



Efficient Allocation of Resources under Group Dependencies and Availability Uncertainties



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HPCS Scheduling Problem



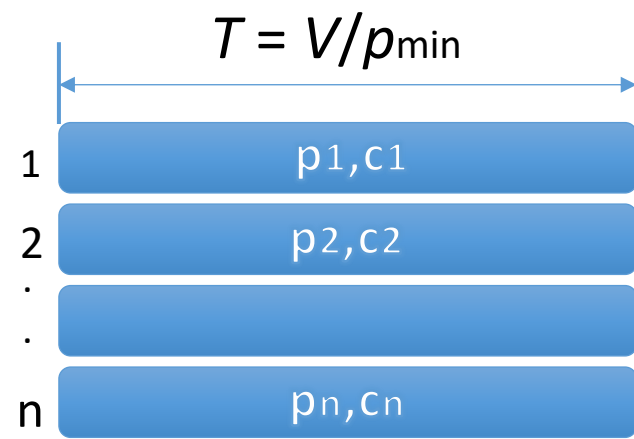
- HPCS and Virtual Organizations should implement efficient procedures for job-flow scheduling, execution and the resources allocation

Job Resource Request and Parallelization

The resource requirements for a single parallel job execution are arranged into a **resource request**:

- n - number of simultaneously requested computational nodes
- p - minimal performance requirement for each computational node
- V - average computational volume for a single node process
- C - maximum total job execution cost (budget)

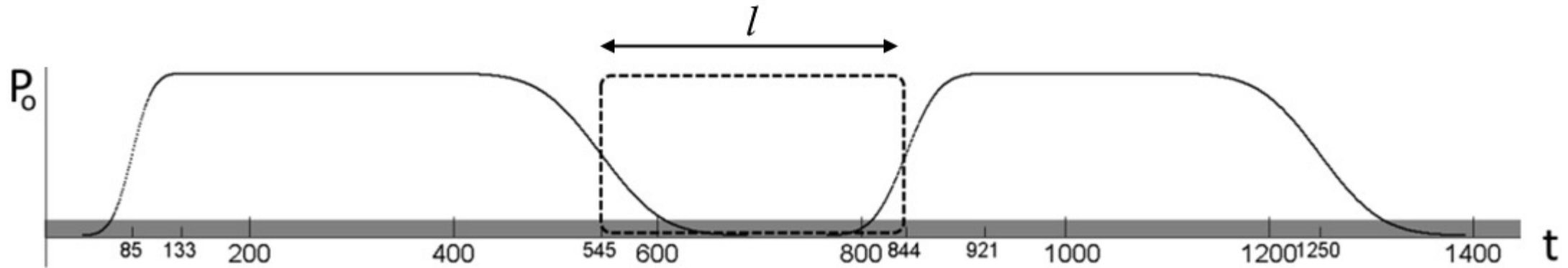
Allocate n simultaneously *available* resources for a time interval T with a total cost constraint C



Availability-based Scheduling

- **Traditional models** consider job-flow scheduling problem in a deterministic way
 - About 20% of Grid computational nodes exhibit **truly random availability** intervals
- In this work the uncertainties are modeled as resources **availability events and probabilities**: a natural way of machine learning and statistical predictions representation
- Resources availability predictions may **originate from**:
 - Historical data
 - Linear regression models
 - Expert and machine learning systems
 - Expert and user estimations

Job Scheduling Under Uncertainties



- Each single node is characterized with a set of availability events
 - Availability event can be described with a random variable distribution
- The node availability probability P_a during the whole interval l depends on the occupation events
- In order to execute a **parallel job** a set of nodes (a window) should be allocated simultaneously
- We want to **maximize** a total **window availability probability**

Window Availability Calculation

The **total window availability probability** may be calculated as follows:

$$P_a^w = \prod_i^n P_a^{r_i} \rightarrow \max,$$

Allocate a set of **n nodes** with a total cost constraint:

$$\sum_{i=1}^n c_i \leq C$$

Dynamic Programming solution (0-1 multiplicative knapsack):

$$f_j(c, v) = \max\{f_{j-1}(c, v), f_{j-1}(c - c_j, v - 1) * P_j\}$$

$$j = 1, \dots, m, c = 1, \dots, C, v = 1, \dots, n,$$

Group Dependencies between the Resources

In general, the resources and their utilization events *are not independent*

Groups $G_i \in G$ represent subsets of resources sharing common properties

Group examples:

- Resources of a parallel job share common utilization events
- Discount provided for resources selected from the same vendor
- Performance benefits for matching resources
- Geographical location and connectivity-based groups

