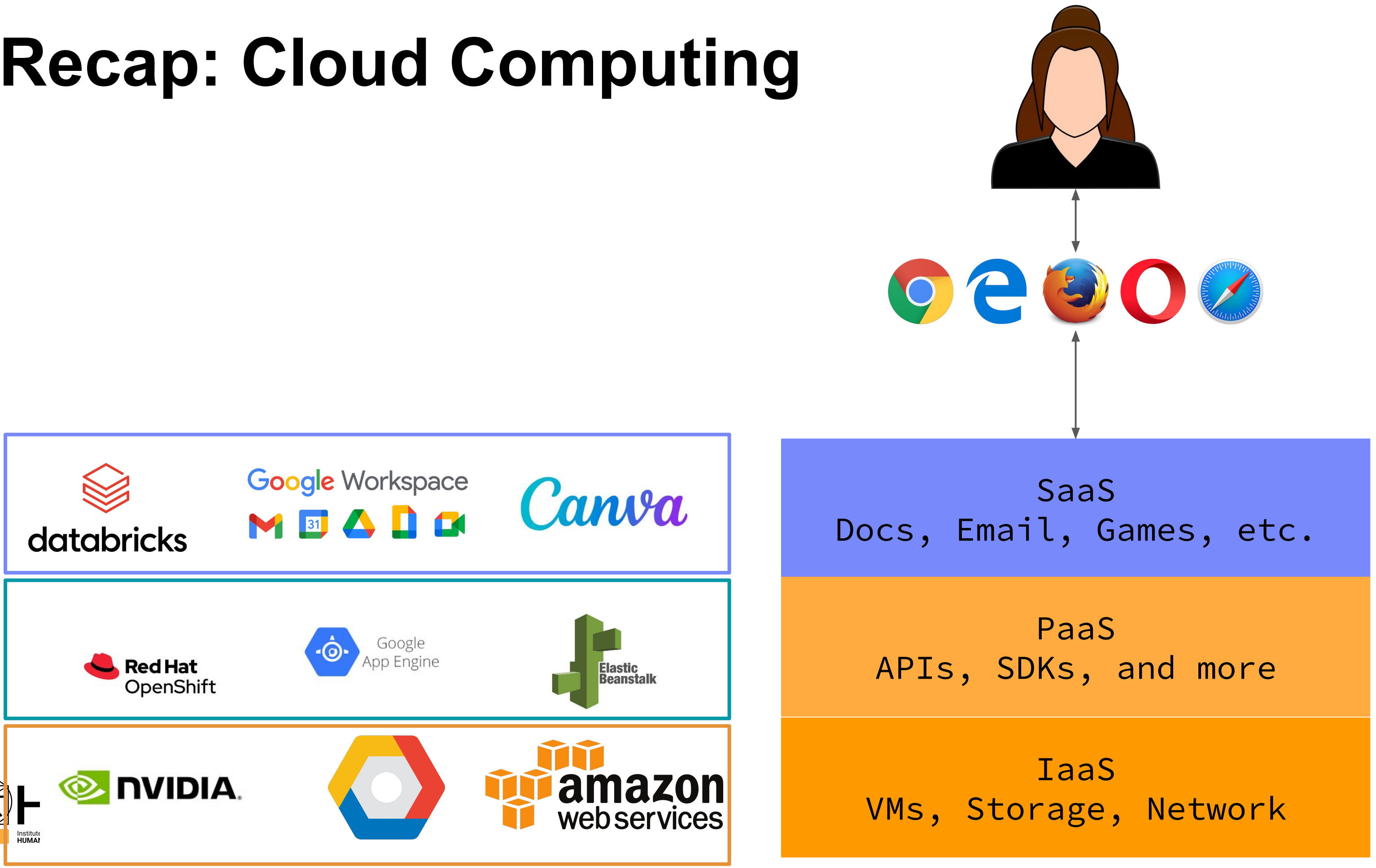
Data Integration and Large Scale Analysis

08- Cloud Resource Management and Scheduling

Institute of
HUMAN-CENTRED COMPUTING

Recap: Cloud Computing



Agenda

- Motivation and Terminology
- Cloud Computing Scheduling
- Activity

Motivation and Terminology

Motivation

- Understand the importance of resource management and **scheduling** in cloud computing.
- Learn about common scheduling algorithms and their applications.
- Explore real-world use cases and research trends in cloud resource scheduling.
- Gain practical competences in scheduling algorithms.

Motivation and Terminology

- How I can feed my hungry app with computing and storage resources?

What is Cloud Resource Management?

Definition: process of efficiently allocating **computational, storage, and network resources** to meet the needs of applications and users in cloud environments.

Key Factors:

- **Availability:** Are resources ready for use?
- **Efficiency:** Are resources optimally utilized?
- **Cost:** Are costs minimized while meeting objectives?

Example:

- Netflix manages server capacity during peak hours to support millions of users streaming simultaneously (live events).
- Fortnite live shows

Types of Cloud Resources

Computational Resources:

- CPUs, GPUs
- Example: Scaleway/Exoscale/ AWS EC2 /NVDIA GPUs .

Storage Resources:

- Datalakes, databases.
- Example: Amazon S3, Google Cloud Storage, AWS RDS.

Network Resources:

- Bandwidth, load balancing, connectivity.
- Example: Cloudflare’s CDN for global content delivery.

What is Scheduling?

Definition:

Scheduling involves assigning tasks to available resources efficiently.

Efficiency is a multi-objective optimization problem (priority, execution time, monetary costs).

Why is it Important?

- Enhances **QoS.**
- Reduces **costs** → better resource utilization.
- Prevents **overloading or underutilization** of resources.

Example:

- Training an AI model on GPUs is scheduled at night to minimize cost.

