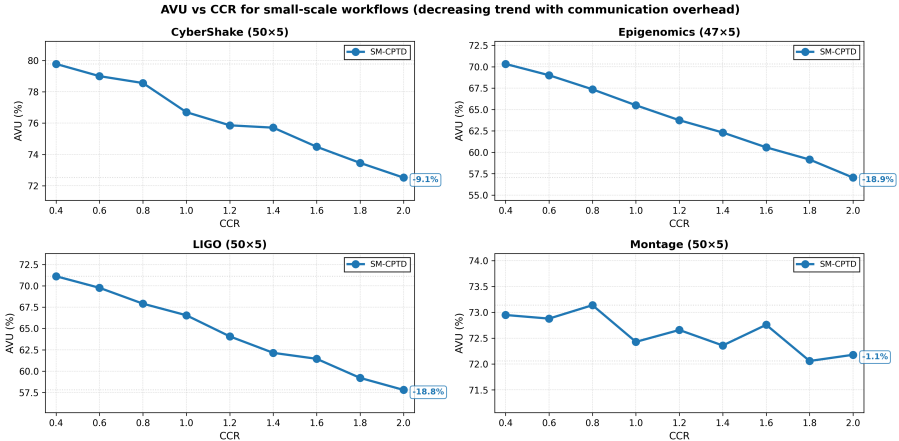
Question: How does communication overhead affect VM utilization?

Observation: AVU decreases with higher CCR.

- Communication costs dominate $\Rightarrow$ increased idle time.
- Effect more pronounced in small-scale workflows.
- Large-scale workflows maintain higher utilization (more parallelism).

VM Utilization Analysis: AVU vs CCR

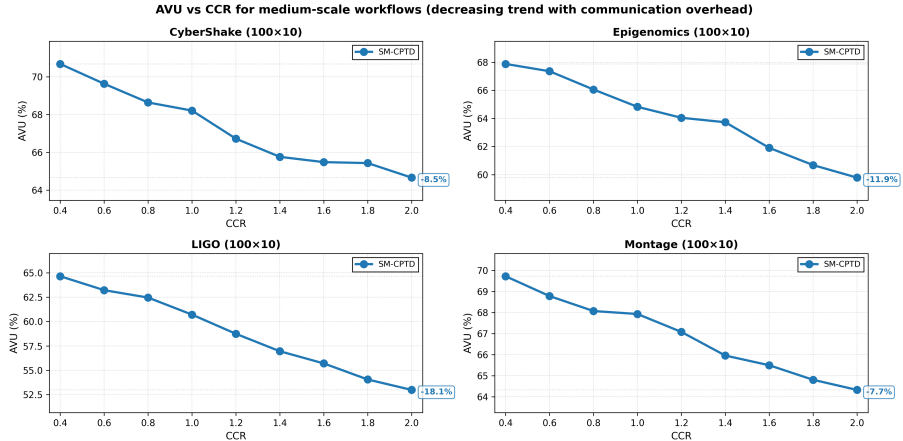
5 Experimental Results



Small-scale workflows show highest sensitivity (up to 19% degradation)

VM Utilization Analysis: AVU vs CCR

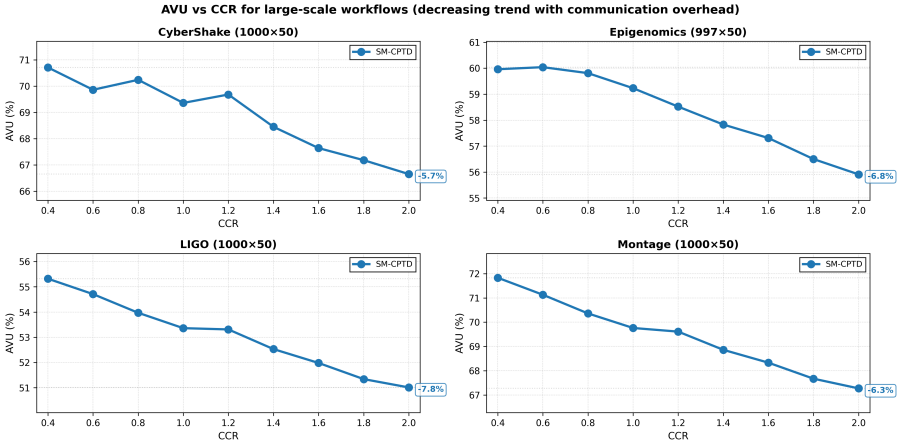
5 Experimental Results



Larger workloads better amortize communication costs

VM Utilization Analysis: AVU vs CCR

5 Experimental Results



Large-scale workflows show more moderate reduction

Scalability: AVU vs Number of VMs

Experiment: Fixed CCR = 1.0, vary number of VMs (from 30 to 70).

