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Performance Inconsistency in Large Scale Data Processing Clusters

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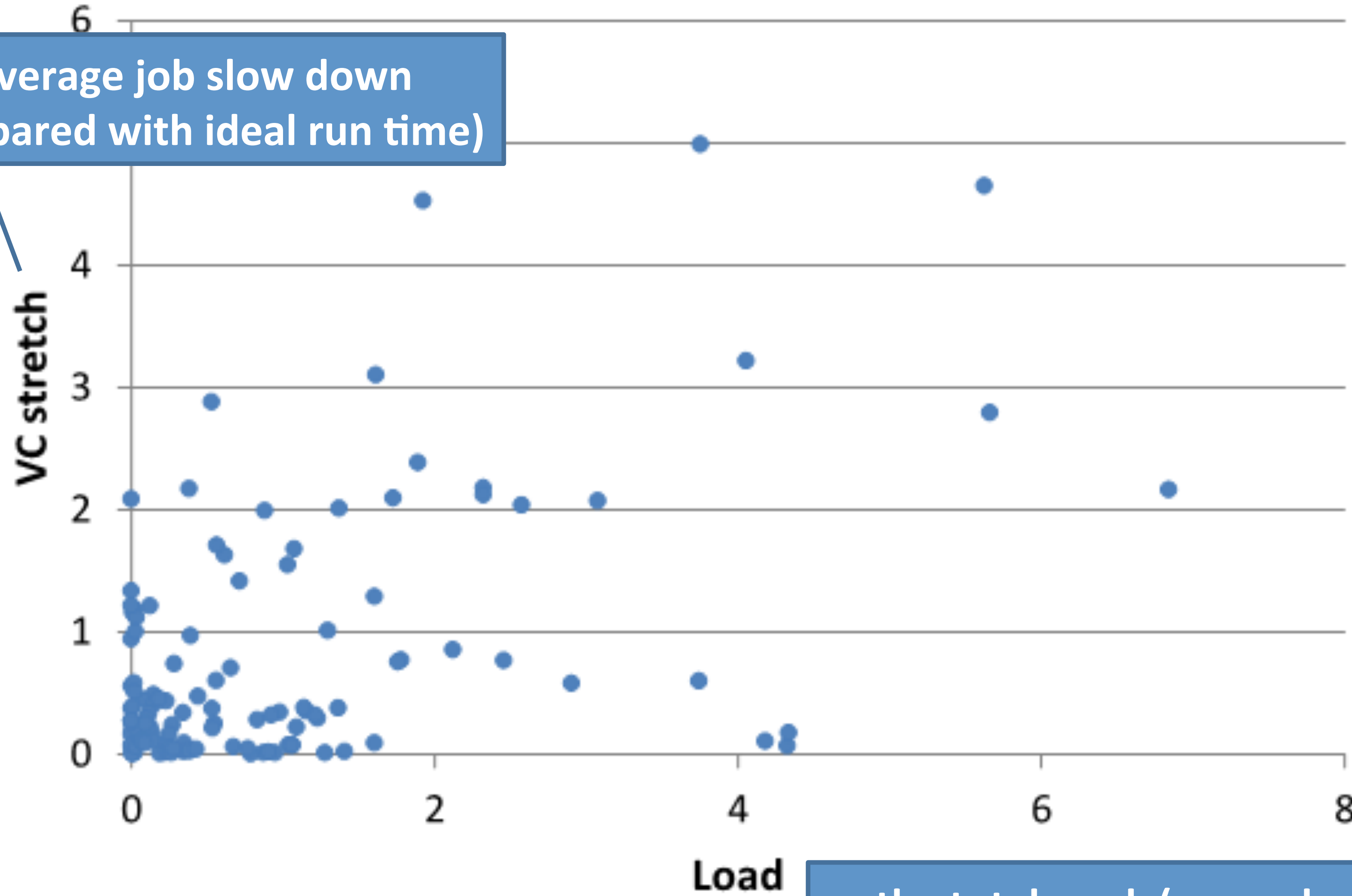
Large Computing Clusters

- e.g., MapReduce, Hadoop, Cosmos
  - Enable large data processing applications

- Sharing
  - Each user pays for using a fraction of the entire cluster (virtual cluster)
  - Fixed capacity, but resources can be shared among VCs to promote utilization

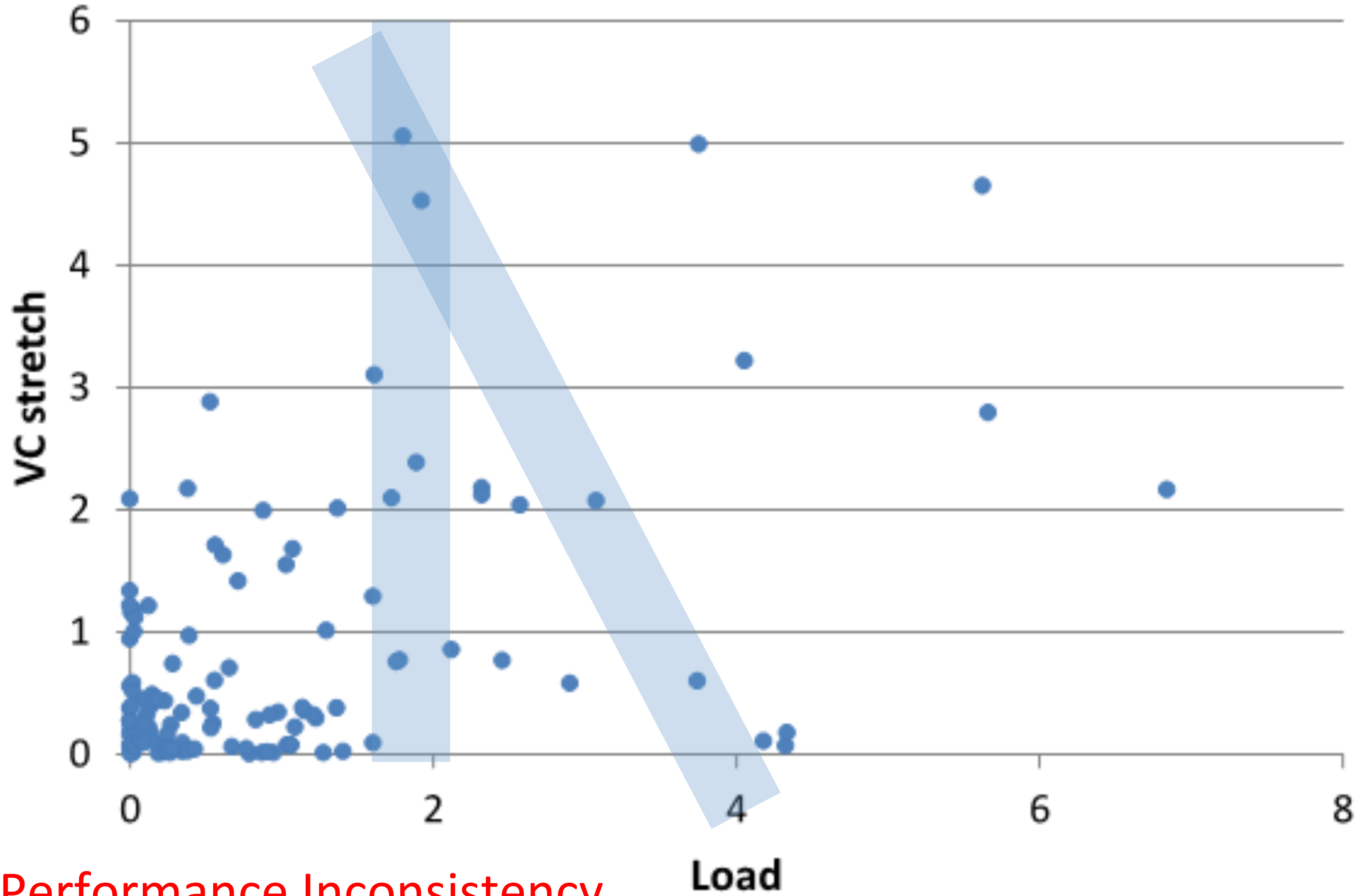
Production trace

average job slow down
(compared with ideal run time)



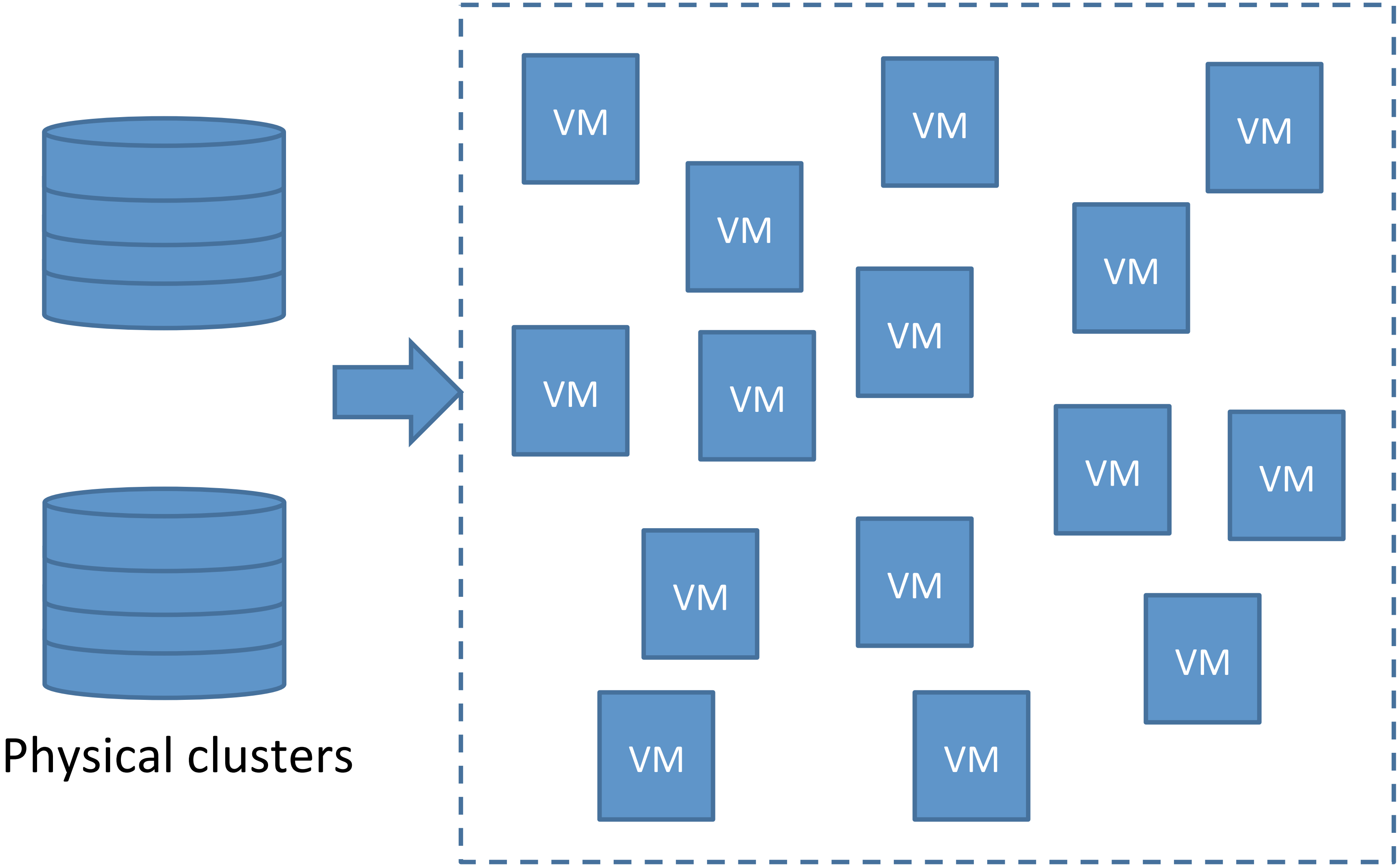
the total work (server hours)
/VC capacity (number of servers)