ID = 1
Mips = 3.0
Ram = 1.86
Price = 2.28
HwIndex = 0.12

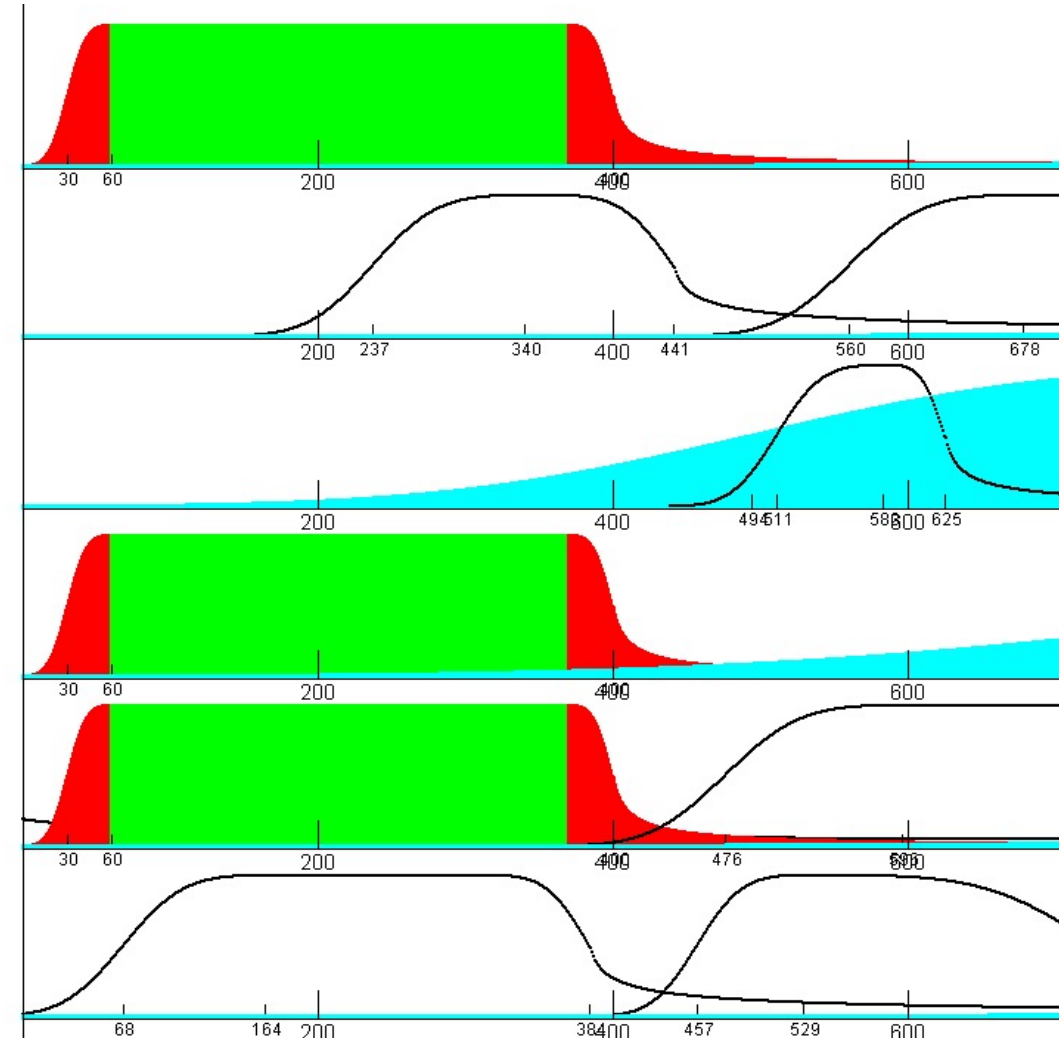
ID = 2
Mips = 7.0
Ram = 5.77
Price = 9.75
HwIndex = 0.65

ID = 3
Mips = 11.0
Ram = 6.87
Price = 15.07
HwIndex = 0.91

ID = 4
Mips = 3.0
Ram = 1.75
Price = 2.43
HwIndex = 0.12

ID = 5
Mips = 3.0
Ram = 2.34
Price = 2.85
HwIndex = 0.18

ID = 6
Mips = 5.0
Ram = 3.12
Price = 4.53
HwIndex = 0.32



Group Dependencies Formalization

- $P_a^{G_i}$ is a common availability probability for group G_i (during interval l)
- If at least one resource from group G_i is selected for window W , then the common probability $P_a^{G_i}$ is included into total availability P_a^W :

