

Decentralized Grid-Scheduling by Means of Co-evolutionary Learned Fuzzy-Systems

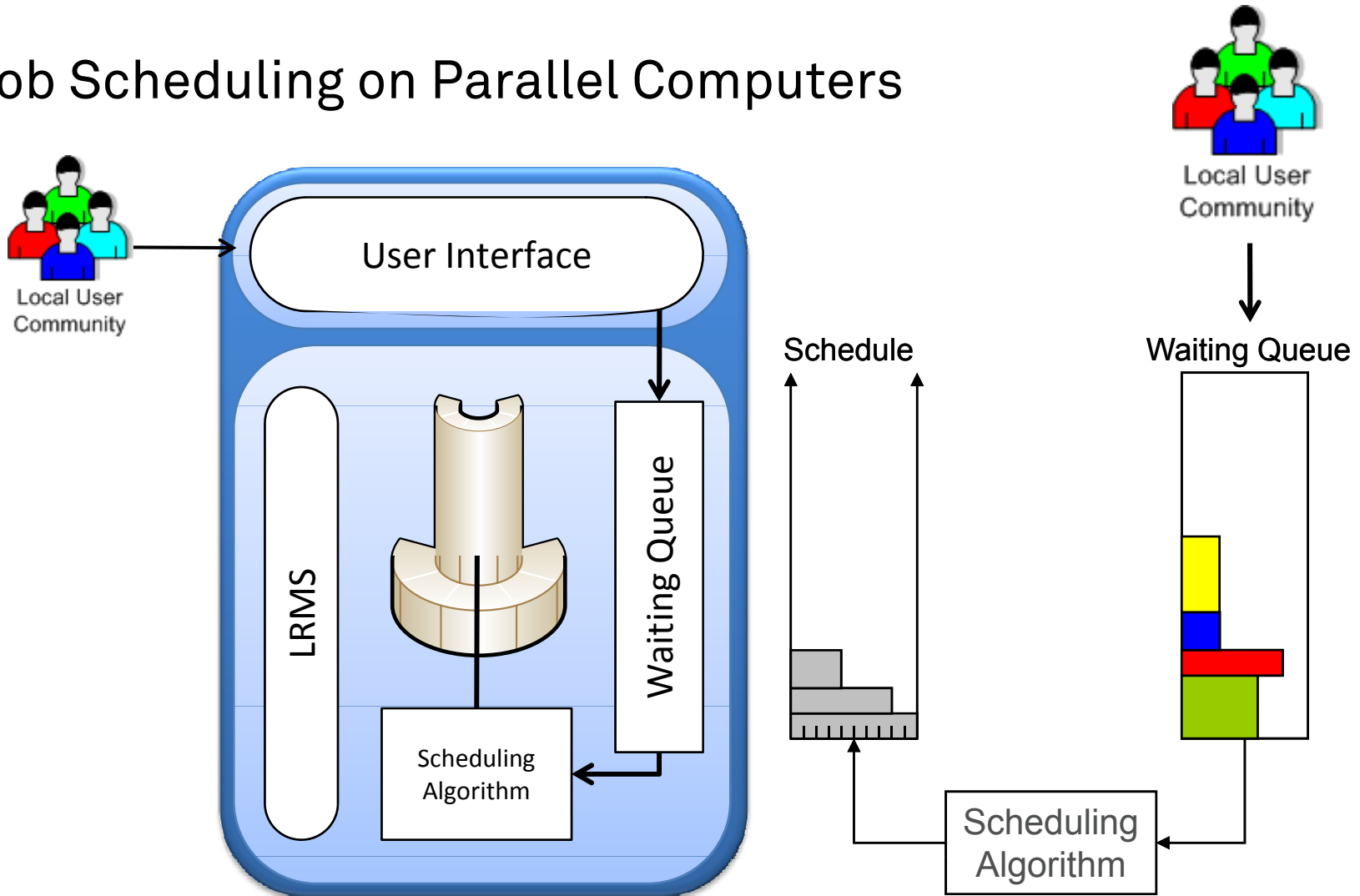
Joachim Lepping and Uwe Schwiegelshohn

3rd "Scheduling in Aussois" Workshop
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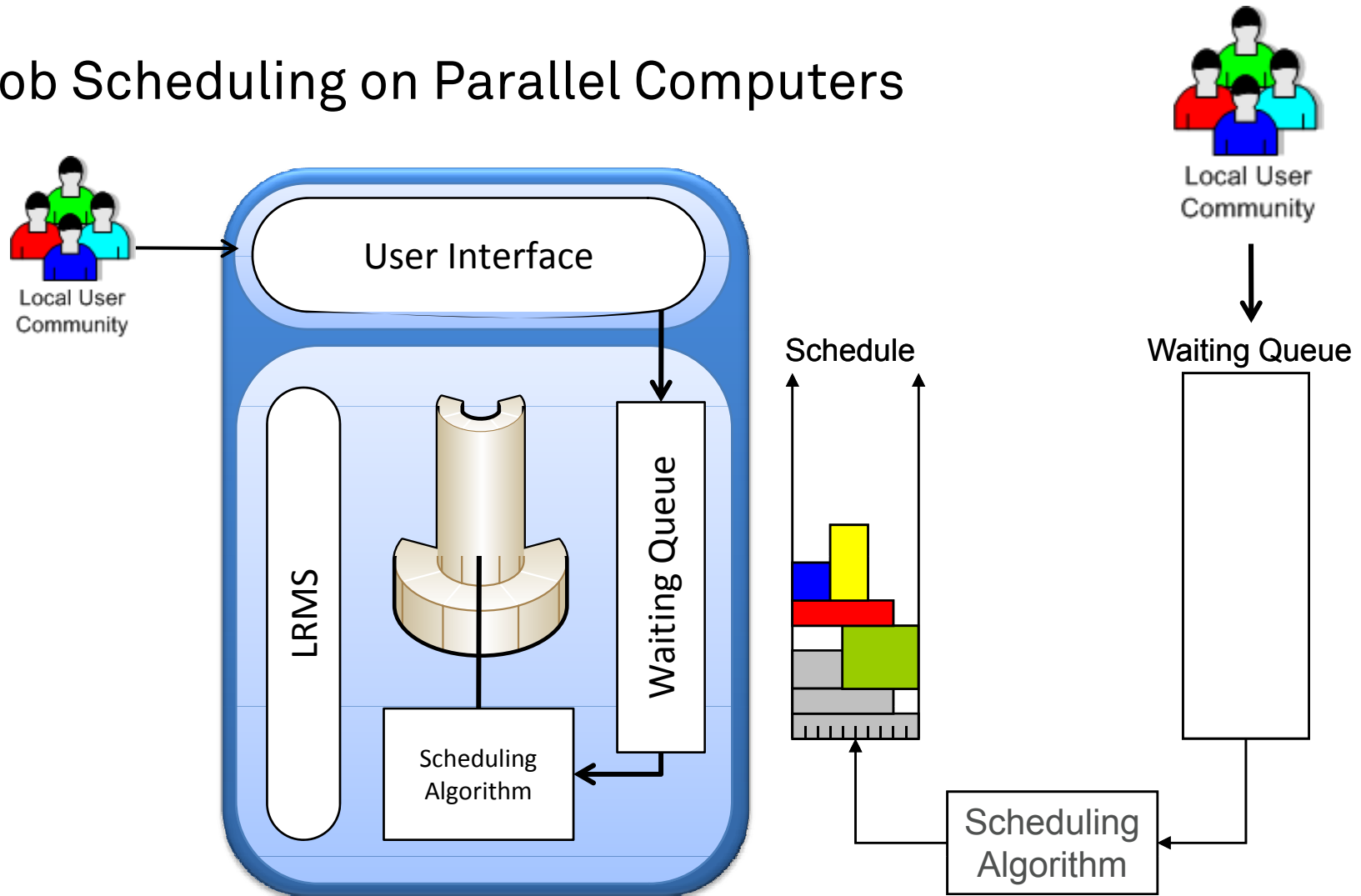
Outline

- Problem introduction
 - Job Scheduling in parallel computers
 - Scheduling in Computational Grids
- General two-layer Grid scheduling architecture
- Fuzzy controller-based Grid scheduling approach
 - Encoding scheme
 - Computation of the controller decision
- Co-evolutionary learning approach
- Evaluation setup and results
- Summary and future work