Production trace

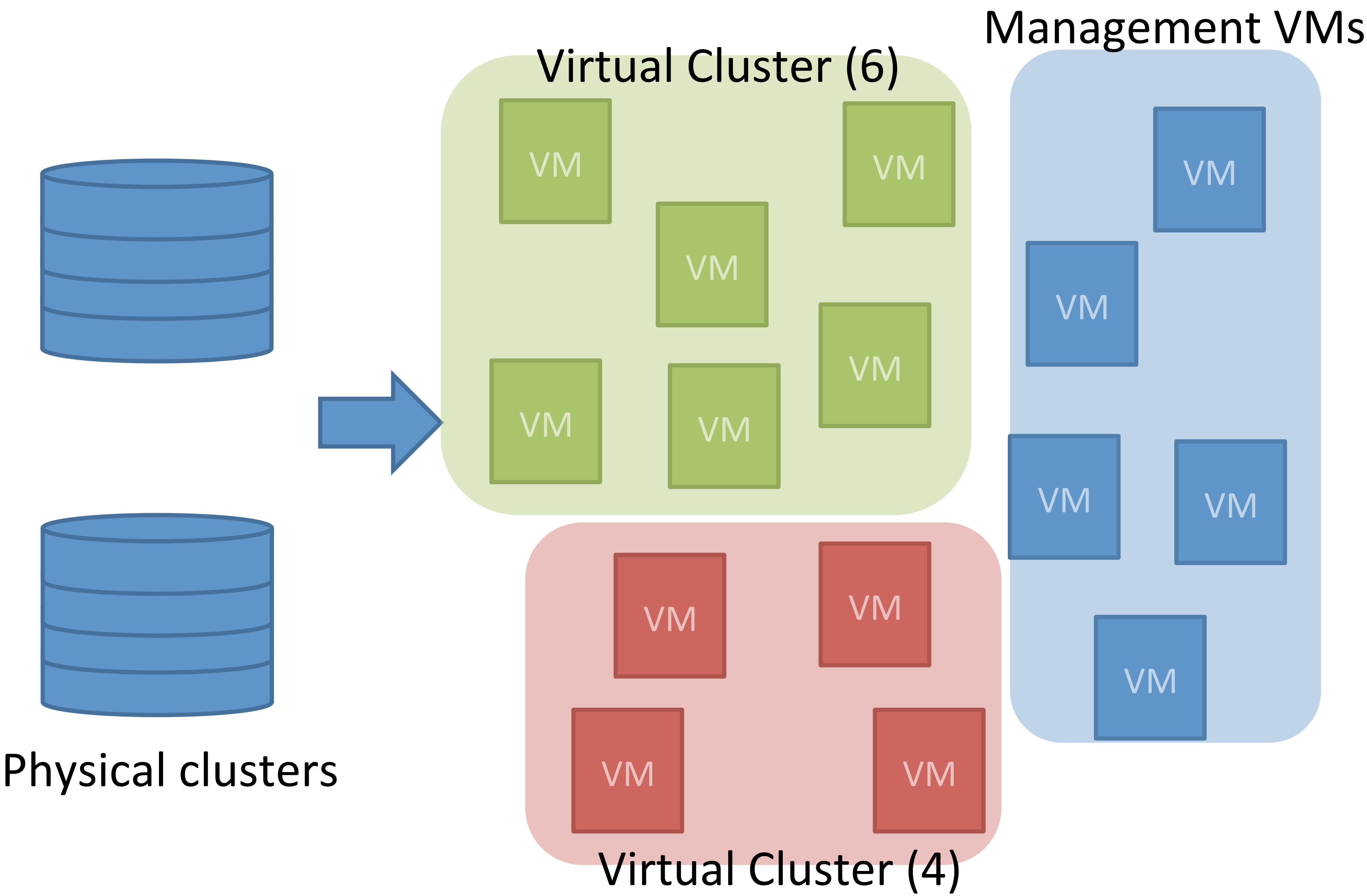


Performance Inconsistency

Cosmos



Cosmos


Management VMs
Virtual Cluster (6)
VM
VM
VM
VM
VM
VM
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VM
VM
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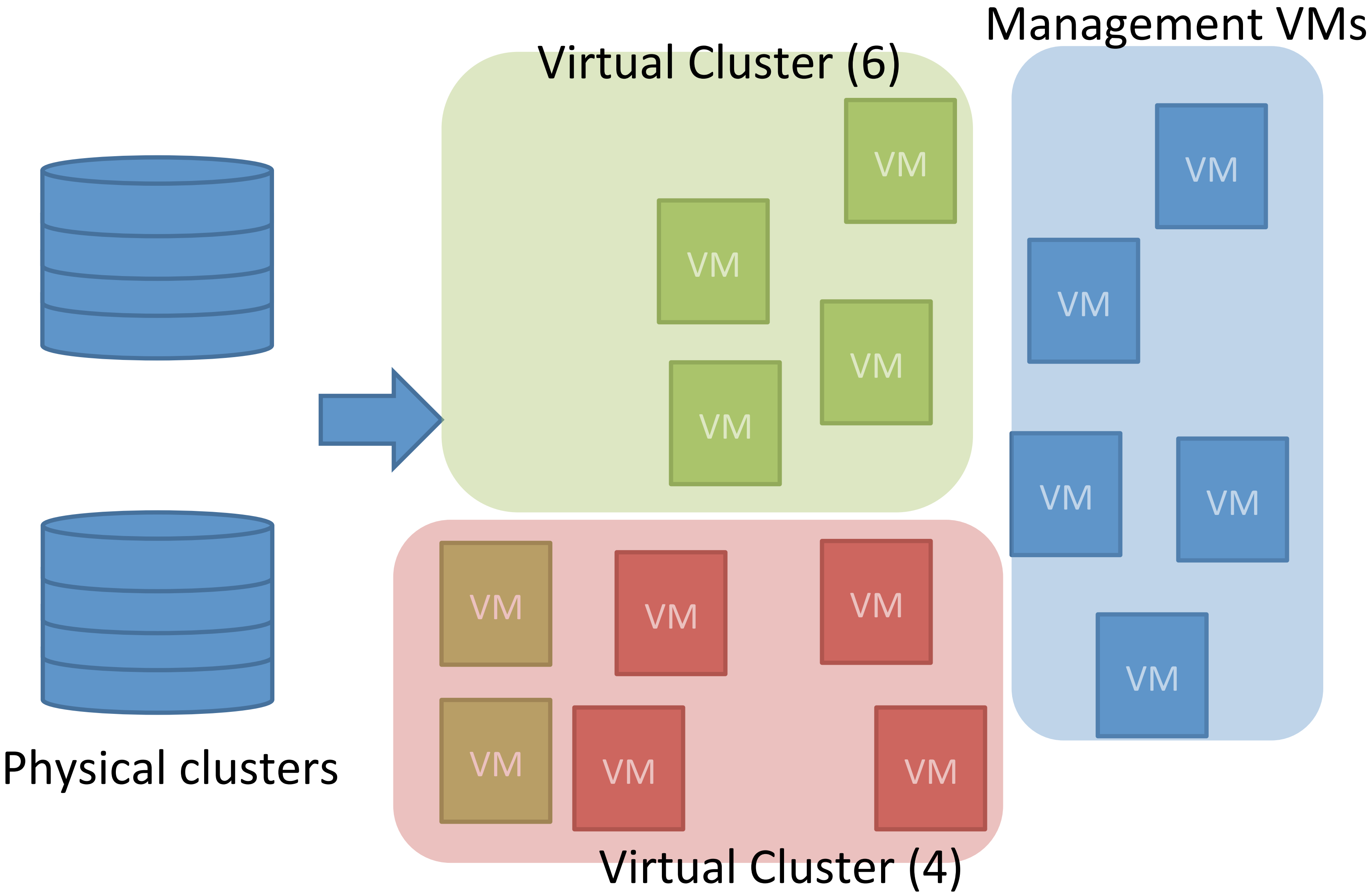
VM
Physical clusters
Virtual Cluster (4)

Cosmos


Management VMs
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VM
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VM
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VM
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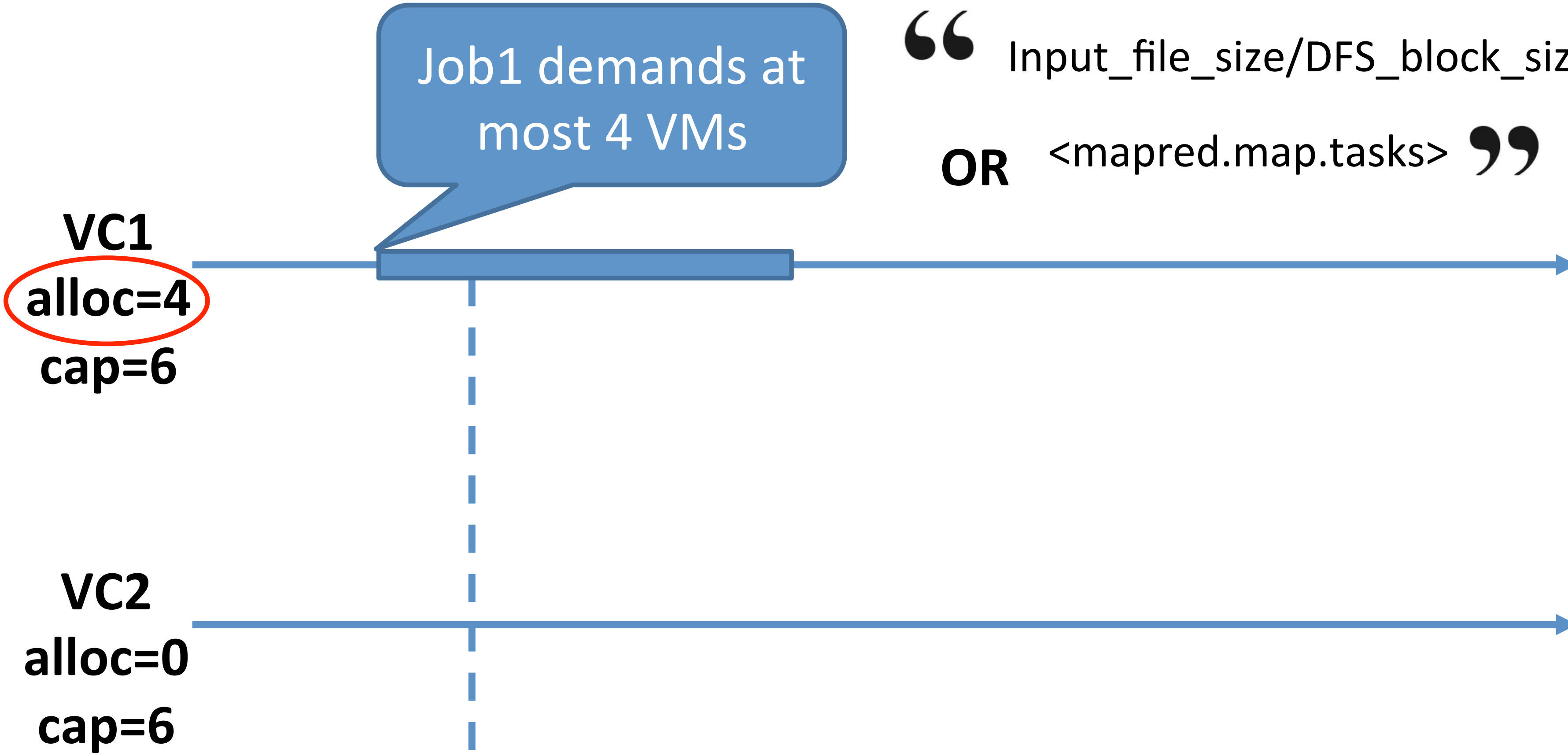
VM
VM
Physical clusters
Virtual Cluster (4)