Question: Does adding more VMs always improve resource efficiency?

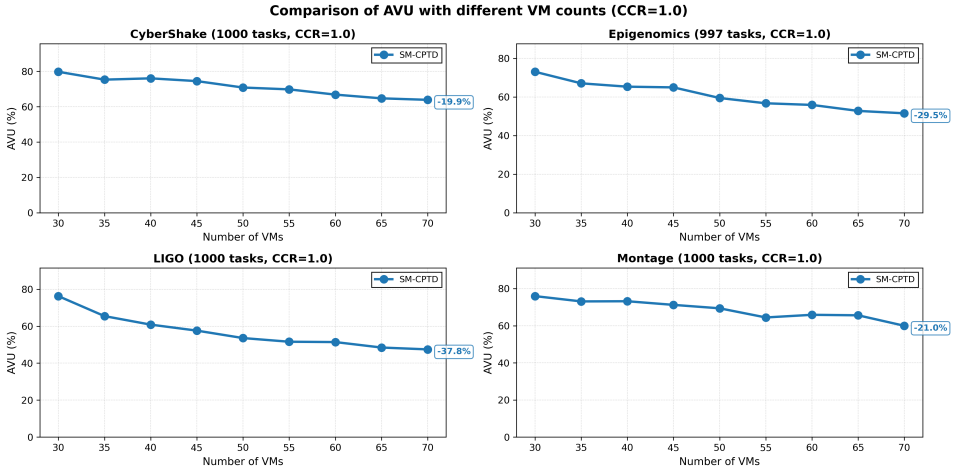
Observation: AVU decreases as the number of VMs increases.

- More VMs $\Rightarrow$ workload spread thinner $\Rightarrow$ lower AVU.
- Execution time per VM decreases relative to total makespan.
- Trend observed consistently across all workflow types.

Adding VMs improves makespan but leads to diminishing utilization efficiency.

AVU vs Number of VMs

5 Experimental Results



Fairness Analysis: VF

5 Experimental Results

Experiment: Large Scale Workflows and fixed CCR=1.

Observation: All workflows exhibit low VF values (well below 1).

- Low dispersion indicates no task is systematically penalized.
- Satisfaction values cluster tightly around the mean.

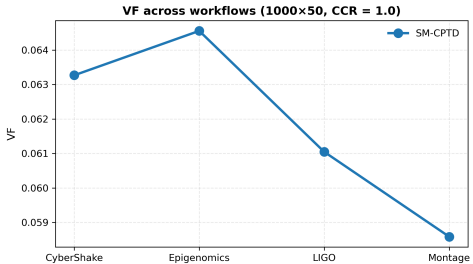


Figure: Variance of Fairness across workflows.

Fairness Analysis

5 Experimental Results

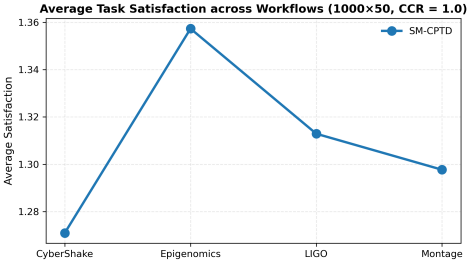


Figure: Average task satisfaction across workflows.

Our Results: VF values < 1 (typically 0–0.1)

Original Paper Issue: Reports VF $\approx$ 1.25–1.47

- Mathematically inconsistent! Variance > 1 impossible given constraints.
- **Hypothesis:** Figure likely shows *average satisfaction*, not variance.
- Our avg. satisfaction values match paper's "VF" range.

Ablation Study

Experiment: Large Scale Workflows and fixed CCR=1. Metrics: VF, SLR, AVU.

Four Configurations

1. **SMGT only** (baseline)
2. **DCP + SMGT** (SM-CP)
3. **SMGT + LOTD** (SM-TD)
4. **DCP + SMGT + LOTD** (full SM-CPTD)

Goal: Evaluate contribution of each component.