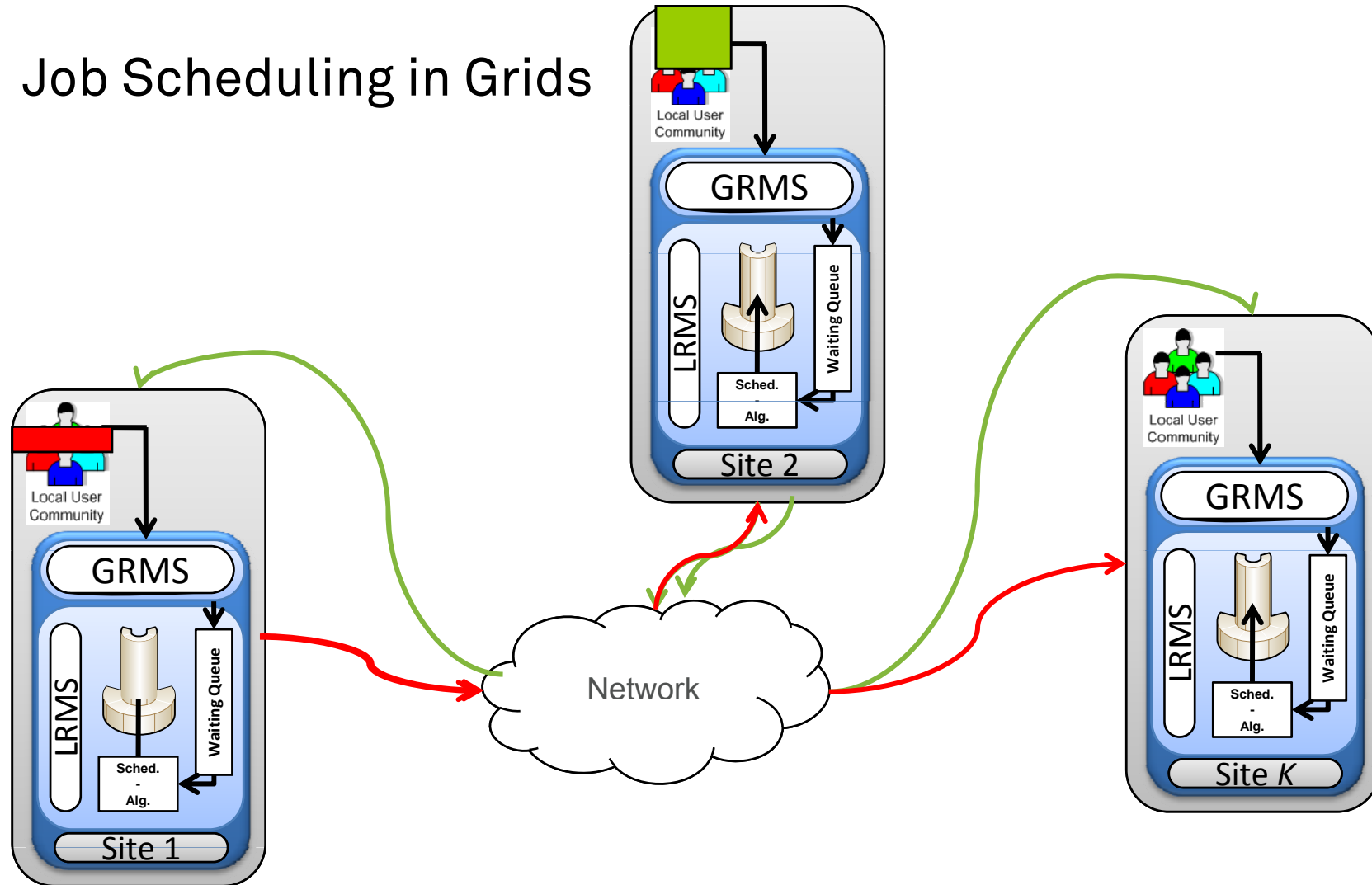
Job Scheduling on Parallel Computers



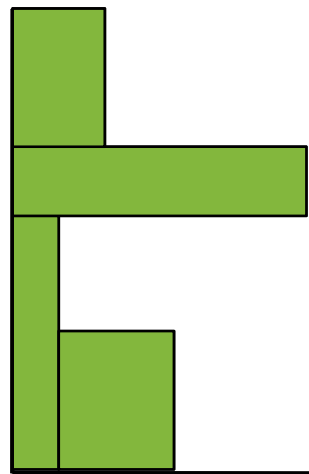
Job Scheduling on Parallel Computers



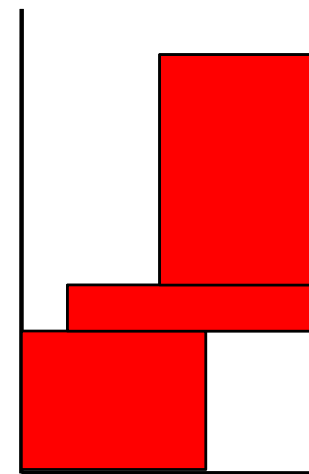
Job Scheduling in Grids



Job Scheduling in Grids



Schedule 1

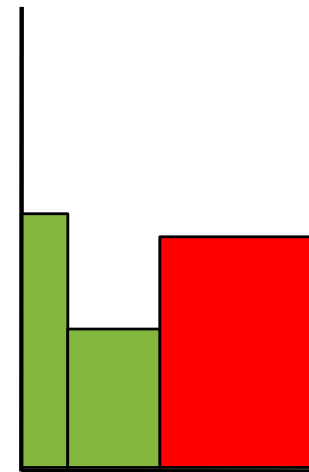


Schedule 2

Job Scheduling in Grids



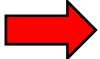