Job execution model

VC1
alloc=0
cap=6

VC2
alloc=0
cap=8

Job execution model

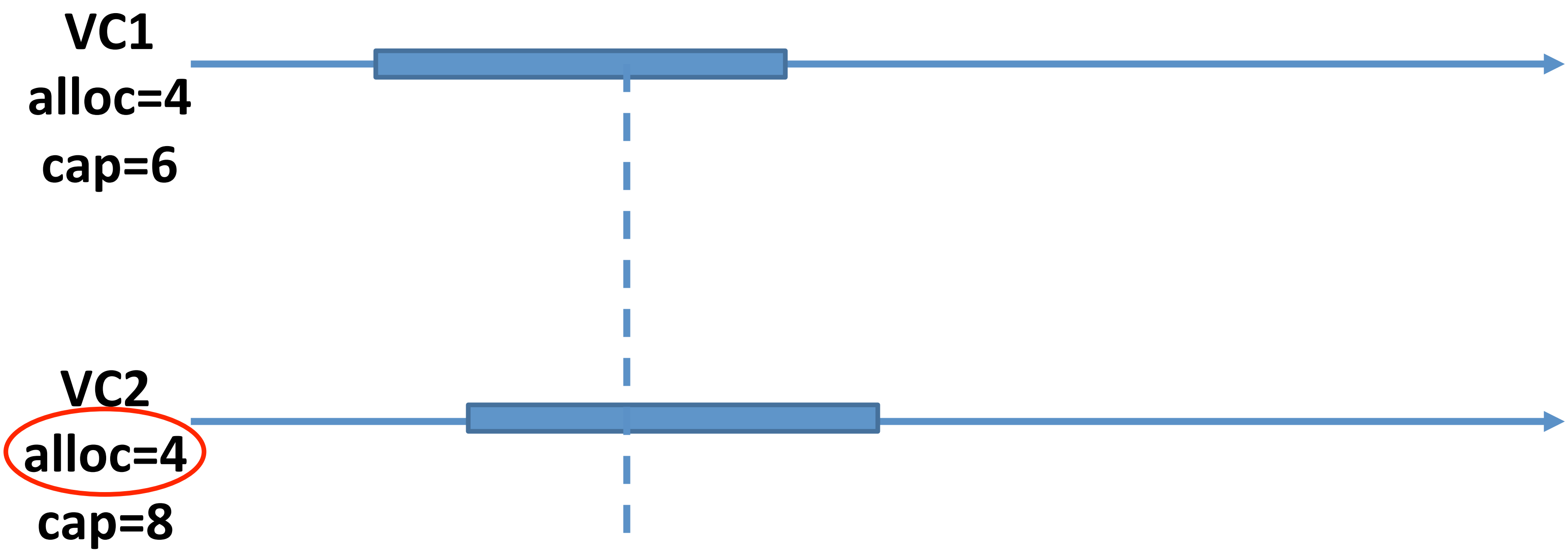


“ Input_file_size/DFS_block_size

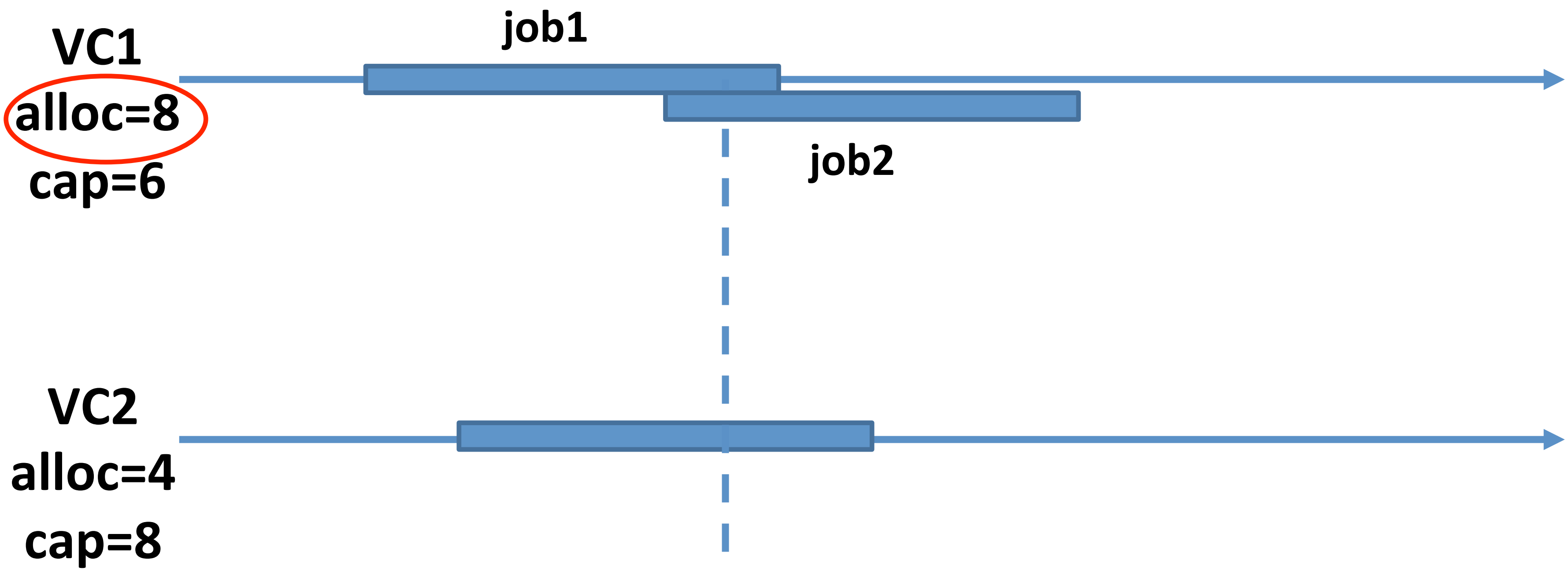
OR <mapred.map.tasks> ”

[1] http://wiki.apache.org/hadoop/HowManyMapsAndReduces

Job execution model

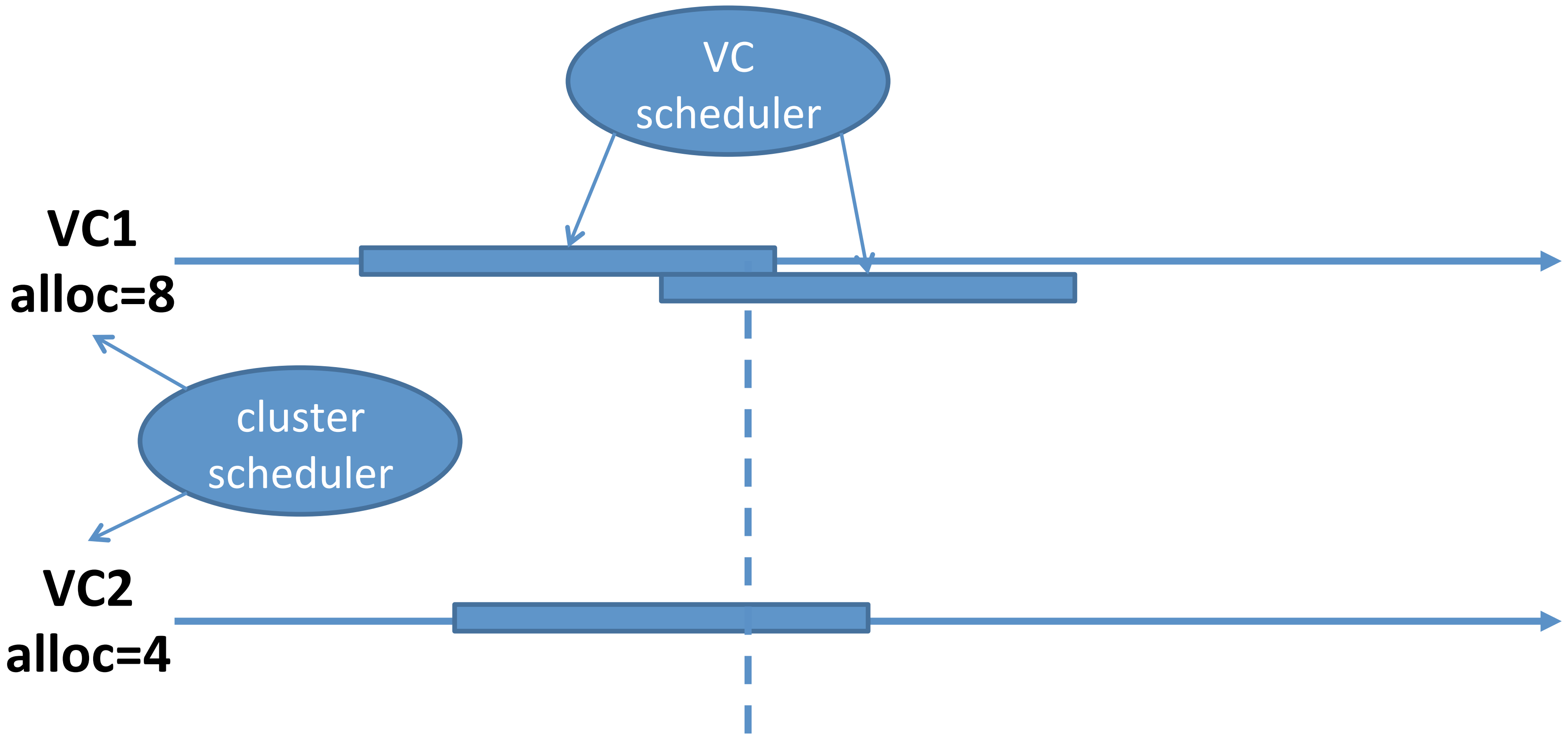


Job execution model



Sharing promotes overall system utilization

Job execution model



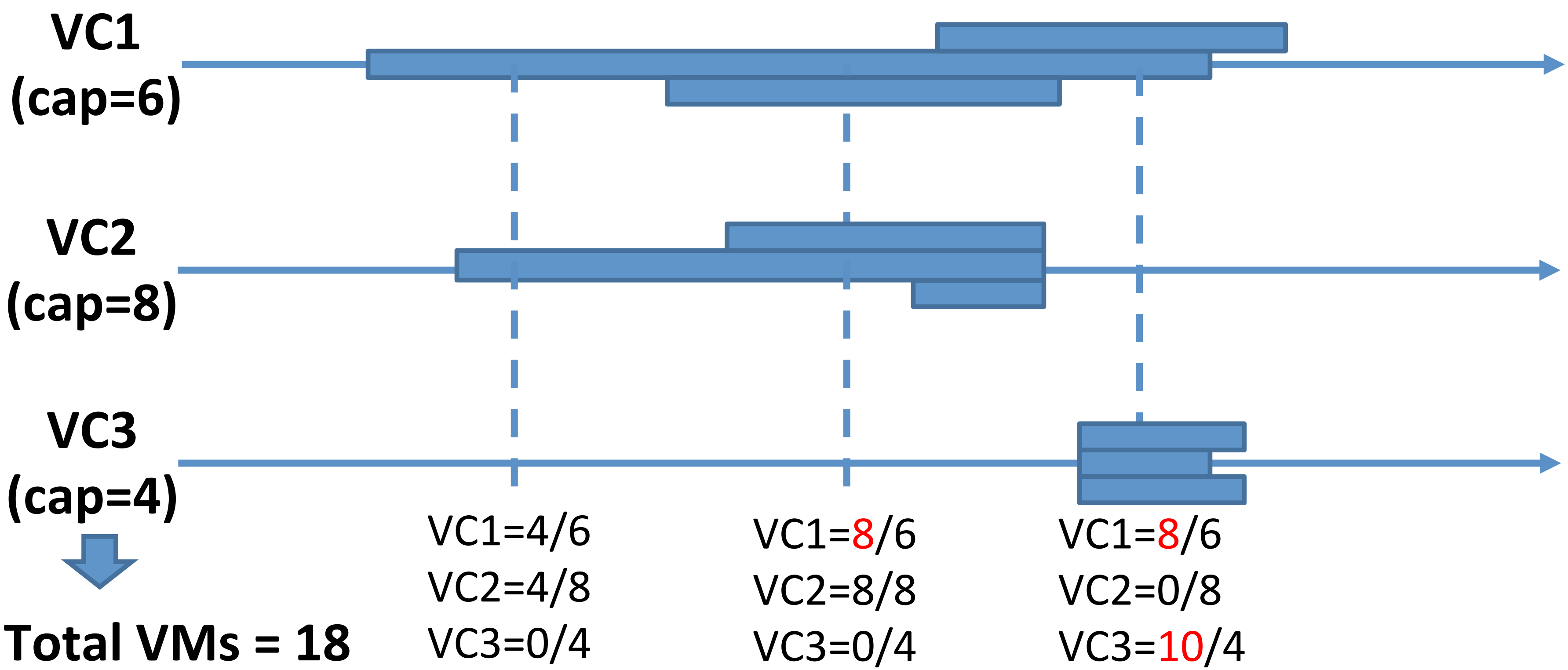
Our work tackles fairness at the cluster scheduler level.

