Dynamic Balancing of Scientific HPC Applications on Institutional Clusters

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Demands on computing resources are greater than the existing supply. Proposed methods allow existing computing resources to complete more large-scale jobs in a given timeframe.

Limited Resources

- Demand on current computing resources in the scientific community is growing rapidly.
- We are reaching the limit of Moore's law and can't wait for faster machines to solve our problems.
- Need to implement more efficient ways of running more jobs on the hardware that we already have in place.

Why Not Cloud?

Current limitations of the cloud:

- Speed severely limited by network latency.
- Current clouds services aren't set up for HPC workflows.
- High level of cloud administrator knowledge needed.
- Fewer tools for test environments.
- Currently incapable of replicating the performance of institutional clusters.

Benefits of using a cloud system:

- Cheap, elastic, and widely available.
- Viable option for smaller workflows.

Methods

Dynamic Right-Sizing Master-Worker applications

Goal: Dynamically allocate the optimal number of machines to a master-worker application.

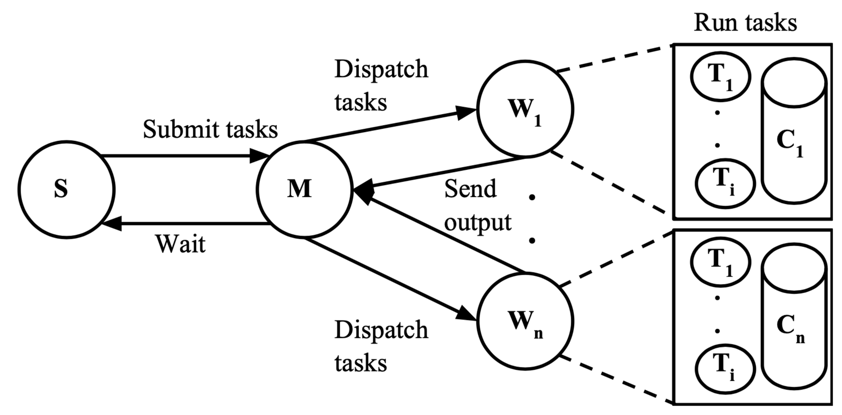
- ***Capacity*** defined as the number of computational nodes that can be effectively utilized by an application
- Correctly allocates machines to the application based on *capacity* during run time.
- Eliminates under and over provisioning of resources to applications.
  - Can increase system throughput and utilization.

Introducing on-demand requests to HPC Clusters

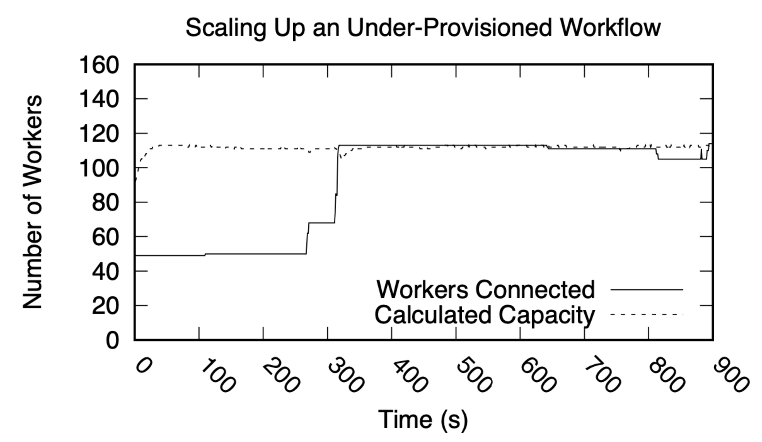
- Traditionally, HPC uses a batch scheduler and on-demand resources have designated computational resources.
- Propose to combine on-demand and batch system resources to increase total computing power.
- Running on-demand requests on a majority batch system.
- Could reduce the investment on on-demand hardware by a massive margin and still be able to handle all cases in a workflow.
- Massive reduction in batch wait times.