What is Scheduling?: Taxonomy

Taxonomy of Cloud Resource Scheduling

Cloud Computing Resource Scheduling and a Survey of Its Evolutionary Approaches

ZHI-HUI ZHAN, XIAO-FANG LIU, YUE-JIAO GONG, and JUN ZHANG, Sun Yat-sen University
HENRY SHU-HUNG CHUNG, City University of Hong Kong
YUN LI, University of Glasgow

A disruptive technology fundamentally transforming the way that computing services are delivered, cloud computing offers information and communication technology users a new dimension of convenience of resources, as services via the Internet. Because cloud provides a finite pool of virtualized on-demand resources, optimally scheduling them has become an essential and rewarding topic, where a trend of using Evolutionary Computation (EC) algorithms is emerging rapidly. Through analyzing the cloud computing architecture, this survey first presents taxonomy at two levels of scheduling cloud resources. It then paints a landscape of the scheduling problem and solutions. According to the taxonomy, a comprehensive survey of state-of-the-art approaches is presented systematically. Looking forward, challenges and potential future research directions are investigated and invited, including real-time scheduling, adaptive dynamic scheduling, large-scale scheduling, multiobjective scheduling, and distributed and parallel scheduling. At the dawn of Industry 4.0, cloud computing scheduling for cyber-physical integration with the presence of big data is also discussed. Research in this area is only in its infancy, but with the rapid fusion of information and data technology, more exciting and agenda-setting topics are likely to emerge on the horizon.

Categories and Subject Descriptors: I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*Heuristic methods*; G.1.6 [**Numerical Analysis**]: Optimization—*Global optimization*; D.4.1 [**Process Management**]: Scheduling; H.3.5 [**Online Information Services**]: Web-based Services; Commercial Services; H.3.4 [**Systems and Software**]: Distributed Systems; Performance Evaluation; C.1.4 [**Parallel Architectures**]: Distributed Architectures; C.2.1 [**Network Architecture and Design**]: Network Communications; Network Topology; Wireless Communication; C.2.3 [**Network Operations**]: Network Management; Network Monitoring; C.5.5 [**Servers**]; K.1 [**The Computer Industry**]: Suppliers

General Terms: Algorithms, Management, Design, Performance

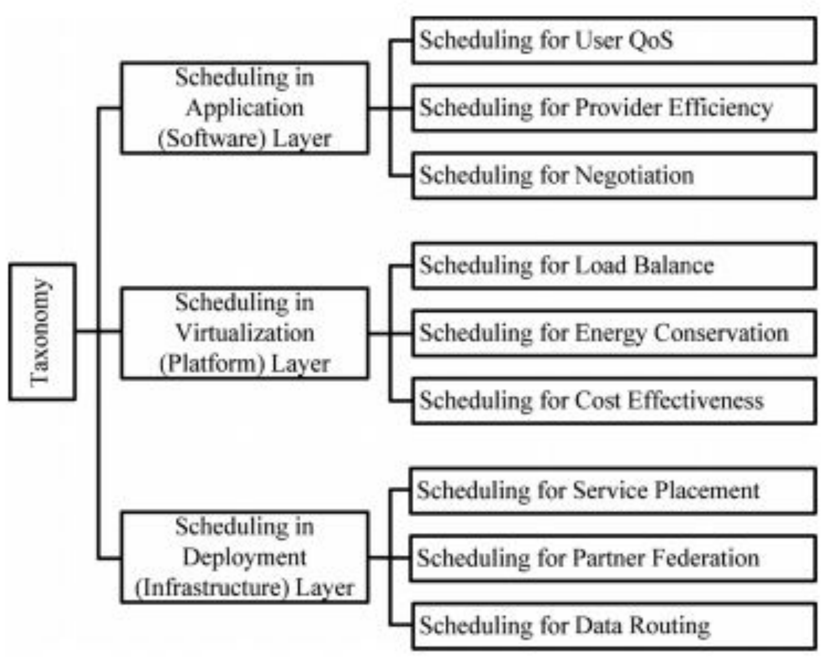
Additional Key Words and Phrases: Cloud computing, resource scheduling, evolutionary computation, genetic algorithm, ant colony optimization, particle swarm optimization

This work was supported in part by the National Natural Science Foundations of China (NSFC) with No. 61402545, the Natural Science Foundations of Guangdong Province for Distinguished Young Scholars with No. 2014A030306038, the Project for Pearl River New Star in Science and Technology with No. 201506010047, the Fundamental Research Funds for the Central Universities, the NSFC Key Program with No. 61332002, the NSFC for Distinguished Young Scholars with No. 61125205, and the National High-Technology Research and Development Program (863 Program) of China with No. 2013AA01A212.
Authors' addresses: Z.-H. Zhan (corresponding author), X.-F. Liu, Y.-J. Gong, and J. Zhang, School of Advanced Computing, Sun Yat-sen University, Guangzhou 510275, China, with the Key Laboratory of Machine Intelligence and Advanced Computing, Sun Yat-sen University, Ministry of Education, China, with the Engineering Research Center of Supercomputing Engineering Software, Sun Yat-sen University, Ministry of Education, China, and with the Key Laboratory of Software Technology, Sun Yat-sen University, Education Department of Guangdong Province, China; email: zhanzhh@mail.sysu.edu.cn; H. S.-H. Chung, Department of Electronic Engineering, City University of Hong Kong, Kowloon, Hong Kong, SAR, China; Y. Li, School of Engineering, University of Glasgow, Glasgow G12 8LT, UK.
Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from Permissions@acm.org.
2015 Copyright is held by the owner/author(s). Publication rights licensed to ACM.
ACM 0360-0300/2015/07-ART63 $15.00
DOI: http://dx.doi.org/10.1145/2788397

63

ACM Computing Surveys, Vol. 47, No. 4, Article 63, Publication date: July 2015.

Zhan, Z. H., Liu, X. F., Gong, Y. J., Zhang, J., Chung, H. S. H., & Li, Y. (2015). Cloud computing resource scheduling and a survey of its evolutionary approaches. ACM Computing Surveys (CSUR), 47(4), 1-33.


Taxonomy
Scheduling in Application (Software) Layer
Scheduling in Virtualization (Platform) Layer
Scheduling in Deployment (Infrastructure) Layer
Scheduling for User QoS
Scheduling for Provider Efficiency
Scheduling for Negotiation
Scheduling for Load Balance
Scheduling for Energy Conservation
Scheduling for Cost Effectiveness
Scheduling for Service Placement
Scheduling for Partner Federation
Scheduling for Data Routing

What is Scheduling?: Taxonomy

Application (SaaS) Layer: running applications or workflows.

- **User QoS:** minimize response time, meet deadlines, stay within budget.
- **Provider Efficiency:** maximize resource utilization, throughput, or profit.
- **Negotiation-based Scheduling:** user and provider negotiate SLAs, prices, or priorities.

Virtualization (PaaS) Layer: how VMs or containers → mapped onto physical servers.