Instantaneous fairness

- Consider parameters at a given time point
- MaxMin: Maximize the minimum allocation
  - Hadoop's fair scheduler is a variation

MaxMin: how it works

- Maximize the minimum allocation



MaxMin

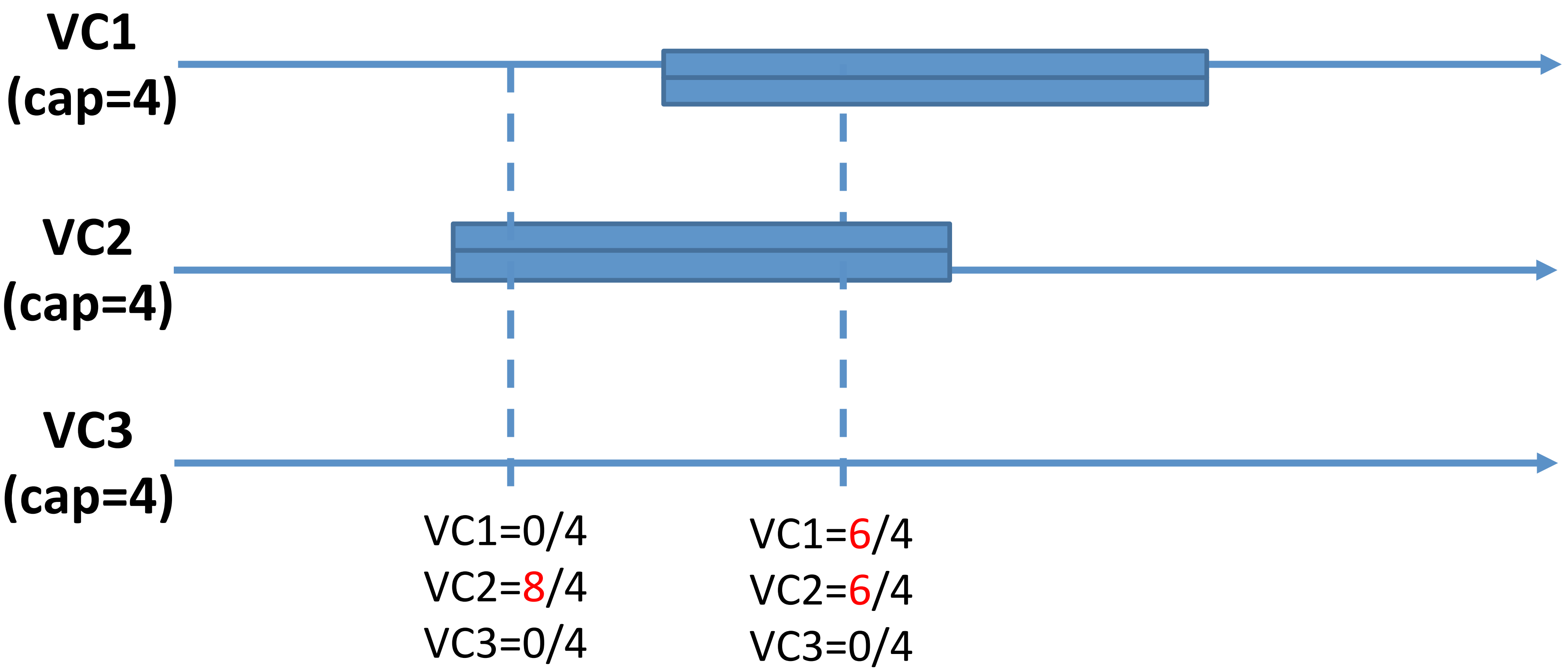
	VC1	VC2	VC3
Allocation	0	0	0
Demand	8	0	12
Capacity	6	8	4

Stage I (8 remaining)			
Allocation	6	0	4
Demand	2	0	8
Capacity	6	8	4

Stage II (4 remaining)			
Allocation	6+2	0	4+2
Demand	0	0	6
Capacity	6	8	4

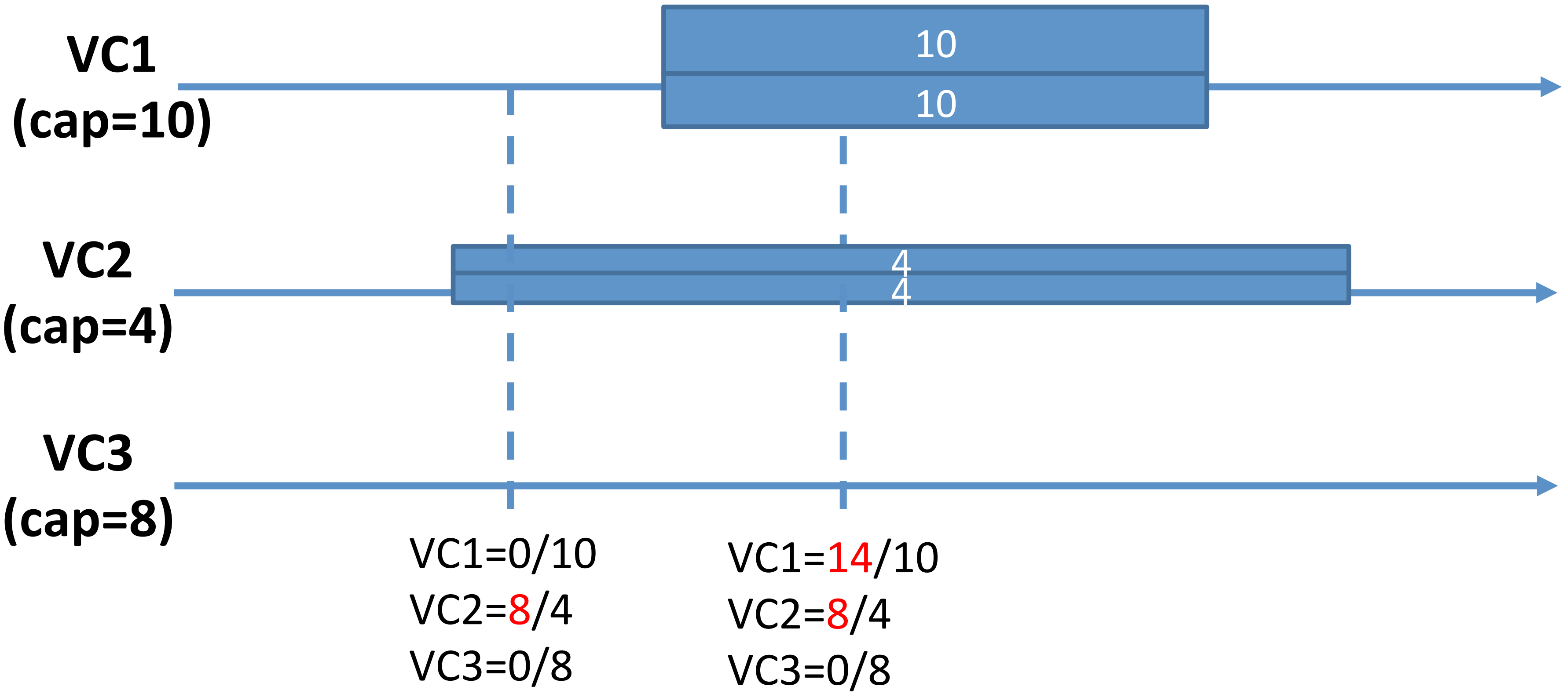
Long-term?

- Previous contribution is not rewarded



Long-term?