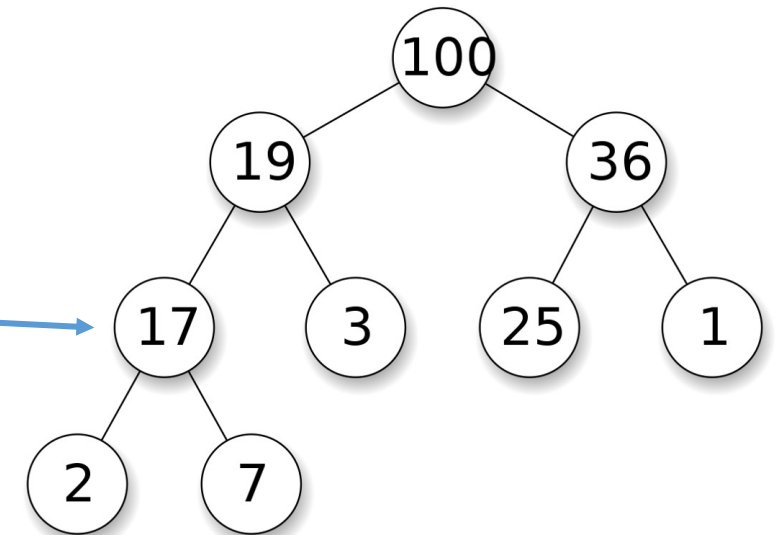
$$P_a^W = \prod_i^{n^*} P_a^{G_i}$$

where n^* is a number of diverse groups used for the window W

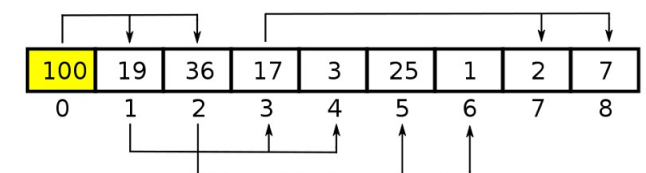
- Total cost constraint: $\sum_{i=1}^n c_i \leq C$

Branch and Bounds Algorithm to Address Group Dependencies

- We implement branch-and-bounds approach to consider resources groupings for the resources' selection
- Max-Heap data structure is maintained for the solution tree
- For each solution node we maintain:
 - G^+ set of groups to be included in the solution
 - G^- set of groups to be excluded from the solution
 - Other groups
 - (Upper estimate) criterion value P_a^w



Array representation



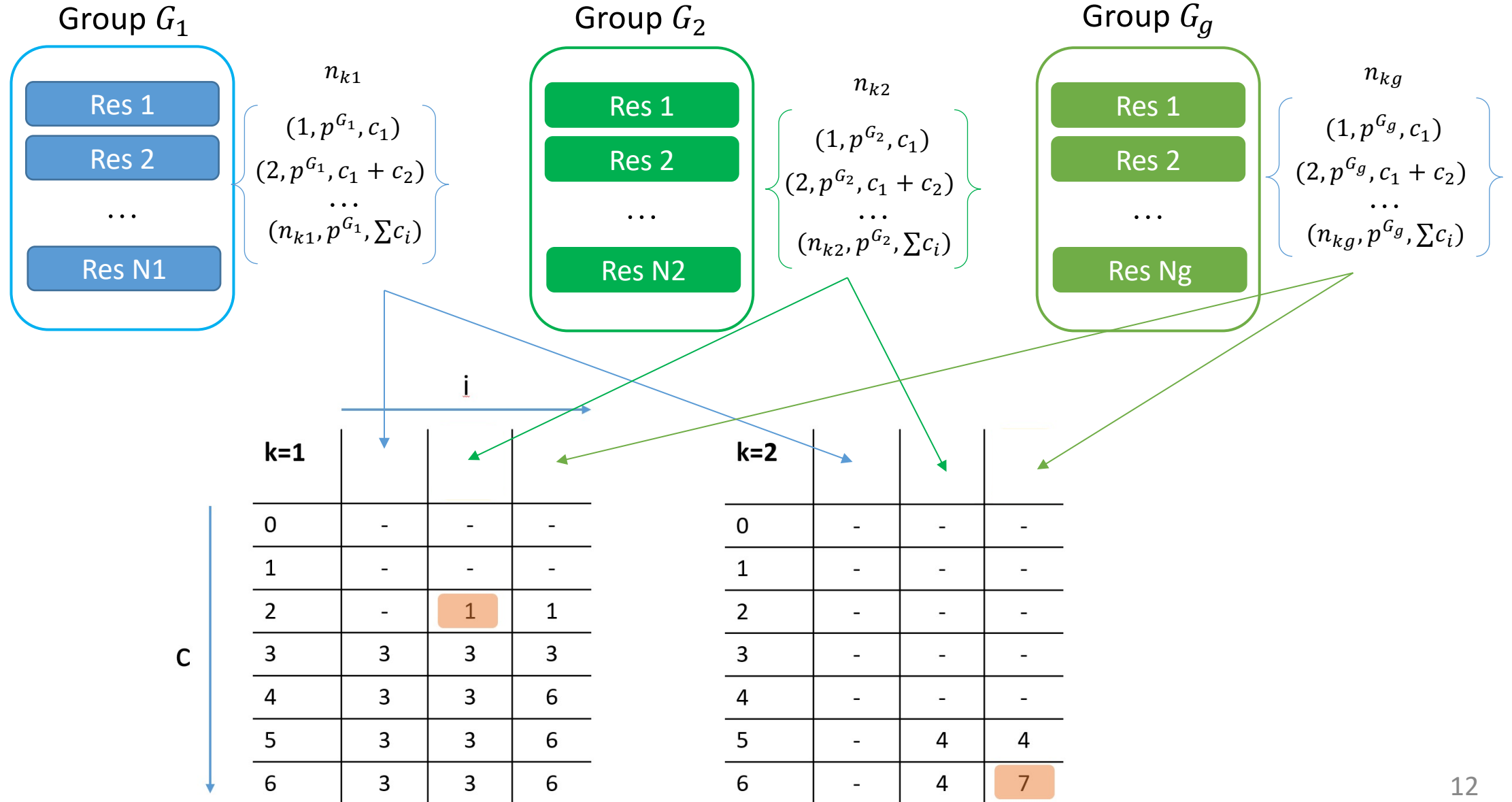
Group Knapsack Algorithm (GKA)