- **Load Balancing:** distribute VM workloads evenly across hosts.
- **Energy Conservation:** reduce power consumption, consolidate VMs, turn off idle servers.
- **Cost Effectiveness:** minimize operational or resource costs.

Deployment (IaaS) Layer: how services or data should be placed across data centers or clouds.

- **Service Placement:** choose optimal data centers or regions for deploying services.
- **Partner Federation:** coordinate resources across multiple clouds or providers.
- **Data Routing:** how data should move or be replicated → minimize latency and maximize performance.

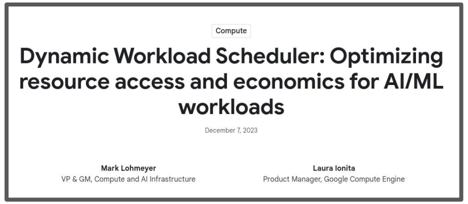
Cloud Computing Scheduling

Institute of
HUMAN-CENTRED COMPUTING

Key Factors in Scheduling

- **Task Priority:**
  - Critical tasks → prioritized.
  - **Example:** Emergency vehicle routing.
- **Execution Time:**
  - Tasks with shorter times prioritized → optimize **throughput.**
  - **Example:** Obstacle detection with drones.
- **Load Balancing:**
  - Ensures resources equally utilized.
  - **Example:** AWS regions balancing traffic loads to compute traffic planning, situational awareness maps, etc.
- **Energy Efficiency:**
  - Optimizes to reduce power consumption.
  - Example: Shutting down idle servers during low usage periods (few vehicles at night).

Challenges in Scheduling



Compute

Dynamic Workload Scheduler: Optimizing resource access and economics for AI/ML workloads

December 7, 2023

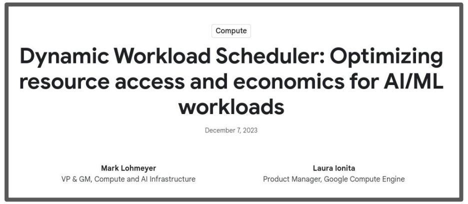
Mark Lohmeyer
VP & GM, Compute and AI Infrastructure

Laura Ionita
Product Manager, Google Compute Engine

Energy Optimization:

- Balancing **performance** with reduced **energy consumption**.

Challenges in Scheduling


Compute

Dynamic Workload Scheduler: Optimizing resource access and economics for AI/ML workloads

December 7, 2023

Mark Lohmeyer
VP & GM, Compute and AI Infrastructure

Laura Ionita
Product Manager, Google Compute Engine

Energy Optimization:

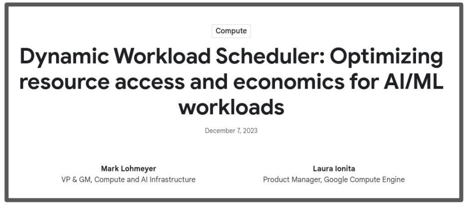
- Balancing **performance** with reduced **energy consumption**.

Scheduling in Hybrid Environments:

- Combining **edge/fog** devices and **cloud servers**.

HCC
Institute of
HUMAN-CENTRED COMPUTING

Challenges in Scheduling


Compute

Dynamic Workload Scheduler: Optimizing resource access and economics for AI/ML workloads

December 7, 2023

Mark Lohmeyer
VP & GM, Compute and AI Infrastructure

Laura Ionita
Product Manager, Google Compute Engine

Energy Optimization:

- Balancing **performance** with reduced **energy consumption**.

Scheduling in Hybrid Environments:

- Combining **edge/fog** devices and **cloud servers**.

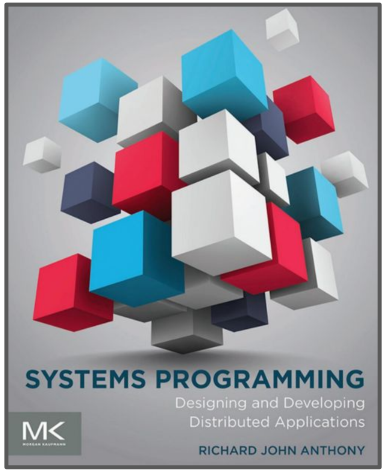
AI-Driven Scheduling:

- Using **Machine Learning** to predict **demand and optimize scheduling**.
- Example: Google Cloud’s Dynamic Workload Scheduler

Scheduling Algorithms

From **FCFS (First-Come First-Served** to **IA)**

Common Scheduling Algorithms



Anthony, R. (2015). *Systems programming: designing and developing distributed applications*. Morgan Kaufmann.

First-Come, First-Served (FCFS):

Assigns tasks in the **order they arrive.**

- **Advantage:** Simple to implement.
- **Disadvantage:** Inefficient if long tasks arrive first.
- **Example**
  a. Tasks: **T1 (2s)**, **T2 (4s)**, **T3 (1s)**
  b. Execution order: **T1** → **T2** → **T3**
- **Total time: 2 + 4 + 1 = 7 seconds.**

First-Come, First-Served

```
Procedure FCFS_Scheduling(tasks):
    Initialize total_time = 0
    For each task in tasks:
        Print "Executing task:", task.id, "Execution time:",
task.execution_time
        total_time = total_time + task.execution_time
    End For
    Print "Total execution time:", total_time
End Procedure
```

1. **Receives a list of tasks with their execution times.**
2. **Iterates through each task and sums its execution time to the total.**
3. **Prints the total execution time.**

Common Scheduling Algorithms: Round Robin

Round Robin:

- Allocates a **fixed time slice (quantum)** to each task in a cyclic order.
- **Example:**
- **Tasks: T1 (2s), T2 (4s), T3 (1s)**
- **Quantum: 1s**
- **Execution order:**
  a. Round 1: **T1** (1s), **T2** (1s), **T3** (1s)
  b. Round 2: **T1** (1s), **T2** (1s)
  c. Round 3: **T2** (1s)
  d. Round 4: **T2** (1s)
- **Total time: 7 seconds.**

Common Scheduling Algorithms: Round Robin

```
Procedure RoundRobin_Scheduling(tasks, quantum):
    Initialize total_time = 0
    While tasks is not empty:
        For each task in tasks:
            If task.execution_time > quantum:
                Print "Executing:", task.id, "for", quantum, "units"
                task.execution_time = task.execution_time - quantum
                total_time = total_time + quantum
            Else:
                 Print "Completing task:", task.id, "Remaining time:",
     task.execution_time
                total_time  = total_time + task.execution_time
                Remove task from tasks
            End If
        End For
    End While
    Print "Total execution time:", total_time
End Procedure
```