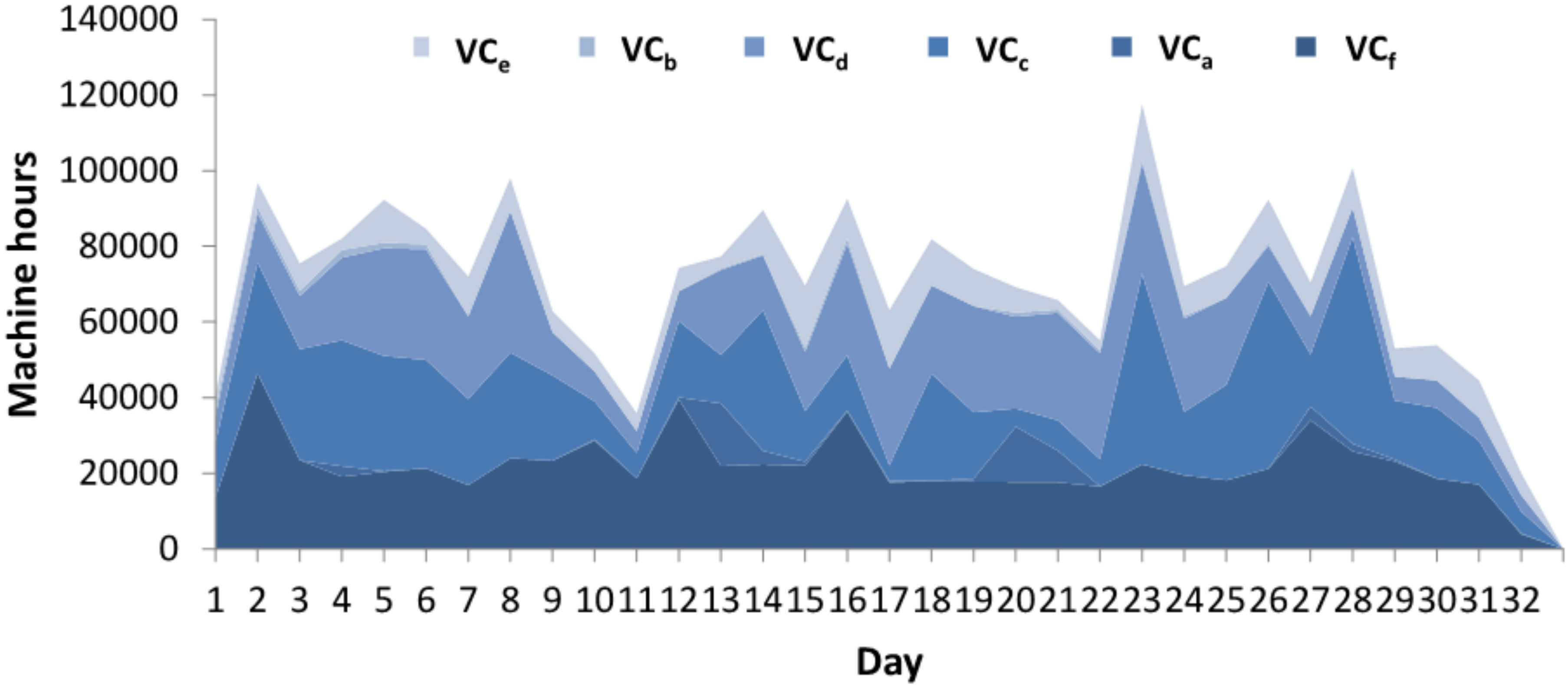
- Large VCs win fewer resources



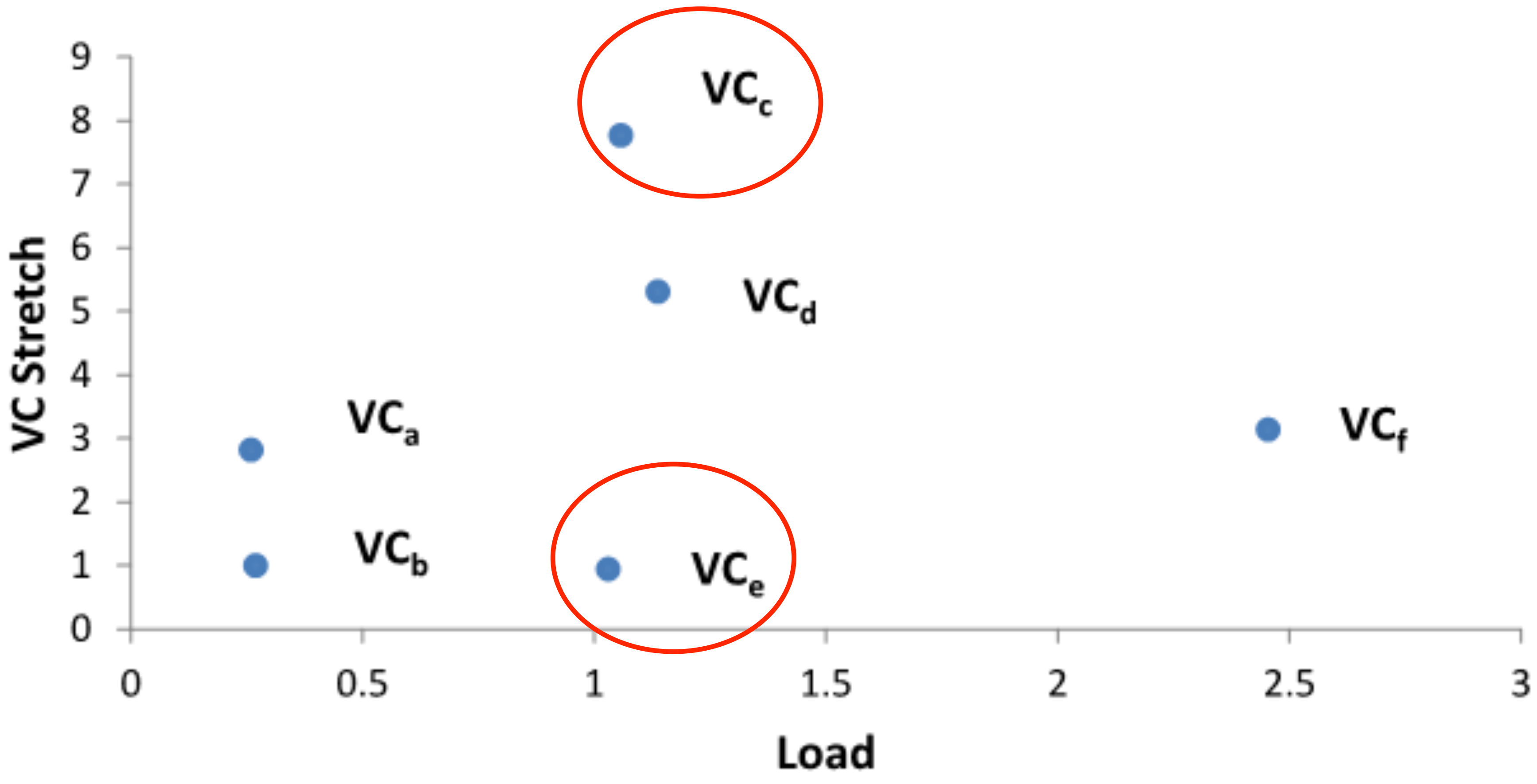
Trace-driven simulation

- Build a simulator
- Production trace from a commercial cluster
  - 50,000 servers shared by 115 VCs
  - One month period
  - Job submit time, size, etc
- Pick 6 VCs (two under-loaded, three full-loaded and one over-loaded) to assess the performance inconsistency