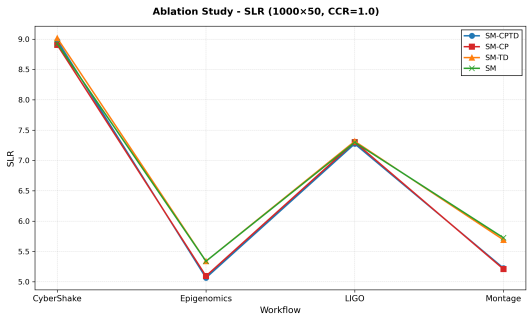
Ablation Study SLR

5 Experimental Results

Question: Which components contribute most to makespan reduction?

Key Findings:

- Full SM-CPTD consistently achieves the lowest SLR.
- Removing CP causes the largest performance degradation.

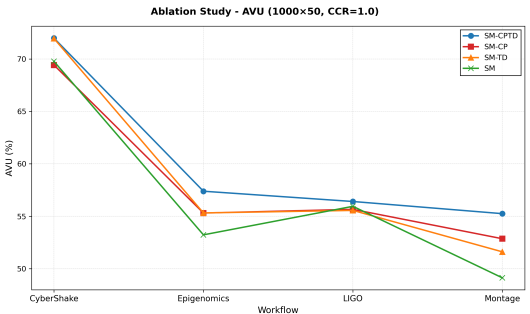


Critical Path optimization is the most critical component for minimizing execution time.

Ablation Study AVU

5 Experimental Results

Question: How do CP and TD interact to improve utilization?



Key Findings:

- Highest AVU reached only when both CP and TD are enabled.
- CP enhances global scheduling efficiency.
- TD improves VM-level utilization through load balancing.

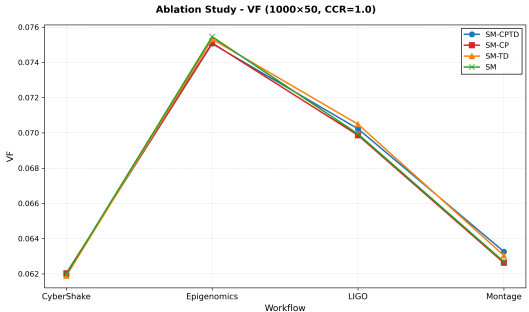
Components are complementary and essential for robustness.

Ablation Study VF

5 Experimental Results

Key Findings:

- VF remains consistently low for all variants.
- Observed differences are small in magnitude.
- Fairness preserved regardless of components.



Interpretation: VF serves as a **sanity check** confirming all variants maintain high fairness. Cannot reliably differentiate between algorithmic variants.

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6 Conclusion

Main Contributions

Full reimplementation of SM-CPTD

- Complete Java reimplementation from scratch
- Modular, documented, and extensible architecture
- Publicly released code ensuring full reproducibility

Extensive experimental evaluation

- Validation on standard scientific workflow benchmarks
- Analysis across multiple workflow sizes, CCR values, and VM counts
- Statistical evaluation over multiple independent runs

Limitations and Challenges

Implementation Challenges

- Some algorithmic details not fully specified in original paper
- Required interpretation and design decisions
- Fairness metric definition inconsistency

Experimental Limitations

- Simulated environment (not real cloud deployment)
- Fixed workflow structures from benchmarks
- Uniform distributions for parameters
- Limited to four workflow types

Key Experimental Results: CCR Increase

Performance Trends: SLR vs CCR

- SLR increases for all evaluated workflows.
- Communication-intensive and wide workflows are most impacted.
- Large-scale workflows exhibit smoother and more stable trends.

Resource Utilization: AVU vs CCR

- AVU decreases as communication overhead grows.
- Larger workflows better amortize communication costs.

Key Experimental Results: Scalability Trade-offs

Increasing number of VMs

- **SLR** *decreases* due to higher available parallelism.
- **AVU** *decreases* as idle resources become more frequent.

Key insight

- Clear trade-off between makespan reduction and resource efficiency.
- Scalability benefits strongly depend on workflow structure.

Algorithmic Insights

Critical Path optimization (CP)

- Primary contributor to makespan and SLR reduction.
- Most effective in CP-dominated workflows.

Task Duplication (TD)

- Improves resource utilization and scheduling stability.
- Provides complementary gains rather than dominating performance.

Best performance achieved by combining CP and TD

Final Takeaways

SM-CPTD is an effective workflow scheduling strategy that:

- Reduces makespan-related performance metrics.
- Improves overall resource utilization.
- Maintains stable and fair task allocation behavior.

Code and results publicly available

`https://github.com/Cappetti99/stable-matching-game-theory`

Appendix: References

- adnanetalha. DAX-file: workflows dax format. `https://github.com/adnanetalha/DAX-file`
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Thank you for listening!