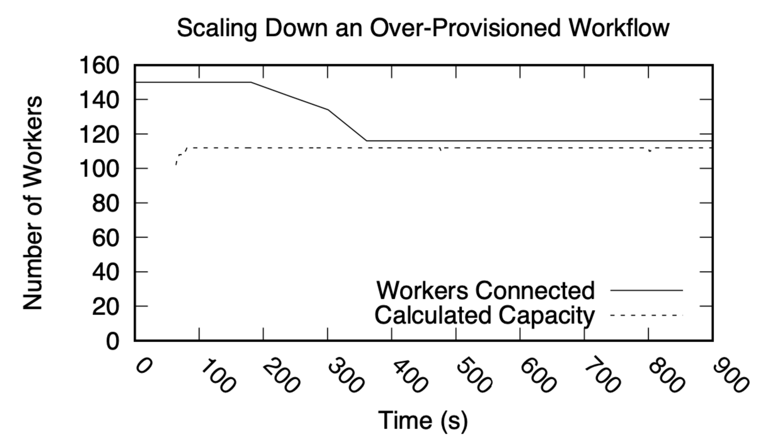
Parameter settings	Static (Baseline)			Dynamic						
	Dedicated batch nodes			W						
	372	304	0	0	5	10	0	5	10	0
	Dedicated on-demand nodes			R						
	0	68	372	0			6			12
Combined utilization	84.4%	80.1%	1.25%	84.9%	85.7%	85.7%	85.3%	85.3%	85.3%	85.3%
Batch utilization	84.4%	78.8%	NA	84.5%	84.4%	84.4%	84.0%	84.1%	84.0%	84.0%
On-demand utilization	NA	1.25%	1.25%	0.38%	1.25%	1.25%	1.25%	1.25%	1.25%	1.25%
Batch wait time (min)	122.5	1002.8	NA	122.0	147.0	147.0	150.0	140.6	150.4	130.0
Rejections	141	0	0	30	3	3	1	1	0	0

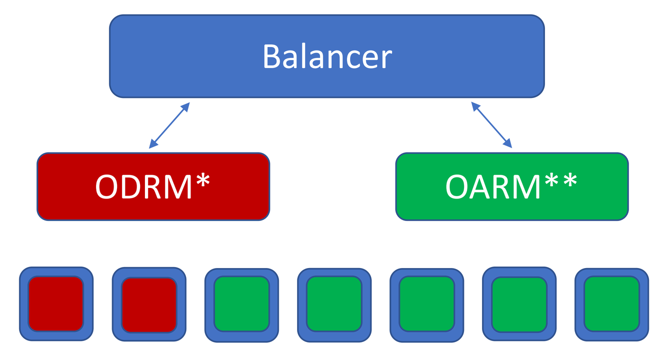
Experimental results of most challenging real-world workflow. Table from Feng Liu 2018.



Top: Master-worker architecture (Nathaniel Kremer Herman, 2018).
Left: Ability of model to scale up/down based on application *capacity* (Nathaniel Kremer Herman, 2018).
Right: Balancer architecture (Feng Liu, 2018).







*On-Demand Resource Manager
**On-Availability Resource Manager

Future Work

- Replication study of both methods using different real-world workflows. Potentially data from researchers at Haverford.
- Testing fault tolerance of the proposed methods.

References:

- Feng Liu, Kate Keahey, Pierre Riteau Jon Weissman (2018). "Dynamically Negotiating Capacity Between On-Demand and Batch Clusters". In: *SC18* (cit. on pp. ii, 5, 11–15, 19).
- Nathaniel Kremer Herman, Benjamin Tovar and Douglas Thain (2018). "A Lightweight Model for Right-Sizing Master-Worker Applications". In: *SC18* (cit. on pp. ii, 9, 10).
- Marco A.S. Netto Rodrigo N. Calheiros, Eduardo R. Rodrigues Renato L. F. Cunha Rajkumar Buyya (2018). "HPC Cloud for Scientific and Business Applications: Taxonomy, Vision, and Research Challenges". In: *ACM Computing Surveys* 51.1 (cit. on p. 7).

Read my entire thesis here!

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