- GKA considers groups of resources G_i as enumeration items instead of individual VMs
- Instead of a single pair of characteristics p_i and c_i , each group item G_i provides a list of NV_i possible resource allocation *variants* $Var_j = (n_j, u_j, c_j)$
- GKA iterates over groups $G_i \in G$ and their variants $\{Var_j\}$ to calculate the following recurrent scheme:

$$f_i(c, n) = \max\{f_{i-1}(c, n), f_{i-1}(c - c_j, n - n_j) + u_j\},$$
$$i = 1, \dots, |G|, j = 1, \dots, NV_i, c = 1, \dots, C_{\max}, n = 1, \dots, n_{\max}$$

- $f_i(c, n)$ then maintains the maximum possible *aggregate* utility U achievable for a subset of n VMs combined from different variants from groups $\{G_1, \dots, G_i\}$ for a budget c
- Estimated computational complexity is bounded by $O(N * n_{\max} * C_{\max})$

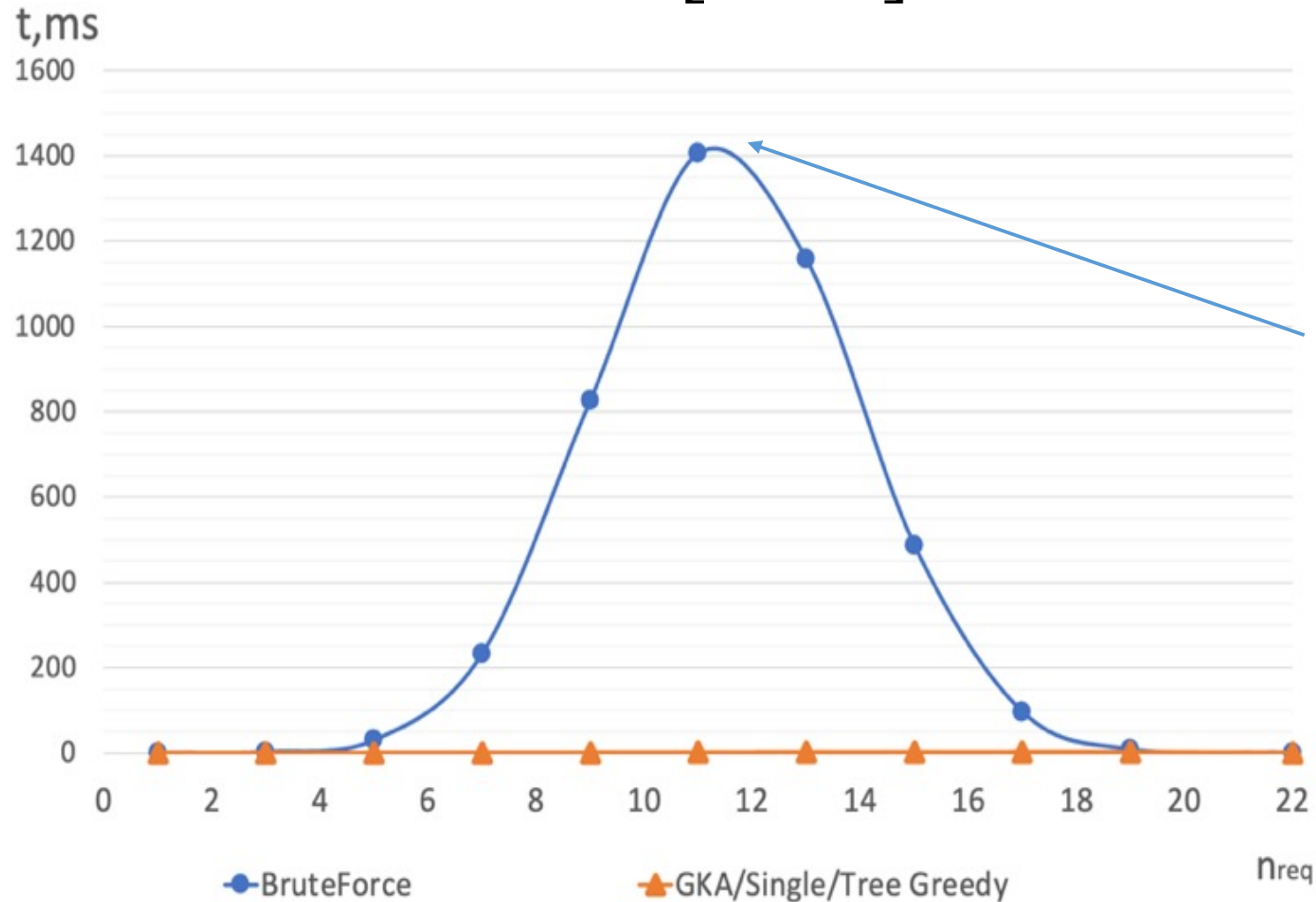
Group Knapsack Algorithm (GKA)