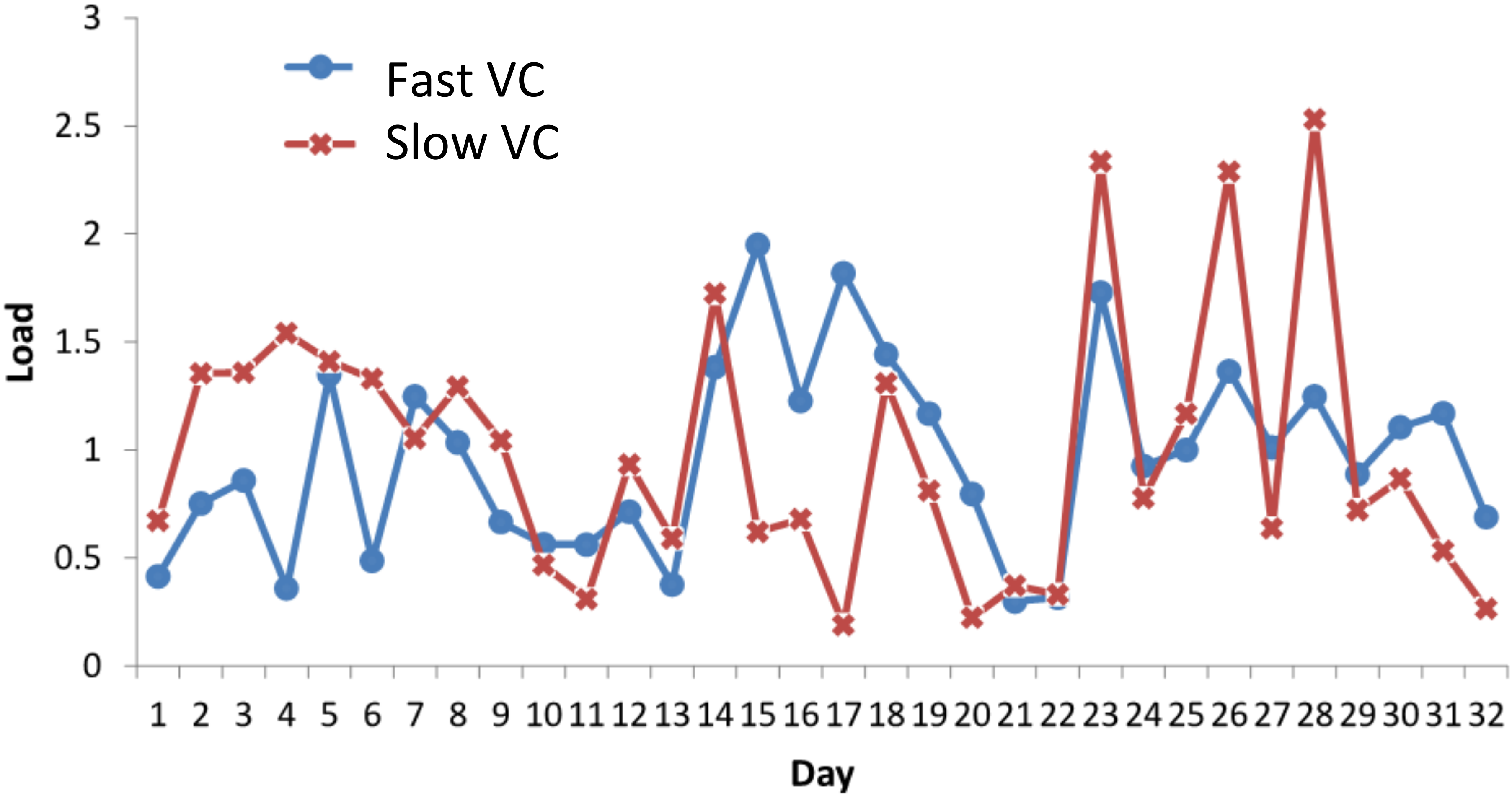
Overall load fluctuation



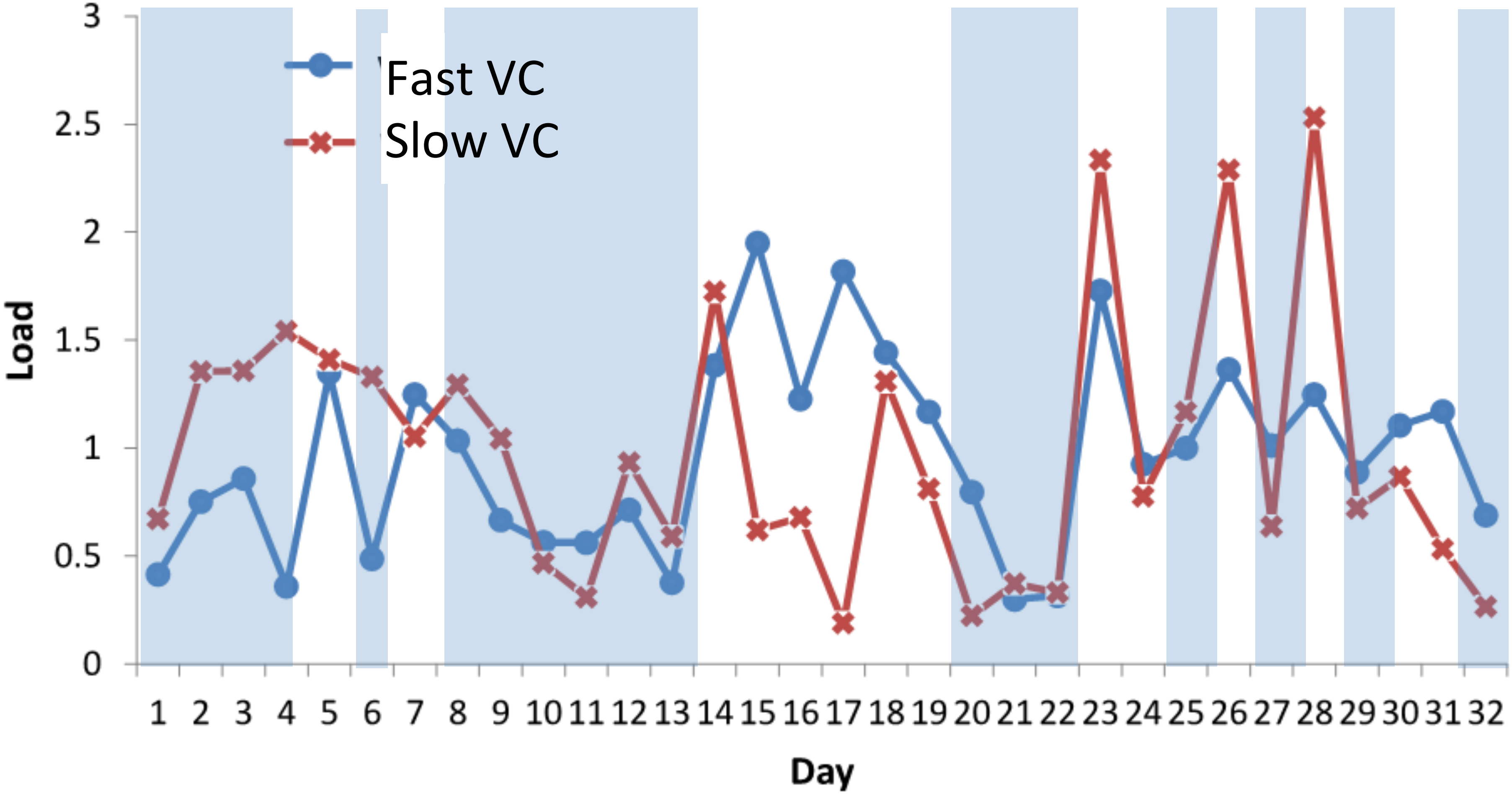
Overall VC performance



Load fluctuation

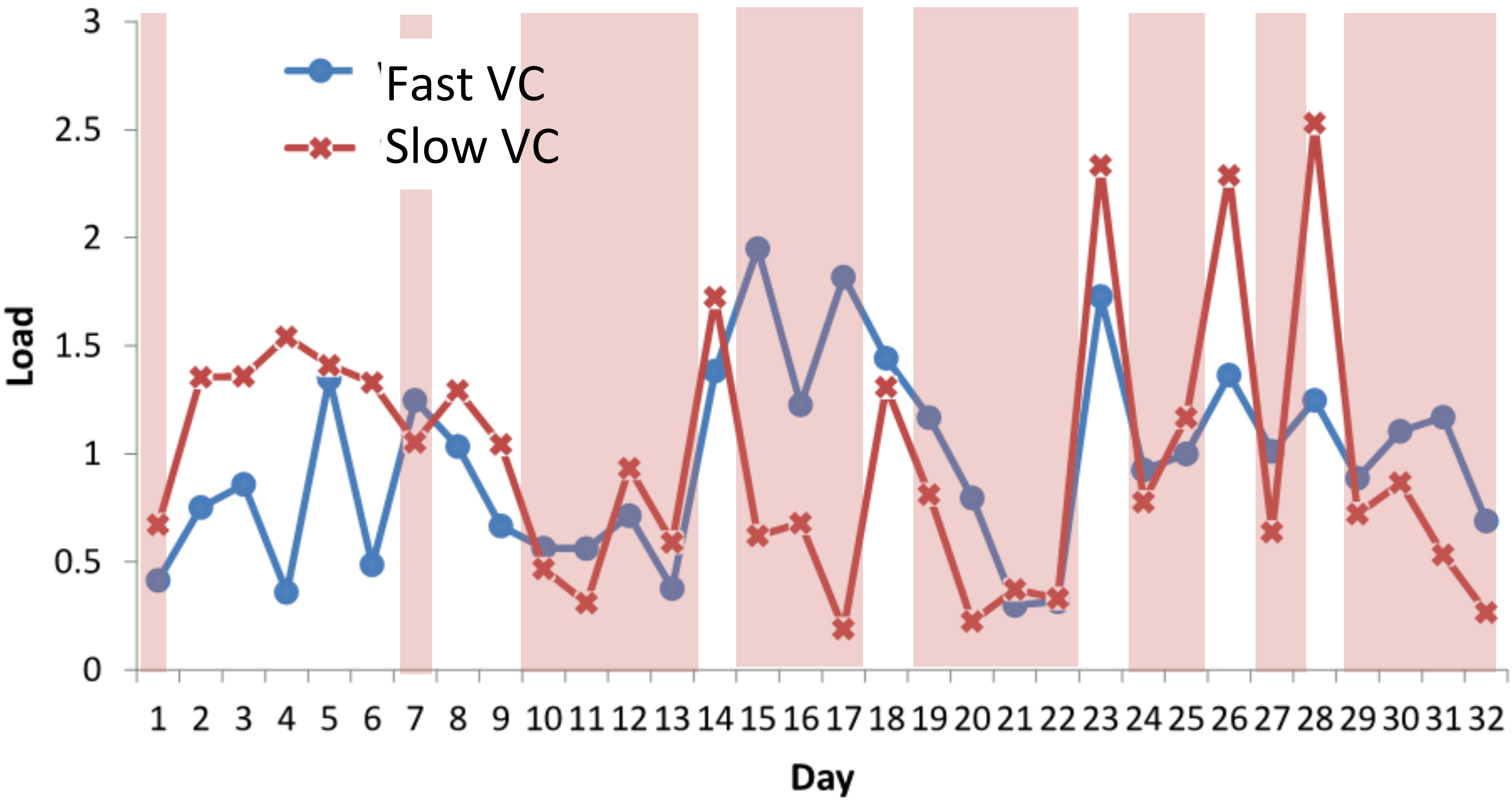


Fast VC: under-loaded days



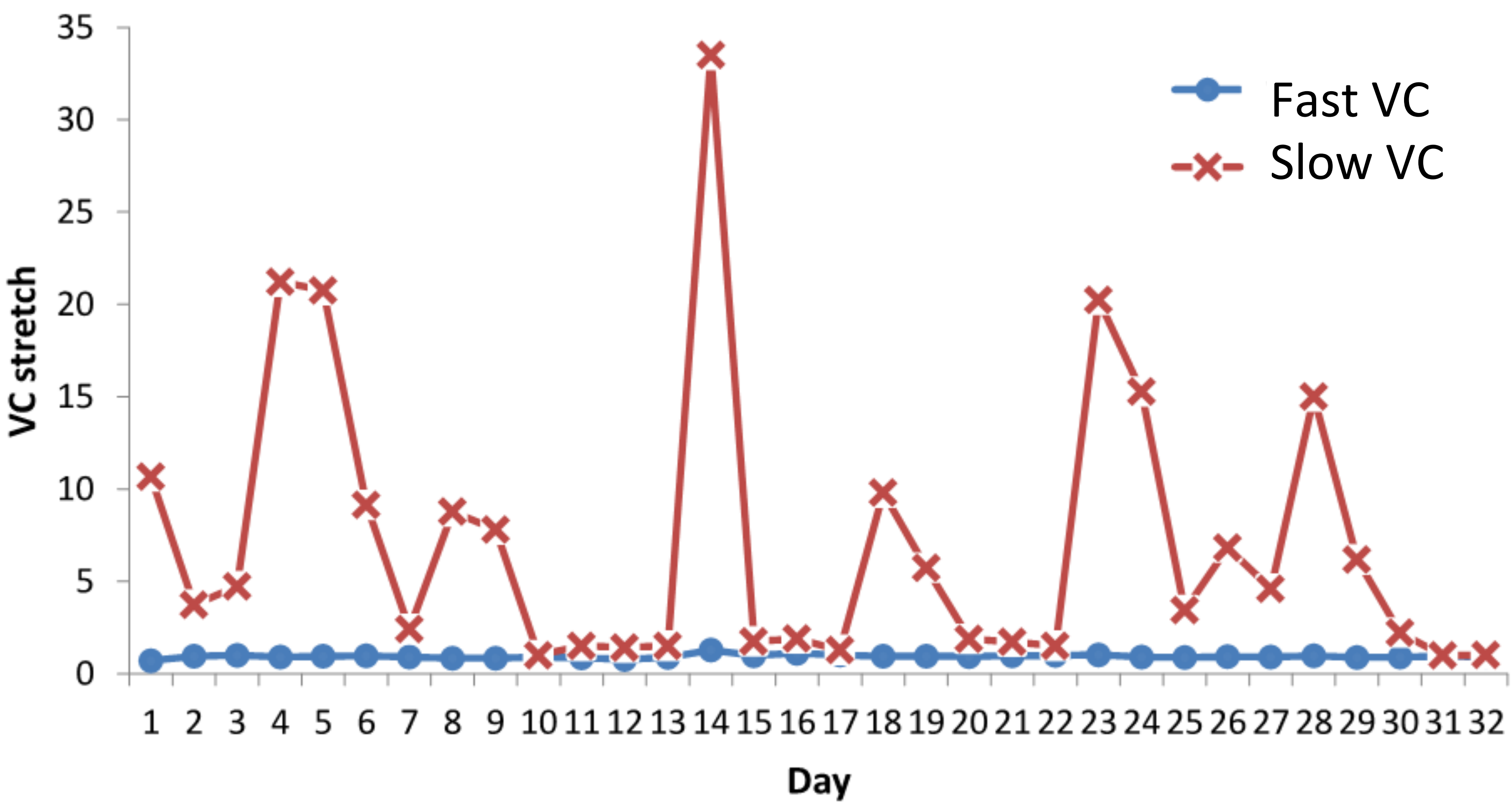
18 under-loaded days

Slow VC: under-loaded days



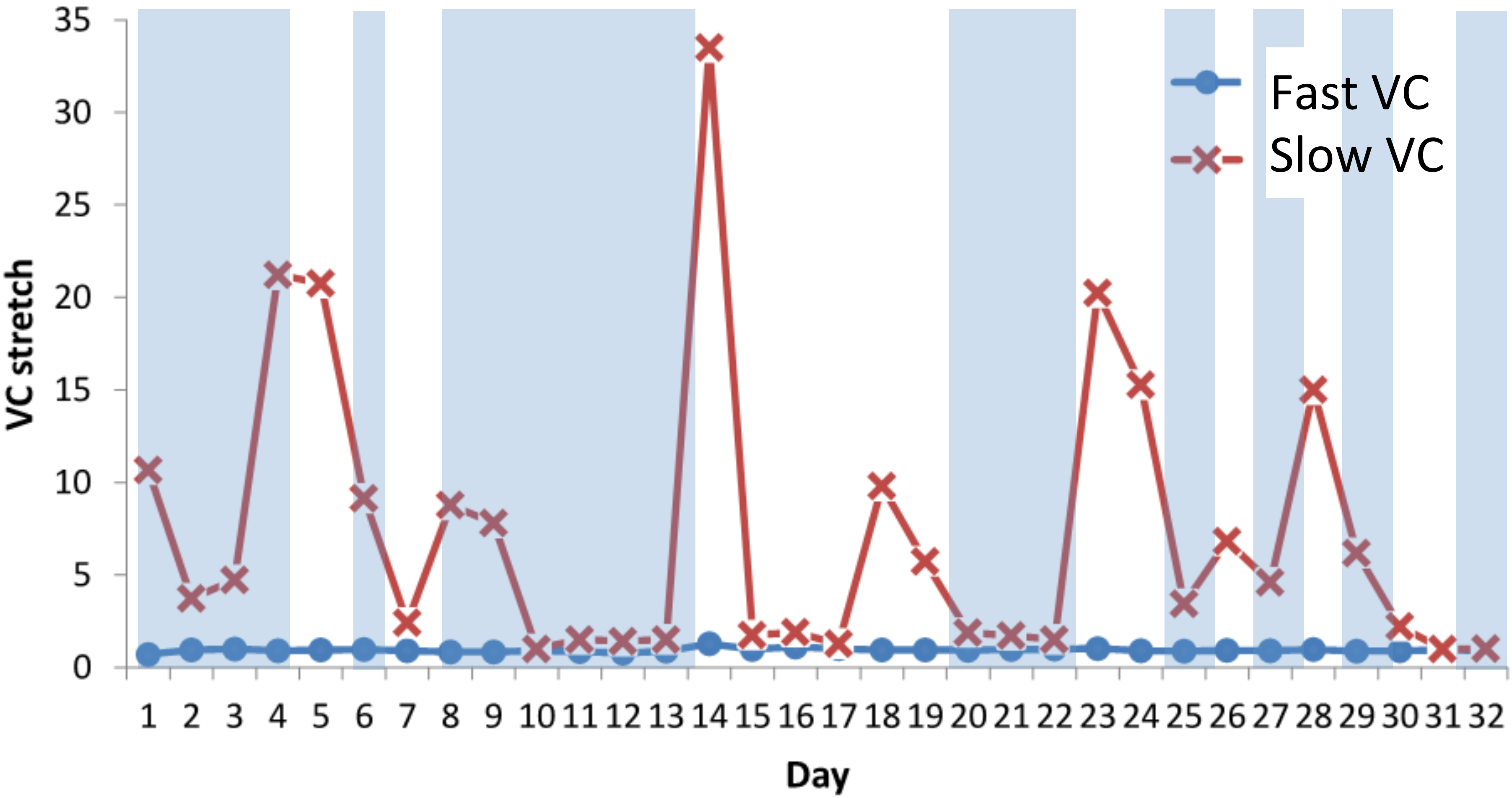
20 under-loaded days