1. **Each task executes for a maximum of quantum time units.**
2. **If a task is not completed, its remaining time is reduced, and it is rescheduled.**
3. **Repeats until all tasks are completed.**

Common Scheduling Algorithms: Min-Min & Max-Min

Min-Min and Max-Min:

- **Min-Min:** Assigns **shortest** tasks **first**.
- **Max-Min:** Assigns **longest** tasks **first**.
- **Tasks:** **T1 (2s)**, **T2 (4s)**, **T3 (1s)**
- **Resources: S1, S2**
- **Assignment order (Min-Min):**
  a. **T3** → **S1**
  b. **T1** → **S2**
  c. **T2** → **S1**
- **Assignment order (Max-Min):**
  a. **T2** → **S1**
  b. **T1** → **S2**
  c. **T3** → **S1**

Common Scheduling Algorithms: Min-Min

```
Procedure MinMin_Scheduling(tasks, resources):
    While tasks is not empty:
        Find task_min = Task with the shortest execution_time
        Assign task_min to the least loaded resource
        Remove task_min from tasks
        Print "Assigning task:", task_min.id, "to the least loaded
resource"
    End While
End Procedure
```

- **Finds the task with the shortest execution time in each iteration.**
- **Assigns the task to the least loaded resource.**
- **Repeats until no tasks are left.**

Common Scheduling Algorithms: Load Balancing

Load Balancing:

- **Distributes tasks equally across all available resources.**
- **Tasks: T1 (2s), T2 (4s), T3 (1s)**
- **Resources: S1, S2**
- **Result:**
  a. **0 → S1, 0 →S2**
  b. **T1 (2s) → S1, 0 → S2 (Total load: 2)**
  c. **T1 (2s) → S1, T2 (4s) → S2 (Total load: 6)**
  d. **T3 (1s) + T1 (2s)→ S1, T2 (4s) →S2 (Total load: 7)**
  e. **S1 = 3s , S2 = 4s**

HCC
Institute of HUMAN-CENTRED COMPUTING

Common Scheduling Algorithms: Load Balancing

```
Procedure LoadBalancing_Scheduling(tasks, resources):
    Initialize resource_load = 0 [for each resource]
    For each task in tasks:
        Find least_loaded_resource = Resource with minimum load
        Assign task to least_loaded_resource
        Update resource_load for least_loaded_resource
        Print "Task:", task.id, "assigned to resource:", least_loaded_resource
    End For
End Procedure
```

1. **Initializes the load for each resource to 0.**
2. **Assigns each task to the least loaded resource.**
3. **Updates the load for the corresponding resource.**

Institute of HUMAN-CENTRED COMPUTING

Common Scheduling Algorithms

Algorithm	Advantage	Disadvantage	Ideal Use Case
FCFS	Simple and easy to implement	Inefficient with long tasks first	Light and homogeneous workloads (e.g. Max and Min temp detection in IoT time series)
Round Robin	Fair, avoids resource blocking	Does not optimize execution times	Interactive processing (Human-Machine interaction)
Min-Min	Optimizes execution times	Requires global analysis	Large workloads with varied tasks (HPC, short tasks + makespan minimization)
Load Balancing	Balances resource usage	Ignores task priority or execution time	Real-time scenarios (Web servers load balance to manage users' requests).

Advanced Scheduling Algorithms

Heuristic-based (knowledge frameworks from other domains transferred to a new one)

- Genetic Algorithms
- Particle Swarm Optimization
- Others (simulated annealing, etc.).

Used for **complex, large-scale** systems (and multi-objective optimization).

Advanced Scheduling Algorithms: Metaheuristics

Definition:

- High-level optimization algorithms → **approximate solutions** for problems that are **complex to solve using traditional methods**.

Advanced Scheduling Algorithms: Metaheuristics

Key Features:

- **General Framework:** Not problem-specific.
- **Exploration and Exploitation:** Search new domains (exploration) and refining existing solutions (exploitation).
- **Scalability:** Works well with large, complex problems.

Examples:

- Genetic Algorithms (GA)
- Particle Swarm Optimization (PSO)
- Simulated Annealing

Advanced Scheduling Algorithms: Metaheuristics

Complexity of Scheduling:

- Traditional algorithms (e.g., FCFS, Round Robin) struggle with **high-dimensional** or **dynamic scheduling problems**.

Dynamic Environments:

- **Real-time** adjustments based on **changing workloads** and **resource availability.**