Schedule 1



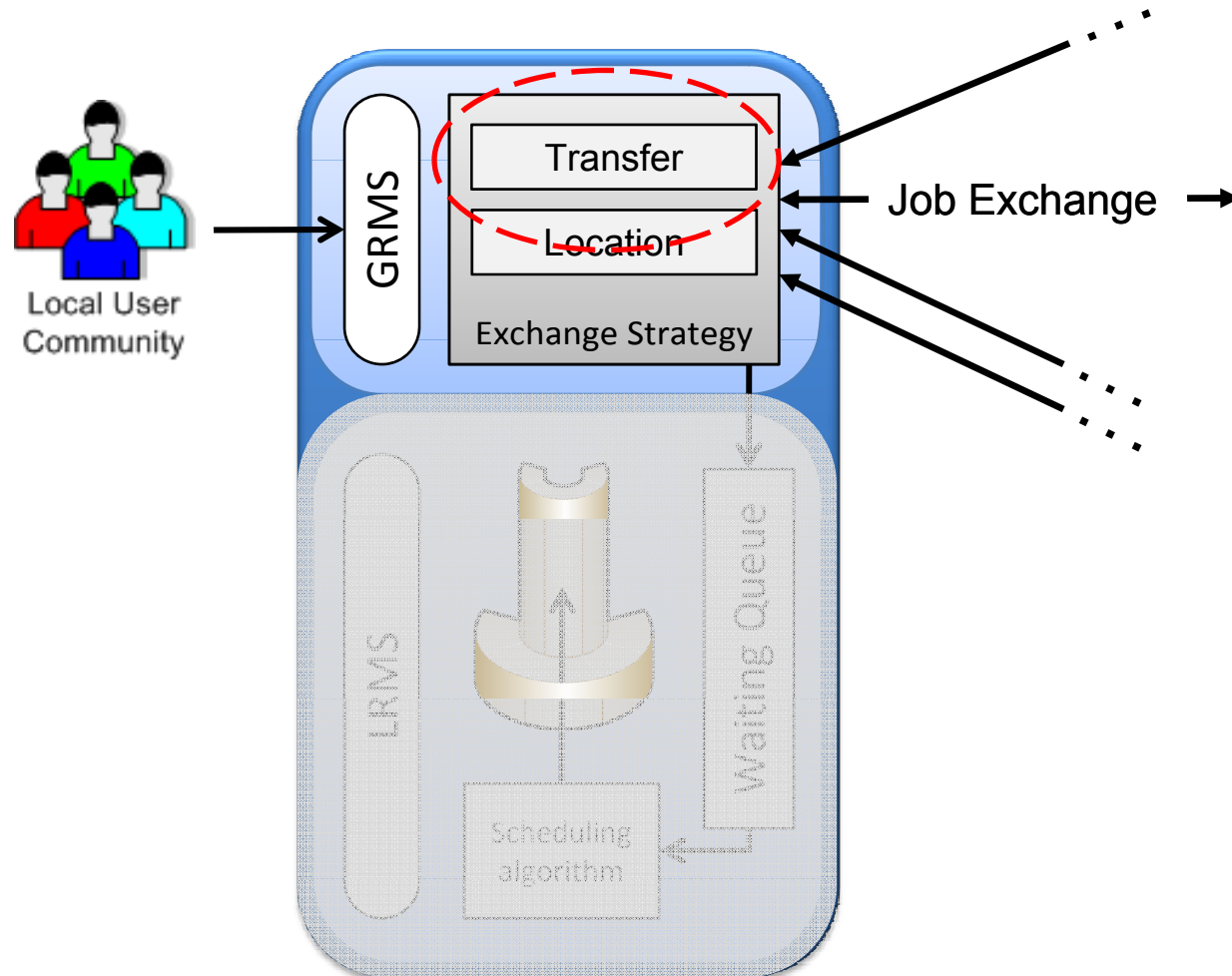
Schedule 2

Challenges in Decentralized Grid Scheduling

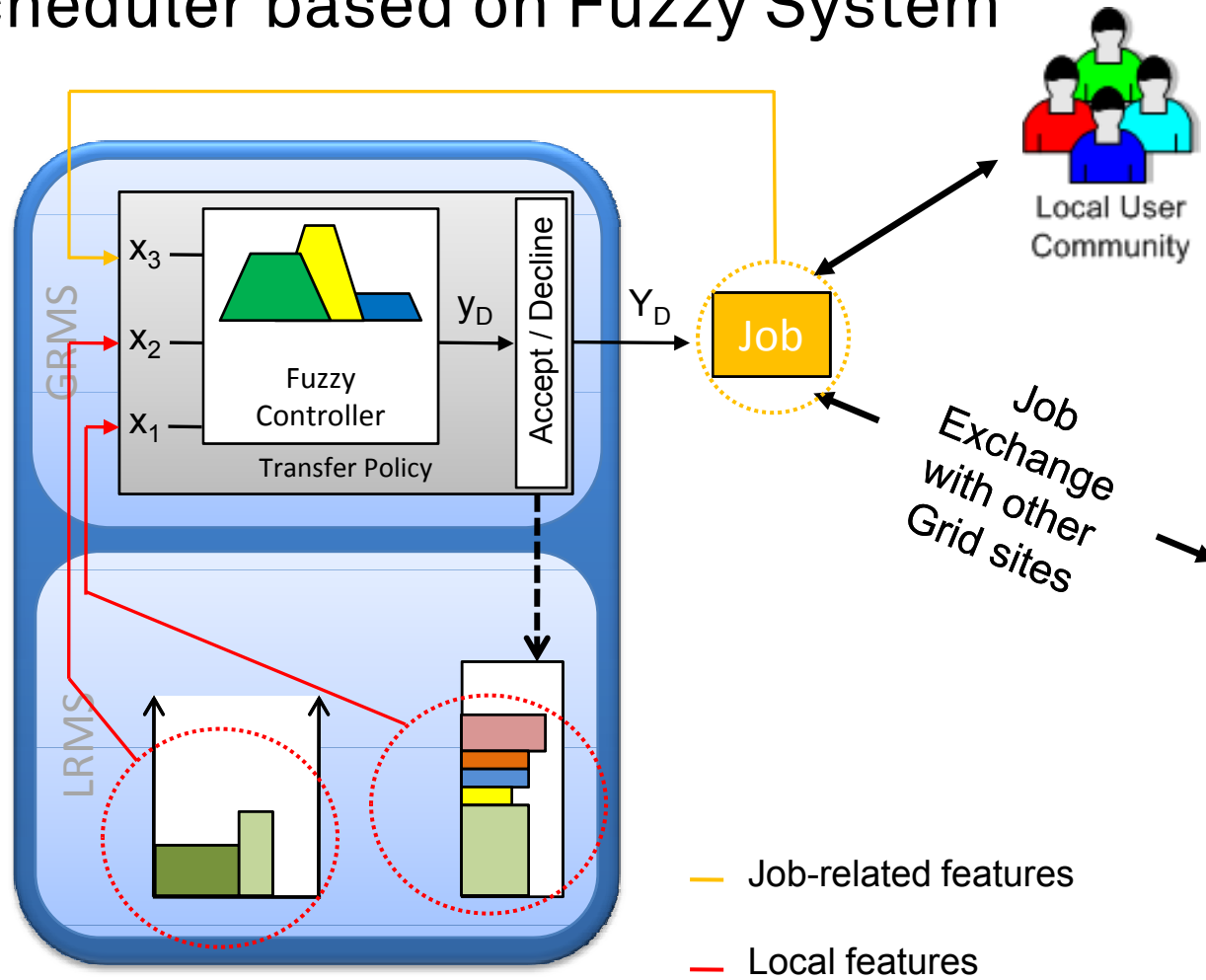
- Independent and autonomous sites
 - Each site favors its own user community
 - No altruistic view of the overall system
- LRMS must be kept untouched
 - Local administrators' configurations must be obeyed
 - No interaction between Grid and Local scheduling layer allowed
- Restrictive information policy
 - No information about current system state is published
 - Only local information are available at each site

 Opportunistic goal: Each sites strives for short response times for their local user community
(potentially at the expense of other user communities)