Performance



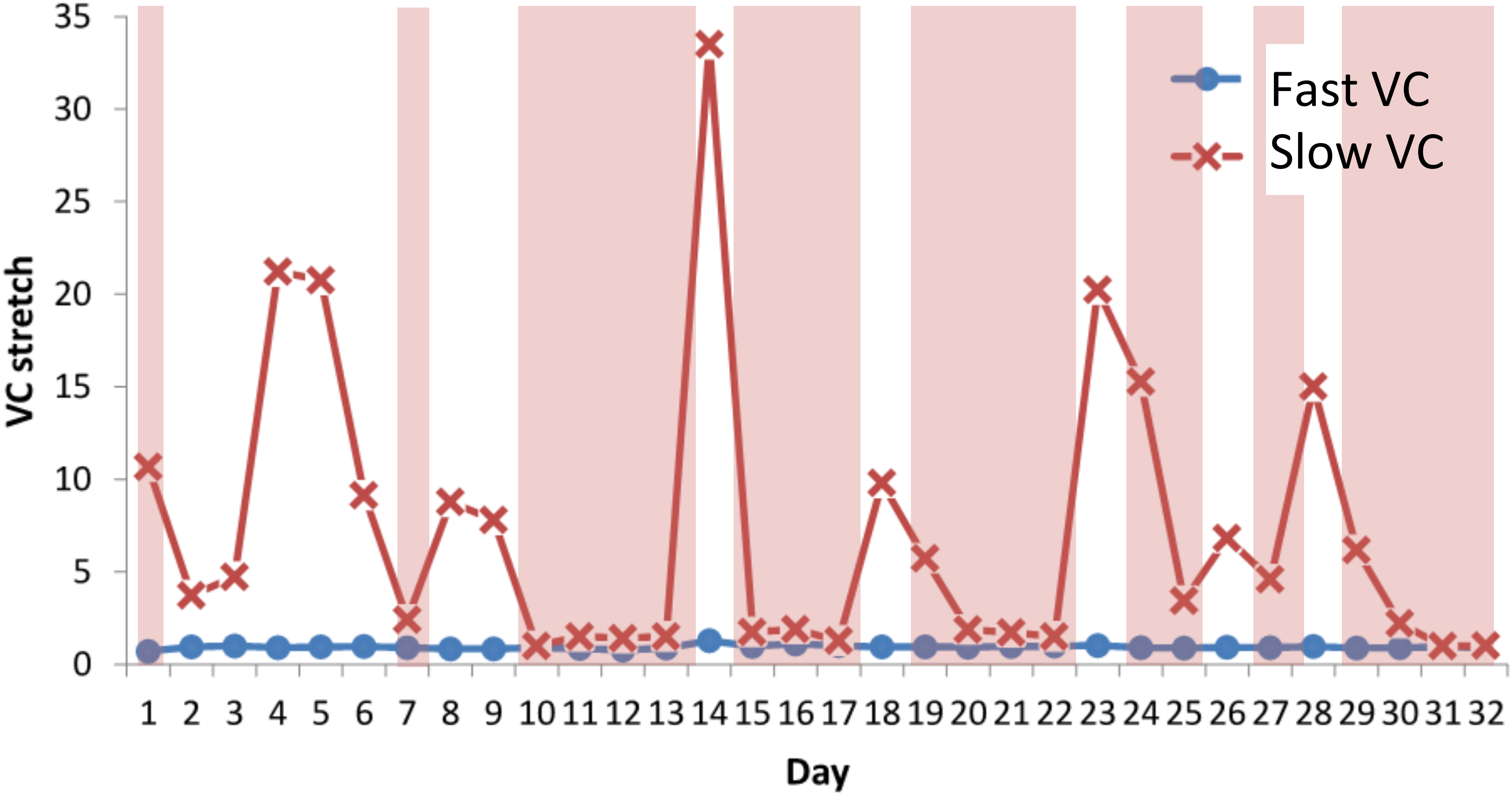
(b) The VC stretch. Lower is better.

Fast VC: Under-loaded day performance



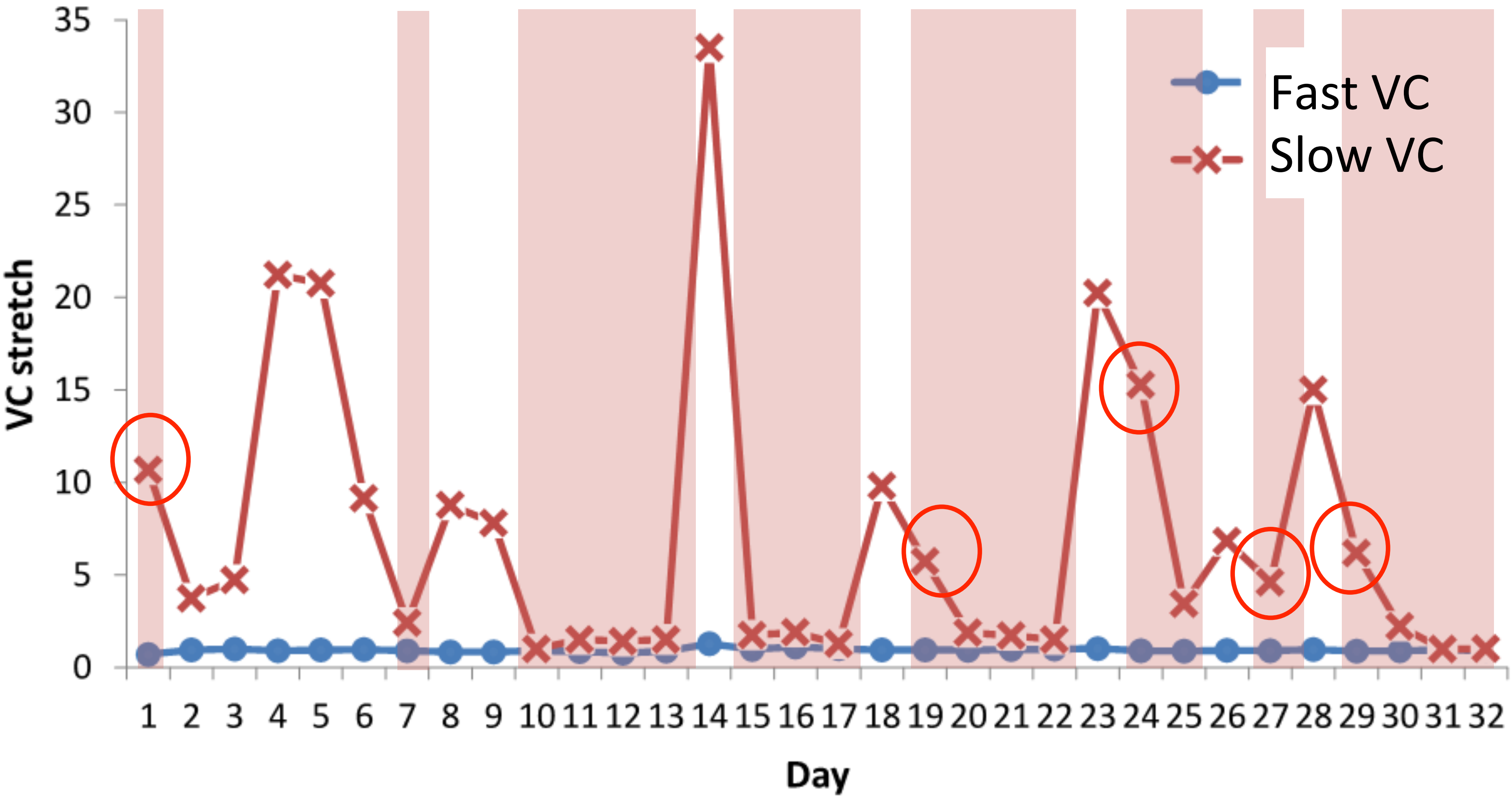
The fast VC performs optimally when it is under-loaded

Slow VC: Under-loaded day performance



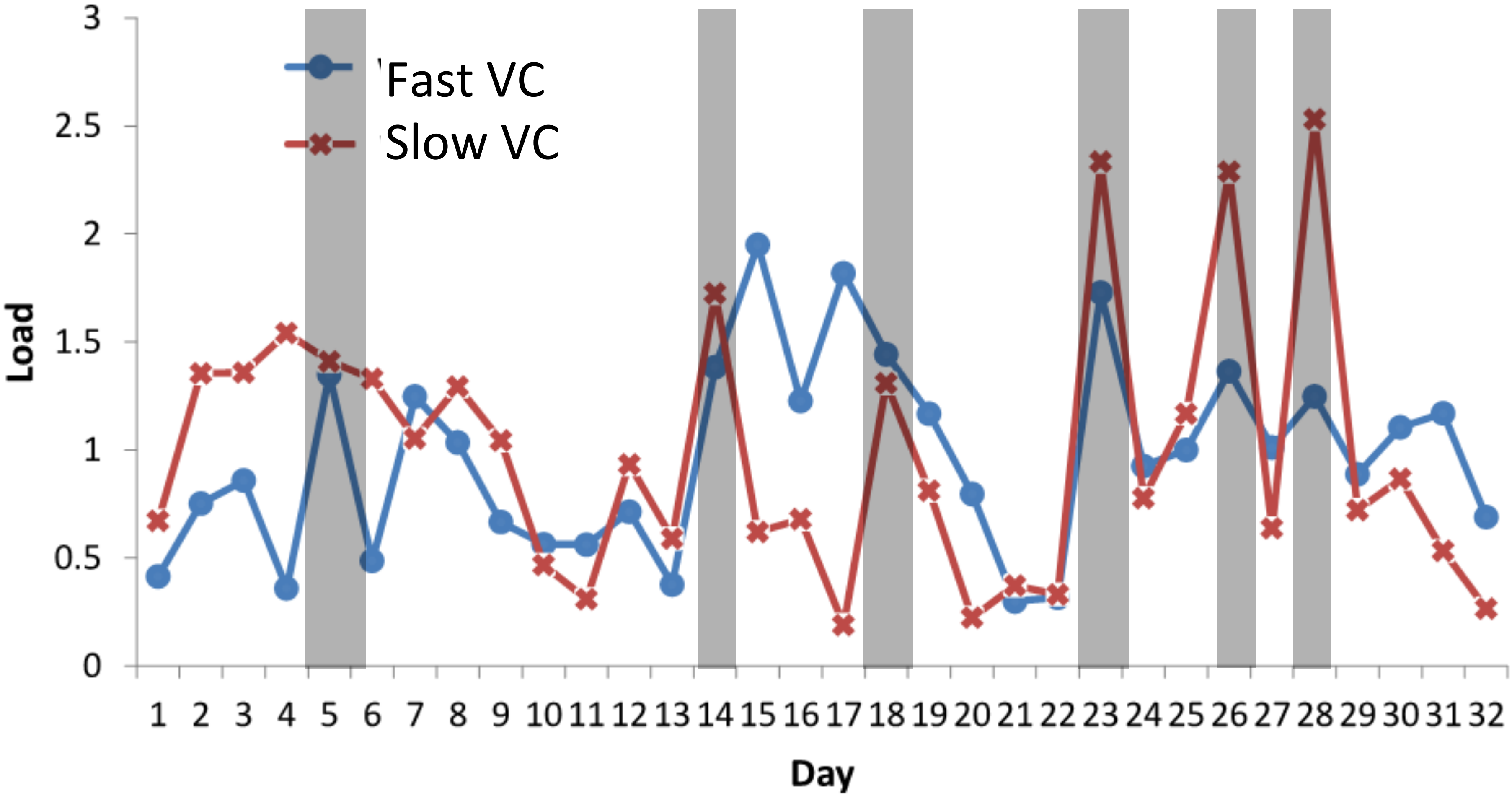
The slow VC performs optimally in most under-loaded days