Advanced Scheduling Algorithms: Metaheuristics

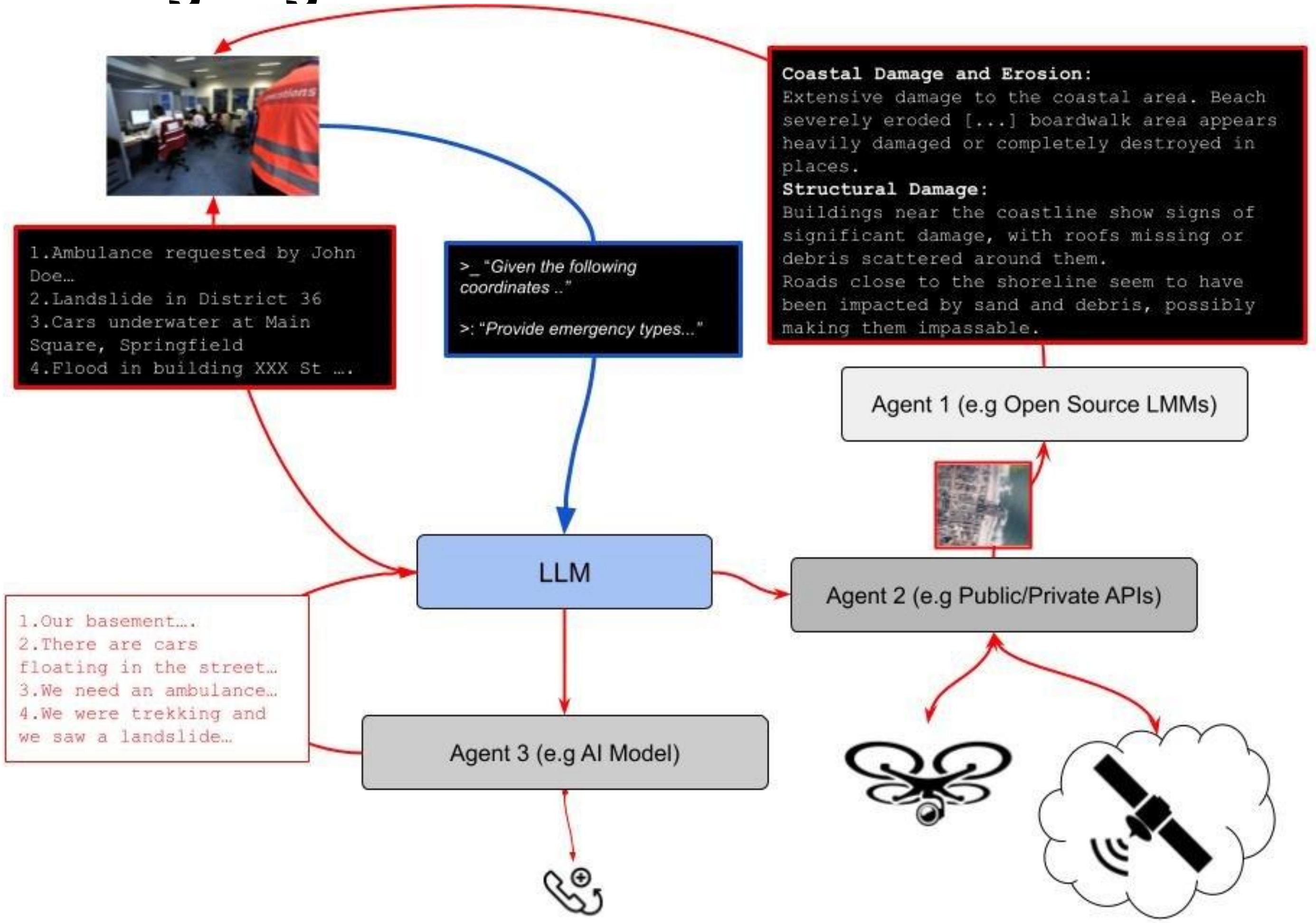
Multi-Objective Optimization:

- **Balances** conflicting goals like **cost, energy consumption, and performance**.

Example:

- Allocating tasks in a hybrid cloud environment where some tasks prioritize speed while others prioritize cost efficiency (e.g. **emergency response**).

Advanced Scheduling Algorithms: Metaheuristics


LLM
Agent 1 (e.g Open Source LMMs)
Agent 2 (e.g Public/Private APIs)
Agent 3 (e.g AI Model)

Coastal Damage and Erosion:
Extensive damage to the coastal area. Beach severely eroded [...] boardwalk area appears heavily damaged or completely destroyed in places.
Structural Damage:
Buildings near the coastline show signs of significant damage, with roofs missing or debris scattered around them.
Roads close to the shoreline seem to have been impacted by sand and debris, possibly making them impassable.

1. Ambulance requested by John Doe…
2. Landslide in District 36
3. Cars underwater at Main Square, Springfield
4. Flood in building XXX St ….

>_ *"Given the following coordinates .."*

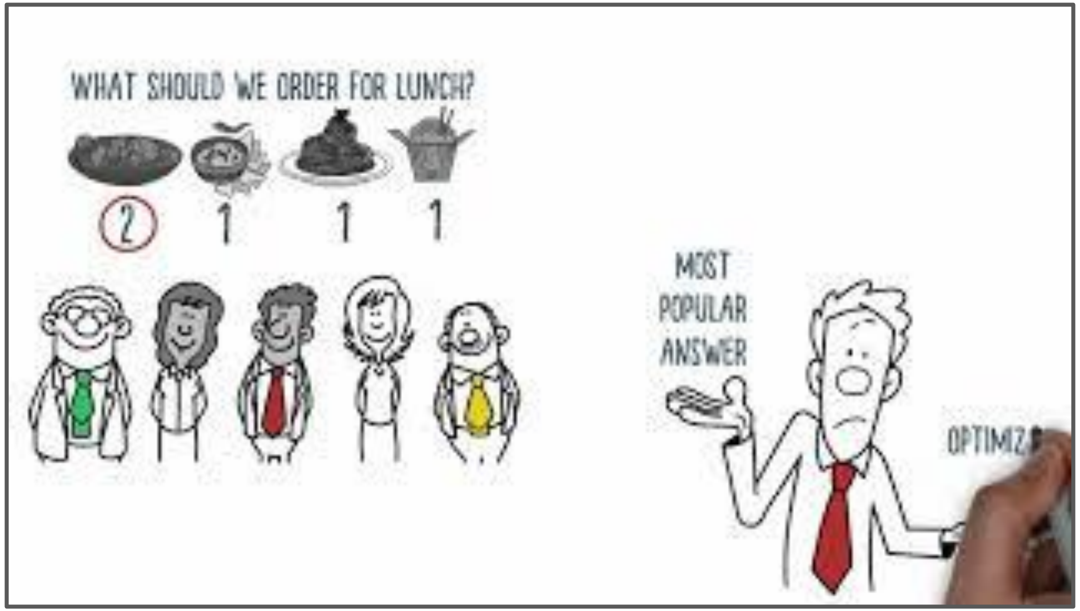
>: *"Provide emergency types..."*

1. Our basement….
2. There are cars floating in the street…
3. We need an ambulance…
4. We were trekking and we saw a landslide…

HCC
Institute of
HUMAN-CENTRED COMPUTING

Advanced Scheduling Algorithms: Metaheuristics

Particle Swarm



Advanced Scheduling Algorithms: Metaheuristics

Particle Swarm Optimization: Frost Prediction

- **Application**: Frost Prediction
- **Challenge:** Efficient scheduling of CPU-intensive tasks in federated clouds, minimizing makespan (**execution time**) and **monetary cost**.
- **Federated Clouds:** Utilized for distributed computing across geographically dispersed data centers.