Algorithms for Analysis and Comparison

- **Brute Force** provides exact solution but usually not feasible for $N > 35$ resources
- **Knapsack Single** implements resources allocation for $P_a^w = \prod_i^n p_i \rightarrow \max$ without any knowledge of the resources' groupings (**multiplicative knapsack**)
- **Exact Branch and Bounds (Tree)** implements the presented branch-and-bounds approach with *Knapsack Single* for intermediate calculations, thus providing exact solution in integers
- **Greedy Branch and Bounds (Tree Greedy)** implements the same branch-and-bounds approach but uses more performance-efficient greedy approximation for the intermediate calculations
- **Group Knapsack (GKA)** implements group 0-1 knapsack with account for group dependencies

Execution Time selecting $n \in [1; 22]$ from $N = 22$ resources

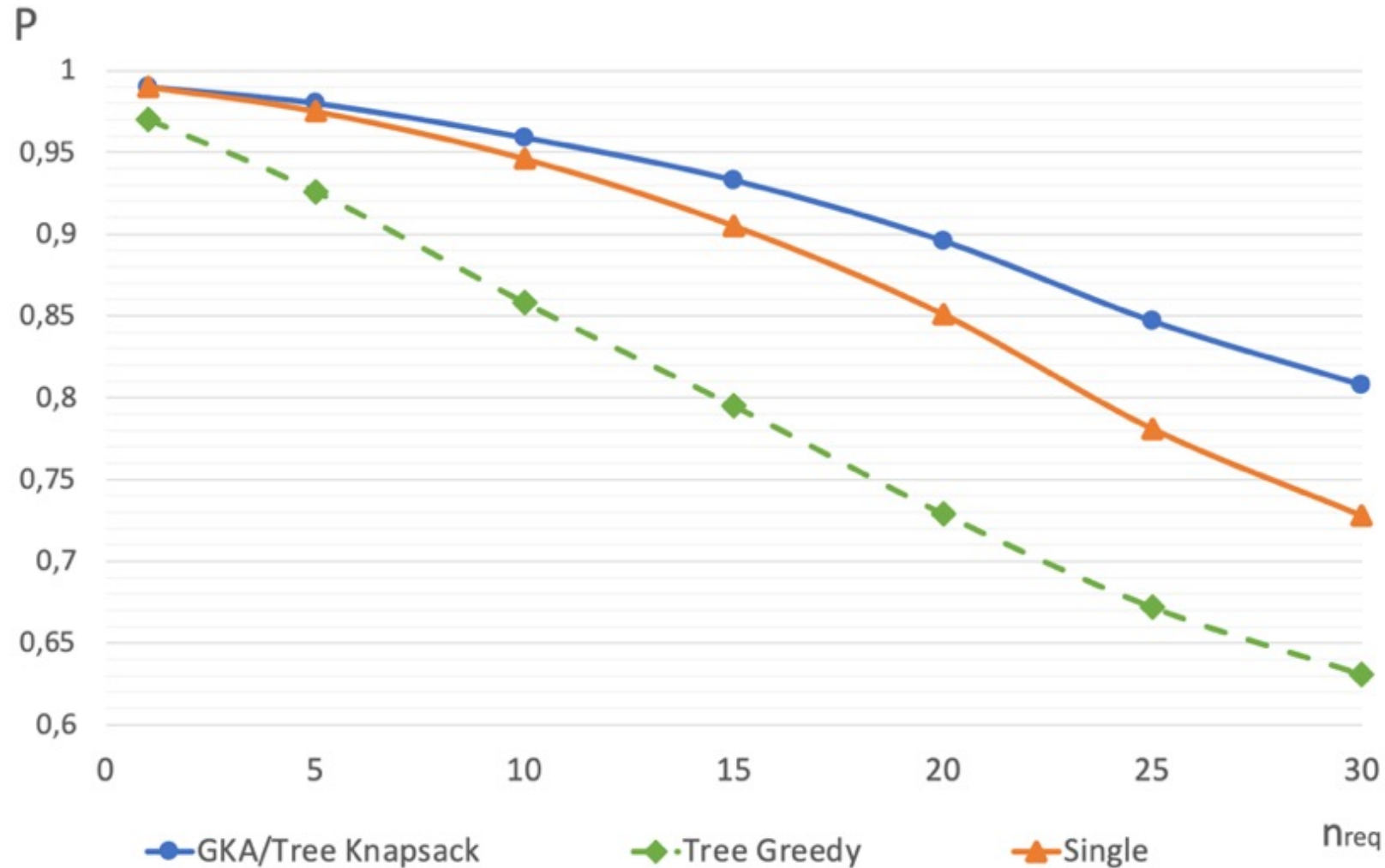


Brute Force, GKA and Branch-n-Bounds
generate exact solution

Brute Force execution time shows its
combinatorial nature

Brute Force took 10,000 times longer to
execute compared to the branch-and-
bounds and GKA in a simplified
environment with $N = 22$ resources