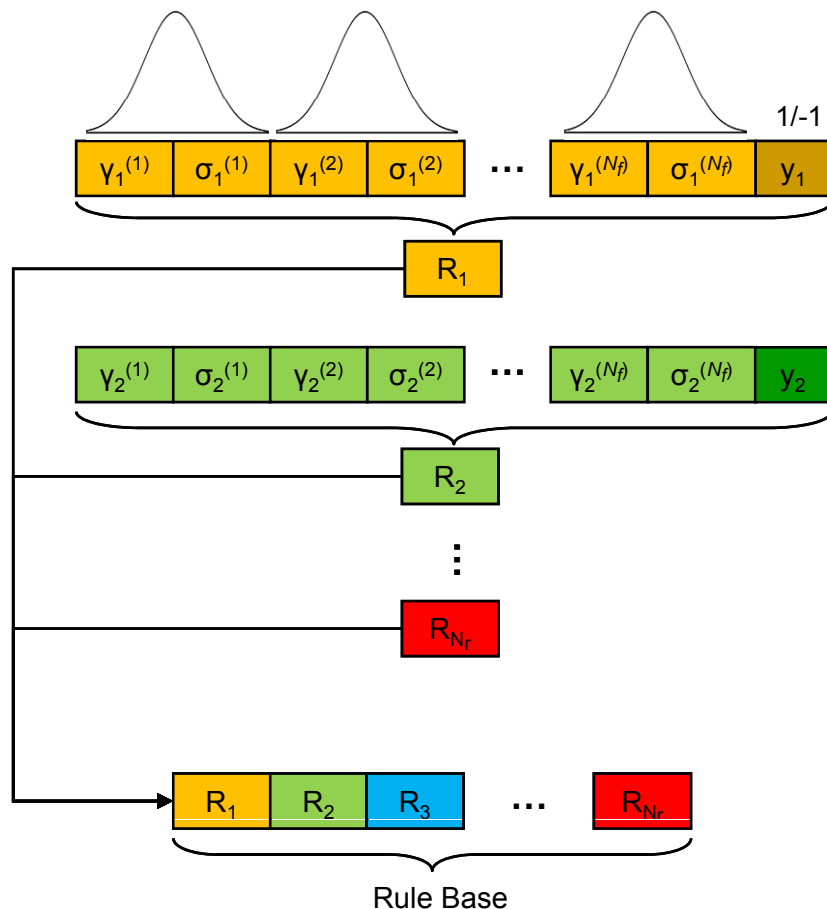
General Scheduling Architecture



Grid Scheduler based on Fuzzy System



Coding of Rules and Rule Bases



- Coding according Pittsburgh-Approach
 - Entire rule base consisting of N_r rules as single individual
- Selection of two features as controller input
 - Normalized Waiting Parallelism (NWP) $NWP_k = \frac{1}{m_k} \sum_{j \in \nu_k} m_j$
 - Normalized Job Parallelism (NJP) $NJP_j = \frac{m_j}{m_k}$
- Binary output variable

$$y_i = \begin{cases} 1, & \text{if job is accepted} \\ -1, & \text{otherwise} \end{cases}$$

Characteristics of Decentralized Grids

- Sites act as egoistic and user-centric agents
 - Tend to delegate much of work to other sites
 - Results in overload of other sites and bad utilization of the Grid

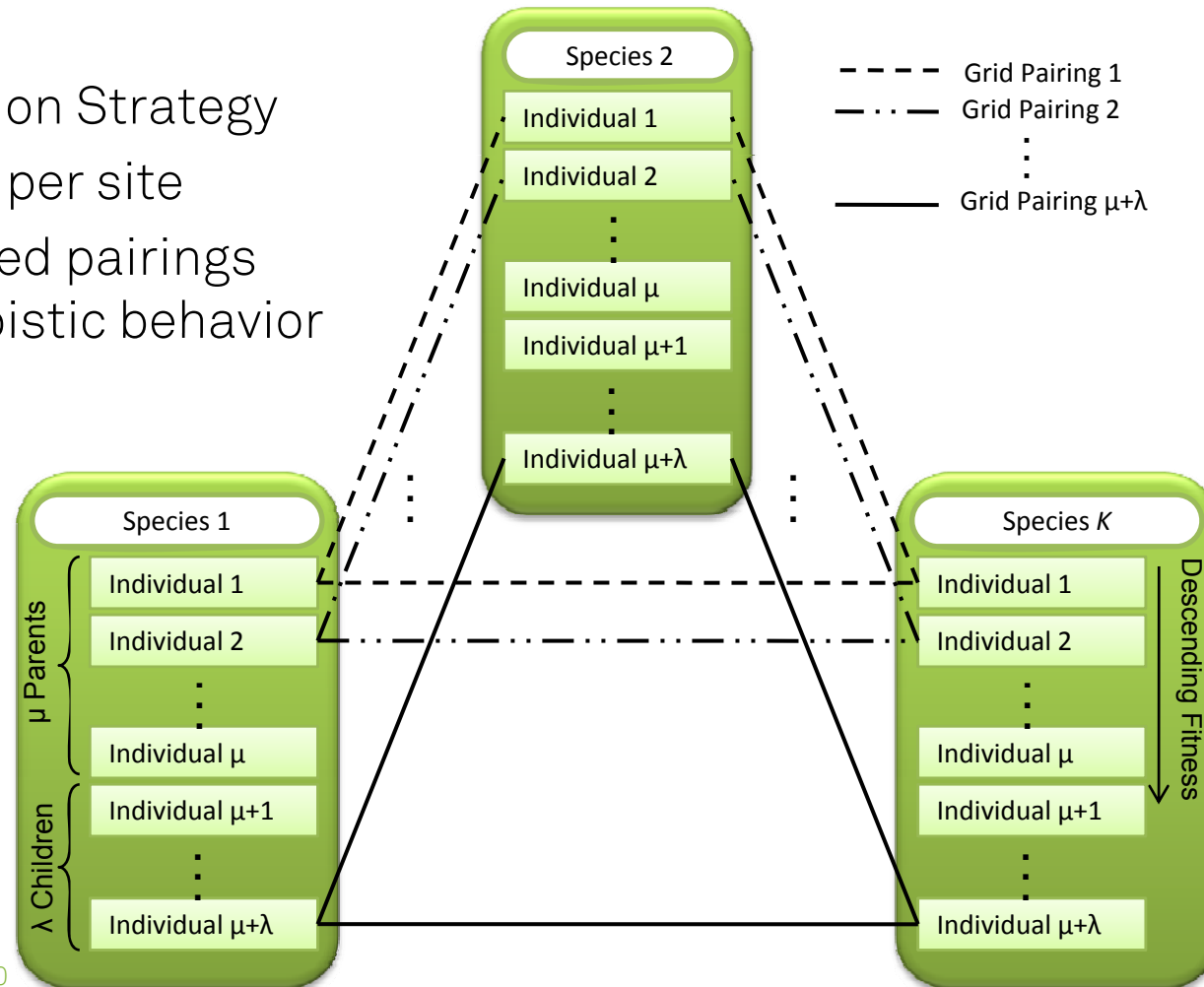
➡ On the long run: bad results for all user communities