Journal of Network and Systems Management (2019) 27:688–729
https://doi.org/10.1007/s10922-018-9481-0

CrossMark

A Bio-inspired Datacenter Selection Scheduler for Federated Clouds and Its Application to Frost Prediction

Elina Pacini[1,2] · Lucas Iacono[1,2] · Cristian Mateos[3] · Carlos García Garino[1]

Received: 14 August 2017 / Revised: 1 November 2018 / Accepted: 8 November 2018 /
Published online: 22 November 2018

Abstract
Frost is an agro-meteorological event which causes both damage in crops and important economic losses, therefore frost prediction applications (FPA) are very important to help farmers to mitigate possible damages. FPA involves the execution of many CPU-intensive jobs. This work focuses on efficiently running FPAs in paid federated Clouds, where custom virtual machines (VM) are launched in appropriate resources belonging to different providers. The goal of this work is to minimize both the makespan and monetary cost. We follow a federated Cloud model where scheduling is performed at three levels. First, at the *broker level*, a datacenter is selected taking into account certain criteria established by the user, such as lower costs or lower latencies. Second, at the *infrastructure level*, a specialized scheduler is responsible for mapping VMs to datacenter hosts. Finally, at the *VM level*, jobs are assigned for execution into the preallocated VMs. Our proposal mainly contributes to implementing bio-inspired strategies at two levels. Specifically, two broker-level schedulers based on Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), which aim to select the datacenters taking into account the network latencies, monetary cost and the availability of computational resources in datacenters, are implemented. Then, VMs are allocated in the physical machines of that datacenter by another intra-datacenter scheduler also based on ACO and PSO. Performed experiments show that our bio-inspired scheduler succeed in reducing both the makespan and the monetary cost with average gains of around 50% compared to genetic algorithms.

Keywords Scientific computing · Frost prediction applications · Cloud computing · Scheduling · Ant colony optimization · Particle Swarm optimization · Genetic algorithms

Pacini, E., Iacono, L., Mateos, C., & García Garino, C. (2019). A bio-inspired datacenter selection scheduler for federated clouds and its application to frost prediction. Journal of Network and Systems Management, 27(3), 688-729.

Advanced Scheduling Algorithms: Metaheuristics

Journal of Network and Systems Management (2019) 27:688–729
https://doi.org/10.1007/s10922-018-9481-0

CrossMark

A Bio-inspired Datacenter Selection Scheduler for Federated Clouds and Its Application to Frost Prediction

Elina Pacini[1,2] · Lucas Iacono[1,2] · Cristian Mateos[3] · Carlos García Garino[1]

Received: 14 August 2017 / Revised: 1 November 2018 / Accepted: 8 November 2018 /
Published online: 22 November 2018

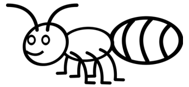
Abstract
Frost is an agro-meteorological event which causes both damage in crops and important economic losses, therefore frost prediction applications (FPA) are very important to help farmers to mitigate possible damages. FPA involves the execution of many CPU-intensive jobs. This work focuses on efficiently running FPAs in paid federated Clouds, where custom virtual machines (VM) are launched in appropriate resources belonging to different providers. The goal of this work is to minimize both the makespan and monetary cost. We follow a federated Cloud model where scheduling is performed at three levels. First, at the *broker level*, a datacenter is selected taking into account certain criteria established by the user, such as lower costs or lower latencies. Second, at the *infrastructure level*, a specialized scheduler is responsible for mapping VMs to datacenter hosts. Finally, at the *VM level*, jobs are assigned for execution into the preallocated VMs. Our proposal mainly contributes to implementing bio-inspired strategies at two levels. Specifically, two broker-level schedulers based on Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), which aim to select the datacenters taking into account the network latencies, monetary cost and the availability of computational resources in datacenters, are implemented. Then, VMs are allocated in the physical machines of that datacenter by another intra-datacenter scheduler also based on ACO and PSO. Performed experiments show that our bio-inspired scheduler succeed in reducing both the makespan and the monetary cost with average gains of around 50% compared to genetic algorithms.

Keywords Scientific computing · Frost prediction applications · Cloud computing · Scheduling · Ant colony optimization · Particle Swarm optimization · Genetic algorithms

Pacini, E. et al. A bio-inspired datacenter selection scheduler for federated clouds and its application to frost prediction. Journal of Network and Systems Management.

Key Aspects:

- Two schedulers **PSO** and **ACO**



- Implemented at the **broker** (**datacenter selection**) and **IaaS (VM allocation)** levels

Multi-objective Optimization:

- Balanced **trade-offs** between **makespan, monetary cost, and resource availability**.
- Included considerations for **network latencies** and **datacenter capacities**.

Advanced Scheduling Algorithms: Metaheuristics

Journal of Network and Systems Management (2019) 27:688–729
https://doi.org/10.1007/s10922-018-9481-0

CrossMark

A Bio-inspired Datacenter Selection Scheduler for Federated Clouds and Its Application to Frost Prediction

Elina Pacini[1,2] · Lucas Iacono[1,2] · Cristian Mateos[3] · Carlos García Garino[1]

Received: 14 August 2017 / Revised: 1 November 2018 / Accepted: 8 November 2018 /
Published online: 22 November 2018

Abstract
Frost is an agro-meteorological event which causes both damage in crops and important economic losses, therefore frost prediction applications (FPA) are very important to help farmers to mitigate possible damages. FPA involves the execution of many CPU-intensive jobs. This work focuses on efficiently running FPAs in paid federated Clouds, where custom virtual machines (VM) are launched in appropriate resources belonging to different providers. The goal of this work is to minimize both the makespan and monetary cost. We follow a federated Cloud model where scheduling is performed at three levels. First, at the *broker level*, a datacenter is selected taking into account certain criteria established by the user, such as lower costs or lower latencies. Second, at the *infrastructure level*, a specialized scheduler is responsible for mapping VMs to datacenter hosts. Finally, at the *VM level*, jobs are assigned for execution into the preallocated VMs. Our proposal mainly contributes to implementing bio-inspired strategies at two levels. Specifically, two broker-level schedulers based on Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), which aim to select the datacenters taking into account the network latencies, monetary cost and the availability of computational resources in datacenters, are implemented. Then, VMs are allocated in the physical machines of that datacenter by another intra-datacenter scheduler also based on ACO and PSO. Performed experiments show that our bio-inspired scheduler succeed in reducing both the makespan and the monetary cost with average gains of around 50% compared to genetic algorithms.

Keywords Scientific computing · Frost prediction applications · Cloud computing · Scheduling · Ant colony optimization · Particle Swarm optimization · Genetic algorithms

Pacini, E., Iacono, L., Mateos, C., & García Garino, C. (2019). A bio-inspired datacenter selection scheduler for federated clouds and its application to frost prediction. Journal of Network and Systems Management, 27(3), 688-729.