Availability Probability selecting $n \in [1; 30]$ from $N = 200$ resources

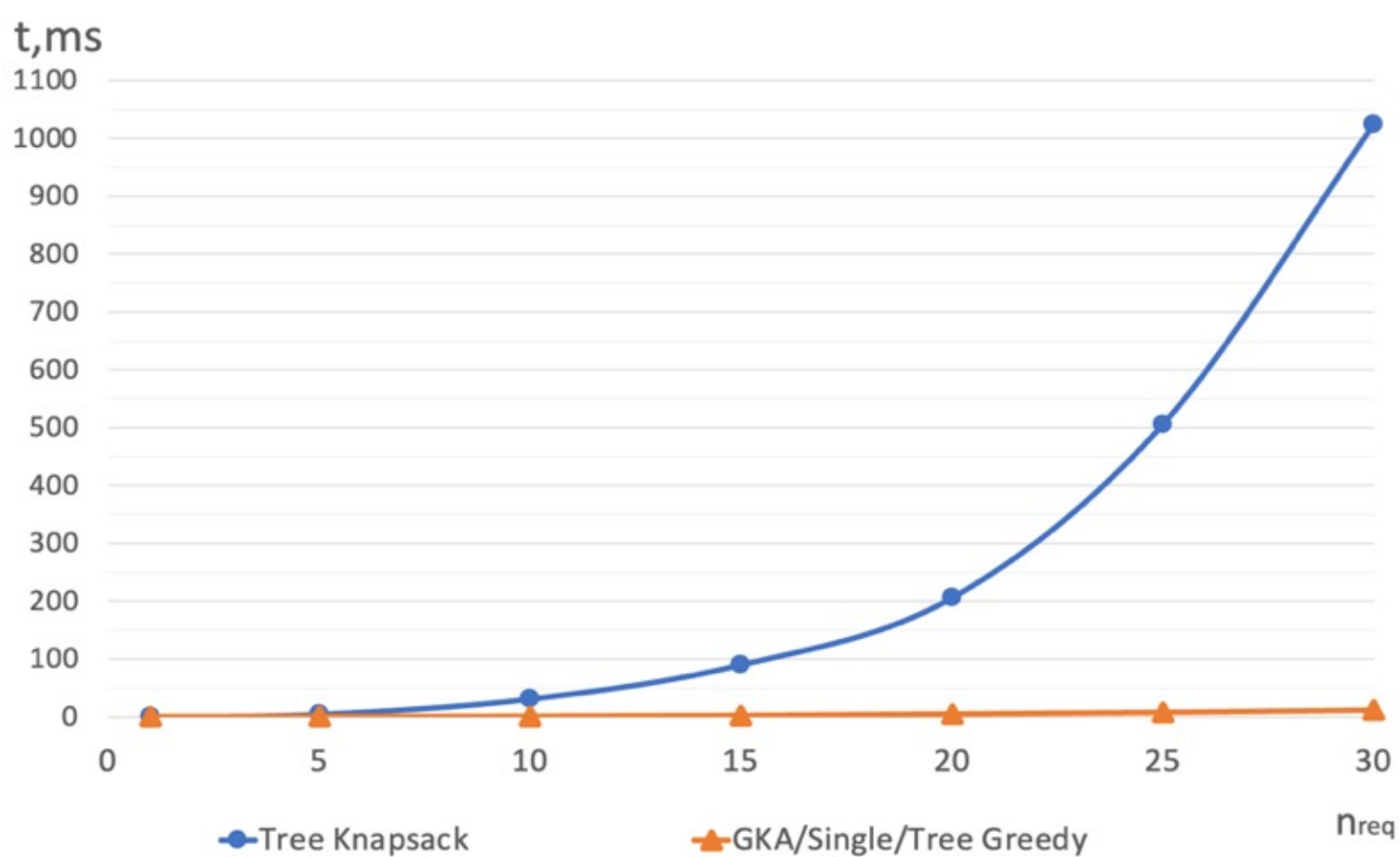


GKA and Branch-n-Bounds
generate exact solution

Other algorithms provide 5-18%
lower values

Execution Time

selecting $n \in [1; 30]$ from $N = 200$ resources

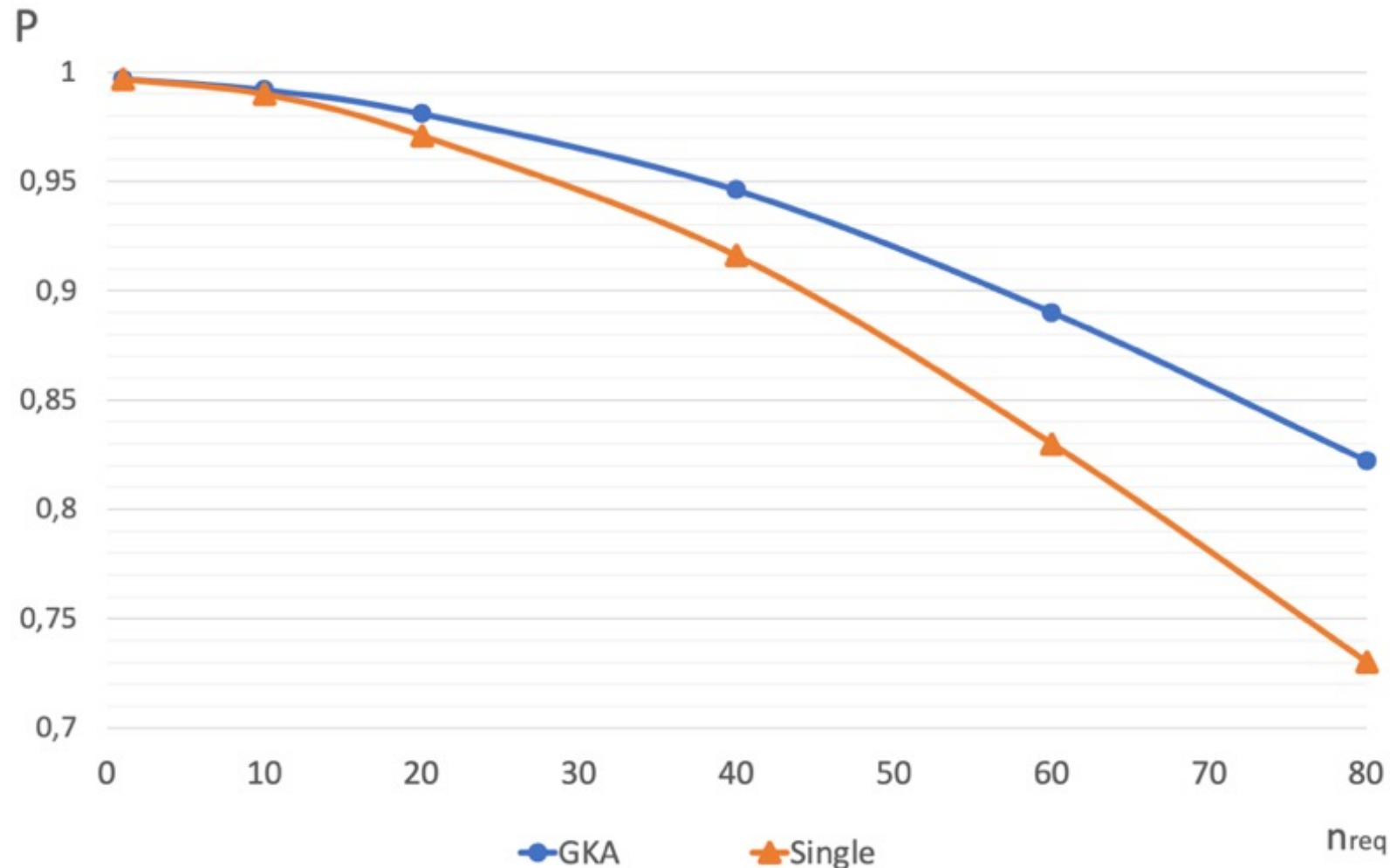


Branch-n-Bounds execution time demonstrates dramatic growth of the decision tree

GKA is at least 100 times faster to solve the same problem

Availability Probability

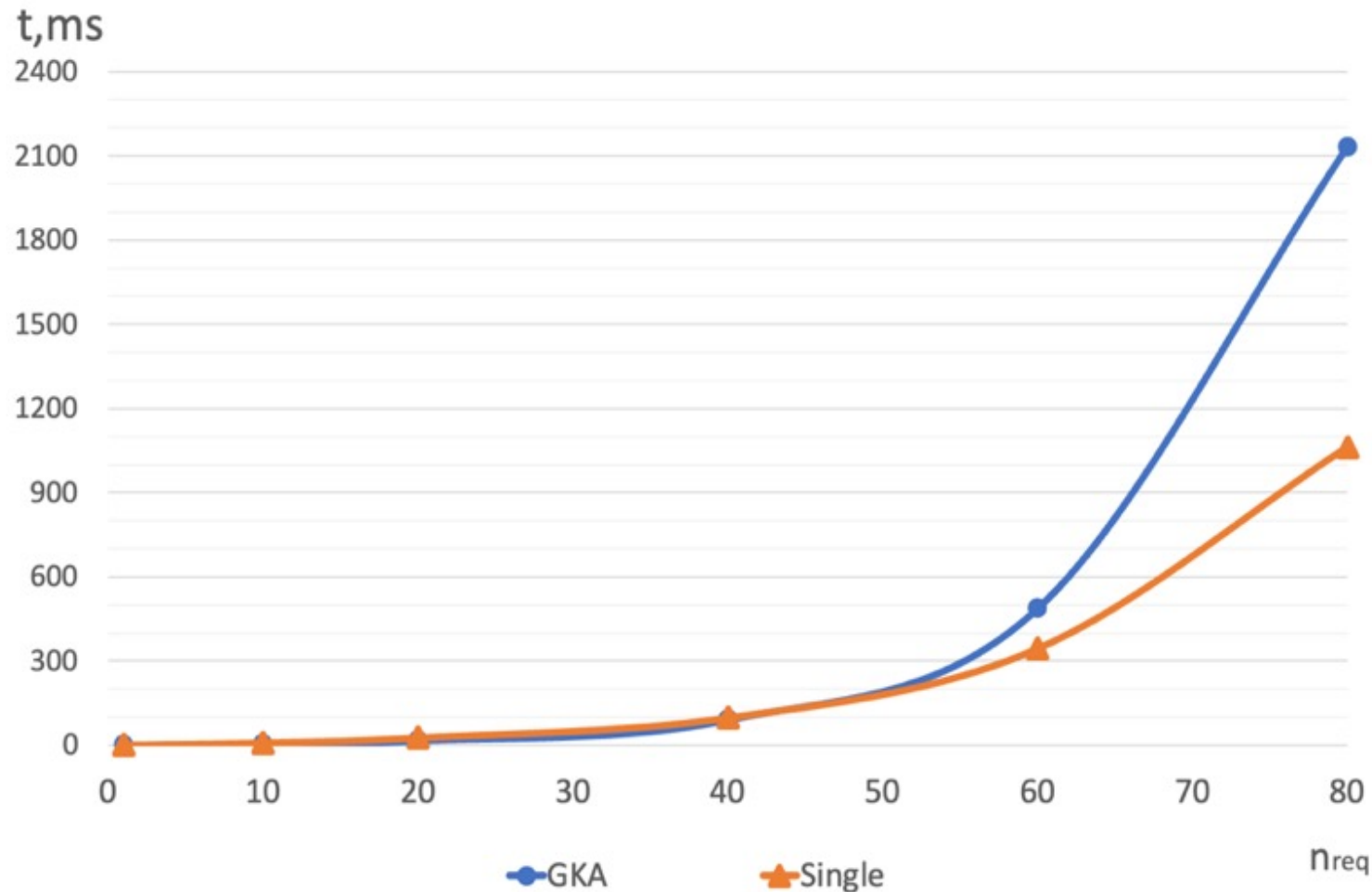
selecting $n \in [1; 80]$ from $N = 1000$ resources



GKA generates exact solution increasingly better compared to Knapsack

Execution Time

selecting $n \in [1; 80]$ from $N = 1000$ resources



GKA and Knapsack execution times and complexity are *comparable*

Algorithms exceed 1 second execution time for the following problem sizes:

Knapsack: $n = 80$ from $N = 1000$

GKA: $n = 65$ from $N = 1000$

BB: $n = 30$ from $N = 200$

BruteForce: $n = 10$ from $N = 22$

Conclusion

- We address the problem of dependable resources co-allocation for parallel jobs in distributed computing with **group dependencies over the resources**
- We compared several algorithms and approaches, including **brute force**, **classical knapsack**, **branch-and-bounds**, **greedy** approximation and a **novel dynamic programming procedure**
- Proposed solution allows to generate accurate solution for problems with **thousands of nodes** , (at least 10x times larger compared to branch-and-bounds approach)
- **In our further work**, we will research possible hybrid approximation schemes and metaheuristics applicable for even larger problems of resources allocation with group dependencies
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Thank You!