- Sites must relax egoism in order to achieve the maximum benefit for their own customers
 - When site accepts jobs, it has more possibilities to get its own jobs accepted by other sites.
 - Vivid job exchange results in shorter response times for all participating user groups

➡ Sites are competing and have to learn to behave cooperatively

Co-evolutionary Learning Approach

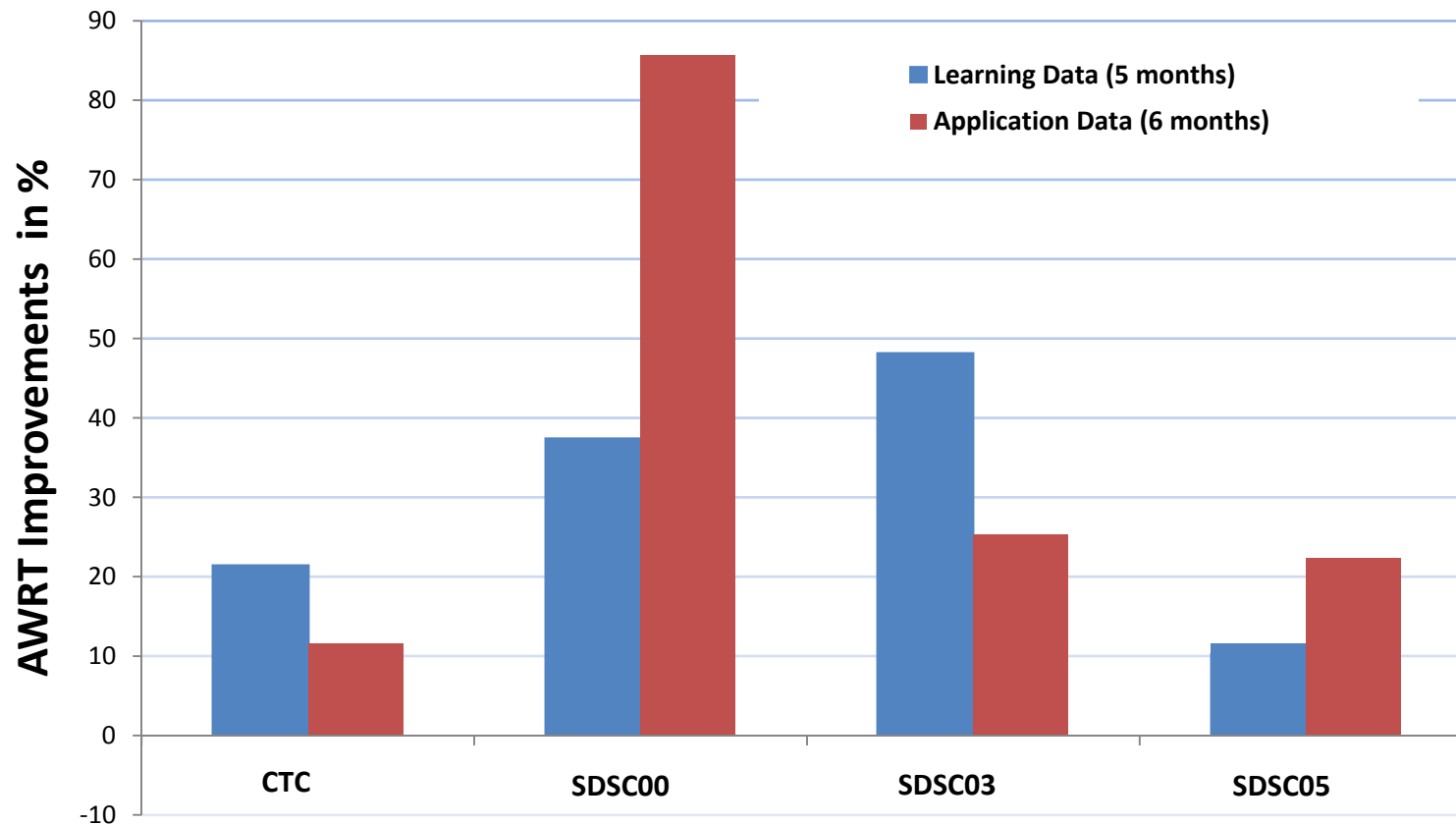
- $(\mu+\lambda)$ -Evolution Strategy
- One species per site
- Fitness-based pairings penalize egoistic behavior