Broker-Level Scheduler (Data center selection):

- **Selects** data centers considering communication latency and monetary cost using PSO and ACO.
- Weighs **monetary cost** (e.g., VM pricing) and **latency** with adjustable parameters.

Infrastructure-Level Scheduler (IaaS):

- **Allocates** VMs to datacenter hosts.
- **Ensures** efficient use of physical resources to **minimize costs and execution delays**.

VM-Level Scheduler:

- **FCFS-based** job scheduling within preallocated VMs.

Advanced Scheduling Algorithms: Metaheuristics

Journal of Network and Systems Management (2019) 27:688–729
https://doi.org/10.1007/s10922-018-9481-0

CrossMark

A Bio-inspired Datacenter Selection Scheduler for Federated Clouds and Its Application to Frost Prediction

Elina Pacini[1,2] · Lucas Iacono[1,2] · Cristian Mateos[3] · Carlos García Garino[1]

Received: 14 August 2017 / Revised: 1 November 2018 / Accepted: 8 November 2018 /
Published online: 22 November 2018

Abstract
Frost is an agro-meteorological event which causes both damage in crops and important economic losses, therefore frost prediction applications (FPA) are very important to help farmers to mitigate possible damages. FPA involves the execution of many CPU-intensive jobs. This work focuses on efficiently running FPAs in paid federated Clouds, where custom virtual machines (VM) are launched in appropriate resources belonging to different providers. The goal of this work is to minimize both the makespan and monetary cost. We follow a federated Cloud model where scheduling is performed at three levels. First, at the *broker level*, a datacenter is selected taking into account certain criteria established by the user, such as lower costs or lower latencies. Second, at the *infrastructure level*, a specialized scheduler is responsible for mapping VMs to datacenter hosts. Finally, at the *VM level*, jobs are assigned for execution into the preallocated VMs. Our proposal mainly contributes to implementing bio-inspired strategies at two levels. Specifically, two broker-level schedulers based on Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), which aim to select the datacenters taking into account the network latencies, monetary cost and the availability of computational resources in datacenters, are implemented. Then, VMs are allocated in the physical machines of that datacenter by another intra-datacenter scheduler also based on ACO and PSO. Performed experiments show that our bio-inspired scheduler succeed in reducing both the makespan and the monetary cost with average gains of around 50% compared to genetic algorithms.

Keywords Scientific computing · Frost prediction applications · Cloud computing · Scheduling · Ant colony optimization · Particle Swarm optimization · Genetic algorithms

Pacini, E., Iacono, L., Mateos, C., & García Garino, C. (2019). A bio-inspired datacenter selection scheduler for federated clouds and its application to frost prediction. Journal of Network and Systems Management, 27(3), 688-729.

Experimental Validation:

- Simulated frost applications with real-world frost prediction data using CloudSim.
- Achieved **50% reduction in makespan and monetary costs compared to traditional Genetic Algorithms**.

Advantages of PSO:

- **Faster convergence** and **adaptability** to dynamic cloud environments.
- **Effective** in **balancing load** among heterogeneous datacenters.

Advanced Scheduling Algorithms: Metaheuristics

```
Procedure PSO(tasks, num_particles, iterations):
    Initialize particles with random positions (schedules) and
velocities
    For iteration in 1 to iterations:
        For each particle:
            Evaluate fitness of the particle's position
            Update personal best and global best positions
            Adjust velocity based on personal and global best
            Update particle's position
        End For
    End For
    Return global best schedule
End Procedure
```

Key Components:

- **Particle: A potential schedule.**
- **Velocity: How a particle adjusts its solution.**
- **Global Best: The best solution found so far.**

Advanced Scheduling Algorithms: Metaheuristics

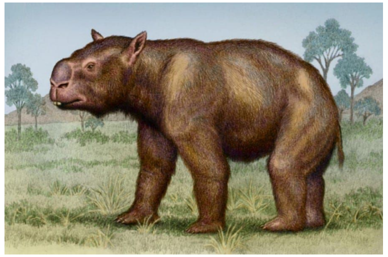
Genetic Algorithms (GA):

- Inspired by **natural selection.**

Process:

- **Selection:** Choose the best solutions.
- **Crossover:** Combine solutions to create new ones.
- **Mutation:** Introduce randomness for diversity.

Use Case: Optimizing resource allocation in data centers.



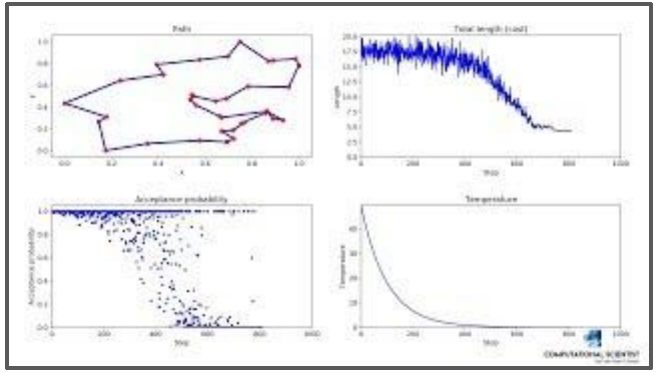
Advanced Scheduling Algorithms: Metaheuristics

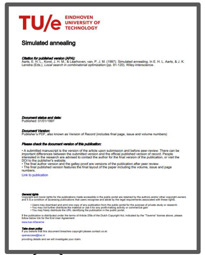
```
Procedure GeneticAlgorithm(tasks, population_size, generations):
    Initialize population with random schedules
    For generation in 1 to generations:
        Evaluate fitness of each schedule
        Select top-performing schedules
        Perform crossover to generate new schedules
        Apply mutation to introduce variability
    End For
    Return best schedule found
End Procedure
```

Key Terms:

- **Fitness: Measure of how well a schedule meets objectives.**
- **Crossover: Combines two schedules to form a new one.**
- **Mutation: Introduces small changes to avoid local optima.**

Advanced Scheduling Algorithms: Metaheuristics





TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

Simulated annealing

Citation for published version (APA):
Aarts, E. H. L., Korst, J. H. M., & Laarhoven, van, P. J. M. (1997). Simulated annealing. In E. H. L. Aarts, & J. K. Lenstra (Eds.), *Local search in combinatorial optimization* (pp. 91-120). Wiley-Interscience.