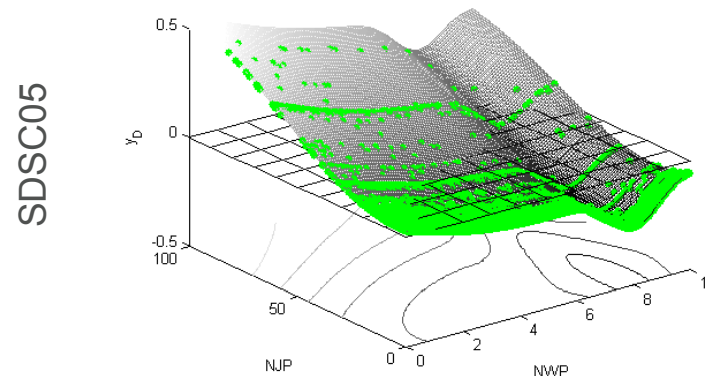
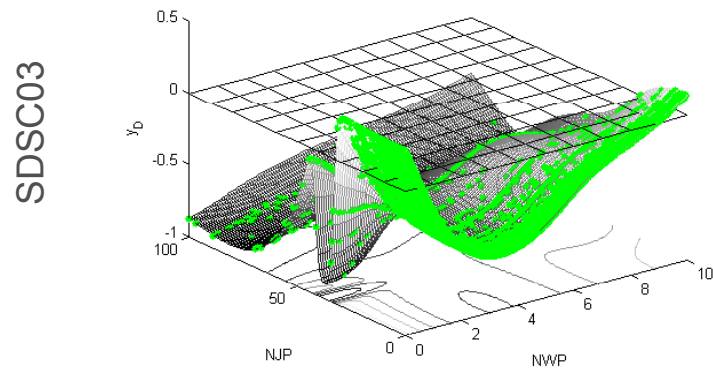
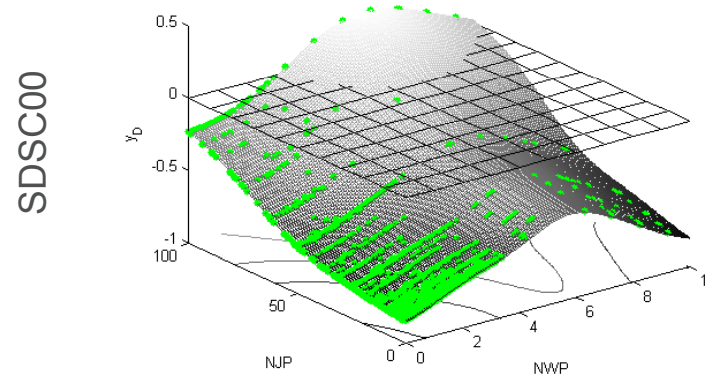
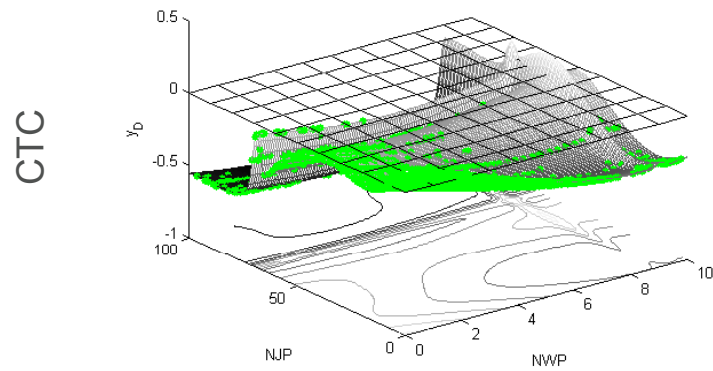
Evaluation Setup

- Input Data
 - Real Workload Traces from Parallel Workloads Archive
 - KTH, SDSC00, SDSC03, SDSC05
 - ~ 100 – 1600 CPUs, ~ 28000 – 74000 Jobs (first 11 months)
 - Splitted in 5 months for training and 6 months for application
- LRMS Layer
 - First-Come-First-Served Scheduling (FCFS)
- Rule bases with $N_r = 10$ rules (results in 50 parameters)
 - (13+91)-Evolution Strategy (executed on 100 node cluster)
- Evaluation objective for optimization
 - Improvements in AWRT compared to exclusive single site execution

Evaluation Results for a Four-Site Grid



Resulting Rule Bases after Optimization



Conclusion / Future Work

- Generation and optimization of Grid Schedulers based on Evolutionary Fuzzy Systems
 - Co-evolutionary learning approach leads to significant objective improvements and shows high robustness
 - Fuzzy-based scheduler and decision maker achieve win-win situation for all participating sites and user communities.
- Evolutionary Fuzzy techniques enables the efficient operation of modern computing Grid environments
- Future Work:
 - Further investigations on competitive/cooperative nature of the problem and application of game theory results
 - Research on zero configuration approaches without input data and offline learning mechanism

Thank You



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