Document status and date:
Published: 01/01/1997

Document Version:
Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

• A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
• The final author version and the galley proof are versions of the publication after peer review.
• The final published version features the final layout of the paper including the volume, issue and page numbers.
Link to publication

Aarts, E., Korst, J., & Michiels, W. (2005). Simulated annealing. *Search methodologies: introductory tutorials in optimization and decision support techniques*, 187-210.

Simulated Annealing (SA):

Inspired by the annealing process in metallurgy.

Process:

- Starts with a **high "temperature"** (randomness).
- **Gradually cools**, refining solutions over time.

Use Case: Task scheduling for **makespan and cost minimization** and **resource load balance**

HCC Institute of HUMAN-CENTRED COMPUTING

Advanced Scheduling Algorithms: Benefits of AI-Driven Scheduling

Adaptive:

- Can respond **dynamically** to changes in **workload or resource availability**.

Efficient for Large-Scale Problems:

- Handles **high-dimensional search spaces** effectively.

Multi-Objective Capabilities:

- Balances **trade-offs like speed, cost, and energy consumption**.

Advanced Scheduling Algorithms: Challenges in AI-Driven Scheduling

Computational Overhead:

- Metaheuristics may require significant computing power, especially for **real-time scheduling**.

Parameter Tuning:

- Algorithms like GA and PSO require **careful tuning of parameters** (e.g., mutation rate, swarm size).

Convergence Issues:

- Risk of “**getting stuck”** in **local optima.**

Example:

- GA might produce suboptimal task allocations if mutation is too low.

Advanced Scheduling Algorithms: Real-World Use Cases

IoT Data Processing:

- **Example:** Real-time sensor data analysis in a smart factory.

Large-Scale Data Analytics:

- **Cloud:** AWS Fargate (Serverless + Containers) or Azure Logic Apps

Advanced Scheduling Algorithms: Real-World Use Cases

Machine Learning:

- **Training and deployment** of large-scale ML models.
- **Example:** Google TPUs for deep learning workloads.

Streaming and Gaming Services:

- **Example:** FORTNITE scaling resources to handle high-demand content.

Hands-on Activity

Institute of
HUMAN-CENTRED COMPUTING

Hands-On Activity

Simulating Scheduling Algorithms

- **Objective:** Implement and compare FCFS, Round Robin, MIN-MIN - Genetic and PSO.
- **Instructions:**
  - Use the provided Jupyter Notebook (Colab - Python)
  - Experiment with different task loads and parameters (e.g. quantum values, random).
  - Analyze execution times for each algorithm.
  - E.g. tasks = [{"id": 1, "execution_time": 2}, {"id": 2, "execution_time": 3}, {"id": 3, "execution_time": 8}, {"id": 4, "execution_time": 5}]

Questions for Discussion:

1. Which algorithm performs better in terms of **total time**?
2. How does the **quantum** value affect Round Robin's performance?
3. Which **factors are critical** when choosing a scheduling algorithm?

Scheduling Example – Computing Power Allocation

Optimizing Task Scheduling in a High-Performance Computing (HPC) Environment

Scenario:

A research institution runs simulations that require a large amount of computing power across multiple servers. Each simulation task has varying computational requirements and deadlines. Efficient scheduling is critical to ensure optimal usage of computing resources while meeting task deadlines.

Details

- **Resources:**
  - 4 servers with different units of computing power:
    - **Server A:** 10 units of computing power.
    - **Server B:** 8 units of computing power.
    - **Server C:** 6 units of computing power.
    - **Server D:** 5 units of computing power.
- **Tasks:**
  - **Task 1**: Requires 20 units of computing power, deadline = 4 hours.
  - **Task 2**: Requires 10 units of computing power, deadline = 2 hours.
  - **Task 3**: Requires 15 units of computing power, deadline = 3 hours.
  - **Task 4:** Requires 5 units of computing power, deadline = 1 hour.

Challenge:

How can we assign tasks to servers to:

1. **Meet** deadlines.
2. **Minimize** the total execution time.
3. **Balance** the computational load across servers.

Scheduling Example – Computing Power Allocation

Solution Using Scheduling

Step 1: Identify Available Resources

Each server contributes **a fraction of the required computing power.**

- Server **A:** Contributes **10 units/hour.**
- Server **B**: Contributes **8 units/hour.**
- Server **C**: Contributes **6 units/hour.**
- Server **D**: Contributes **5 units/hour.**

Step 2: Select Scheduling Algorithm

1. **Round Robin:**
   Assign tasks to servers in a cyclic order until the task's computing requirements are met.
2. **Min-Min:**
   Assign the shortest task (in terms of computing power needed) to the server with the most availability.

Scheduling Example – Computing Power Allocation

Result with Min-Min Scheduling

Task Assignment:

- **Task 1 (20 units):** Assigned to Server A and Server B (10 units/hour each) → Completed in 2 hours.
- **Task 2 (10 units):** Assigned to Server C (6 units/hour) and Server D (4 units/hour) → Completed in 1.67 hours.
- **Task 3 (15 units):** Assigned to Server A (10 units/hour) and Server B (5 units/hour) → Completed in 1.5 hours.
- **Task 4 (5 units):** Assigned to Server D (5 units/hour) → Completed in 1 hour.

Benefits

1. **Efficiency:**
   Resources are utilized optimally, with no idle servers.
2. **Deadline Compliance:**
   Tasks are completed within their respective deadlines.
3. **Balanced Load:**
   The computational load is distributed across servers, preventing bottlenecks.

Summary

Summary

- Resource management and scheduling are **necessary for**:
  - Performance optimization (makespan)
  - Minimize monetary cost.
  - Lower energy consumption.
  - Minimize data management risk
- No optimal algorithm → **trade-off** between strengths and weaknesses
- **AI-driven scheduling** and **energy optimization** are shaping the **future of cloud computing**.

Summary

- Dec 12. Distributed Storage
- Dec 19. Distributed, Data-Parallel Computation
- **January 09. No Lecture (Time to prepare the project submission)**
- January 16. Distributed Stream Processing
- **January 23.** Distributed Machine Learning Systems

Summary

- Motivation and Terminology
- Cloud Computing Scheduling
  - Challenges
  - Basic Algorithms
  - Advanced Algorithms
- Hands-on activity
- Final remarks
- Next lectures

Vielen Dank!