Congestion



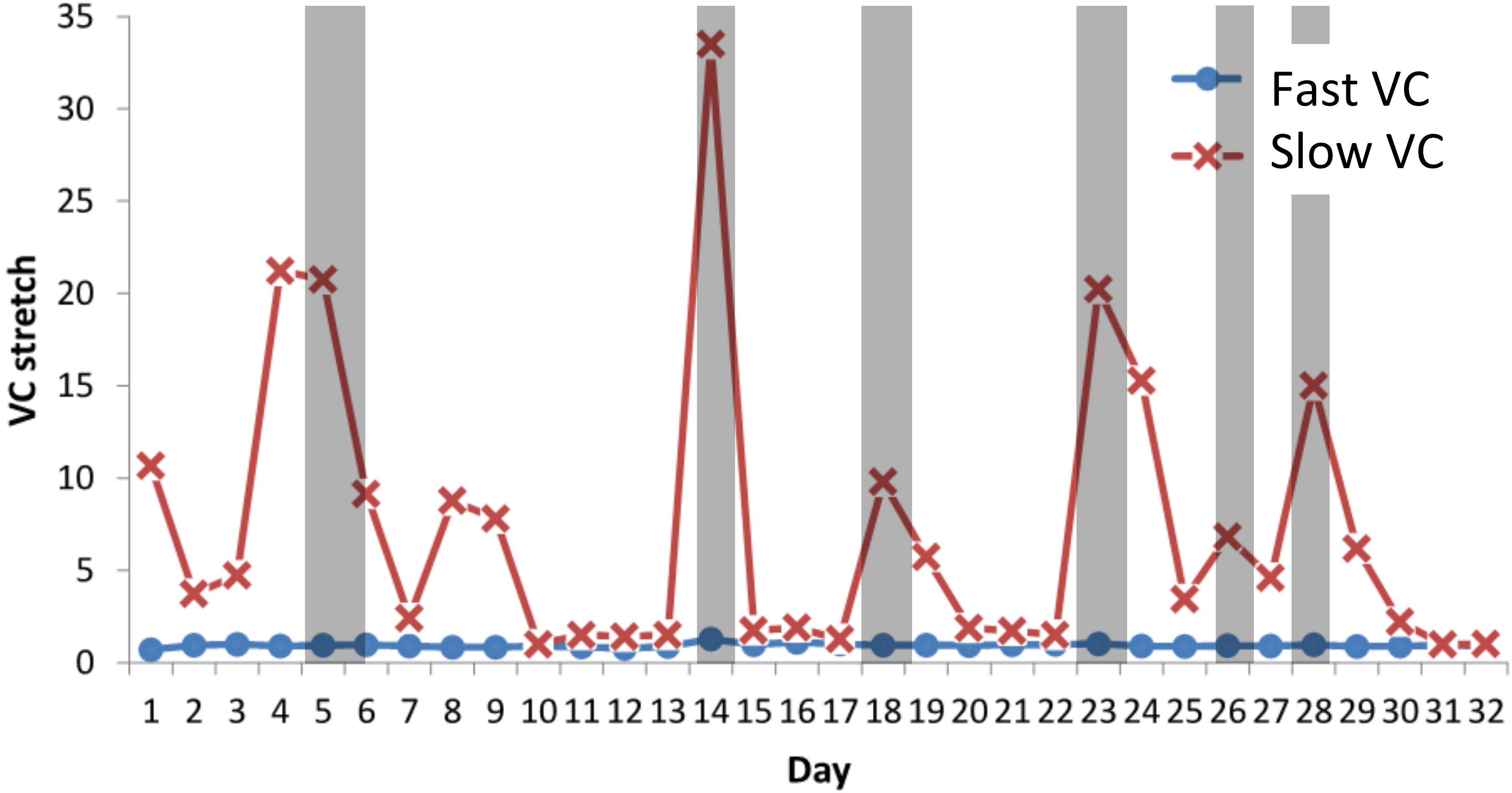
Congestion: a slow day may affect the next upcoming day

Contending days



Six contending days: both VCs are overloaded

Contending day performance



Slow VC loses totally to the fast VC

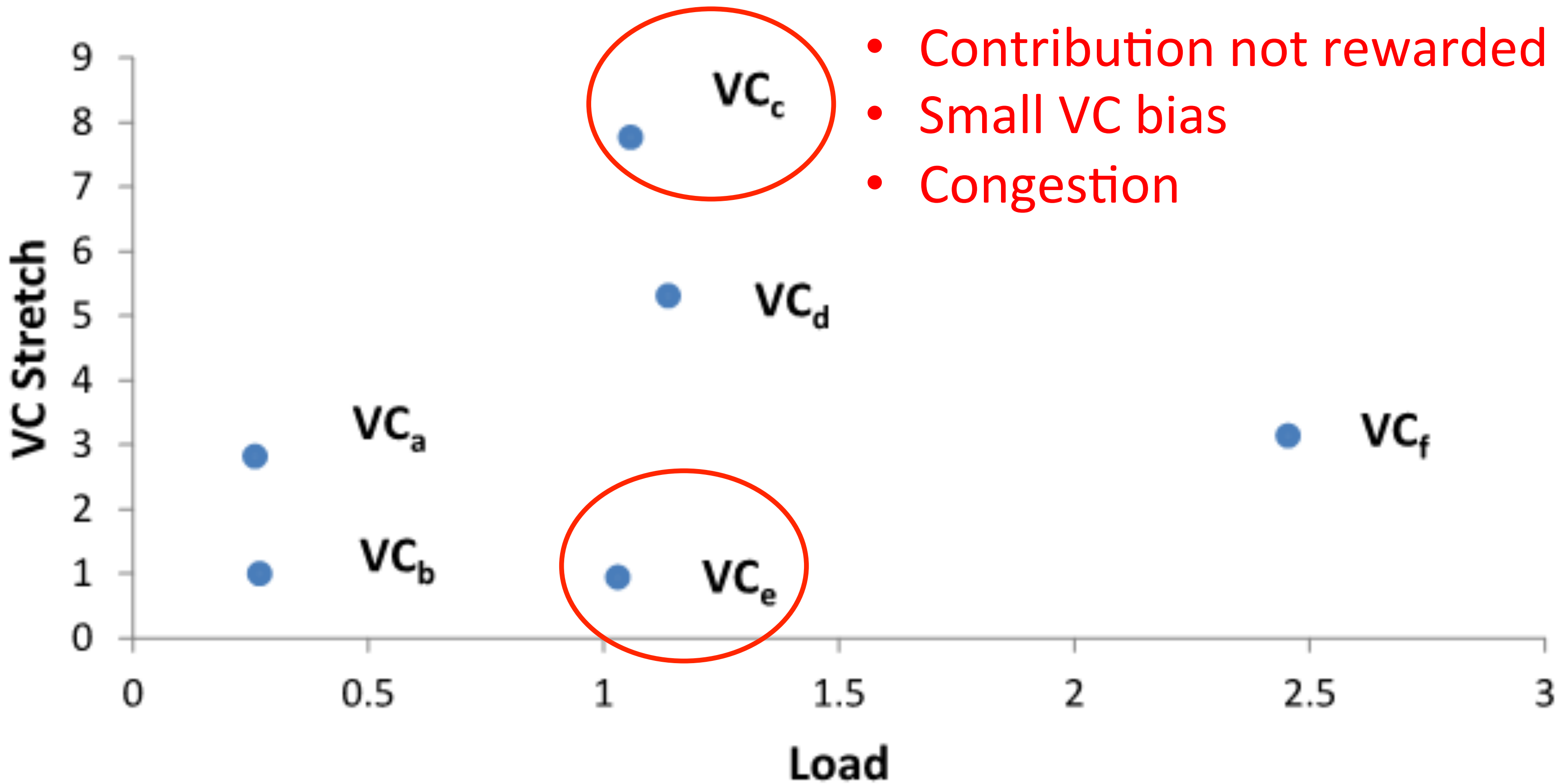
Summary

	Slow VC	Fast VC
Capacity	900	350
Load characteristic (both~=1)	20 under, 11 over (bursty)	18 under, 13 over (smooth)
Under-loaded day performance	- 14 days stretch~=1 - 6 day stretch >1 due to congestion	Stretch~=1

Summary (cont.)

	Slow VC	Fast VC
Capacity	900	350
Load characteristic (both~=1)	20 under, 11 over (bursty)	18 under, 13 over (smooth)
Under-loaded day performance	- 14 days stretch~=1 - 6 day stretch >1 due to congestion	Stretch~=1
(Six) Contending days	Stretch = 10 ~ 35 - contribution not rewarded - Small VC bias	Stretch~=1
(Five) Overloaded days	Stretch = 4 ~ 10 - Meets full-utilized days	Stretch ~=1

Summary



- Contribution not rewarded
- Small VC bias
- Congestion

Solutions?

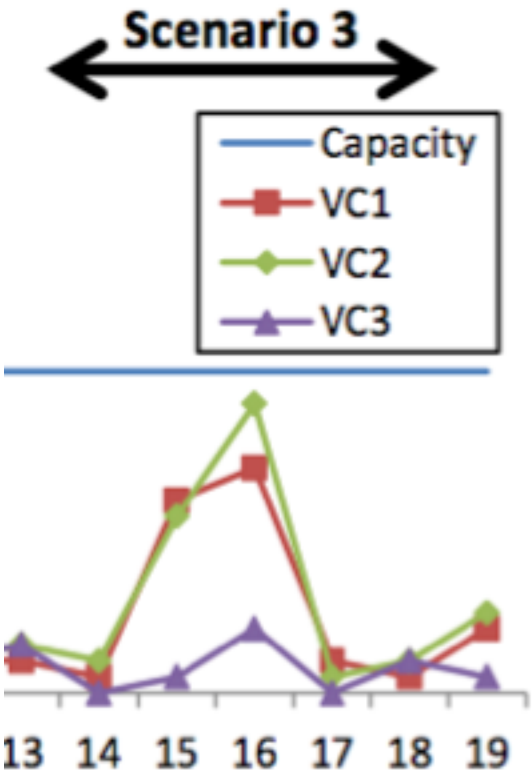
- Consider usage history
  - Idea: gain credits when contributing; lose credits when overusing
  - Higher credits more allocation
  - Deficit Round-Robin (DRR) for network switches
  - Xen credit scheduler
  - Lottery-based scheduler: accumulate “lottery” to increase the chances of wining more resources

A straightforward accounting method

- Open a “saving account” for free resource contribution
  - Contributing free resources -> gain credits
  - Overusing -> lose credits

- Allocate more VMs to VCs with higher credits

Challenges



- Give credits as long as VCs are underutilized
- Make promise for more future allocation
- Users further decrease load to gain more credits
- The system becomes even more underutilized

Challenges

- The counting scheme should provide “good” incentives of user behaviors
- We desire the users to
  - Contribute resources
  - Promote overall system utilization
  - Shape their workload and avoid peaks
- Straightforward scheme may not be enough!

Conclusions

- Show the performance inconsistency with Instantaneous fair schedulers
- Identify three causes
- Usage history should be considered when making scheduling decisions
- Credit counting should enforce fairness while providing incentives to promote overall utilization

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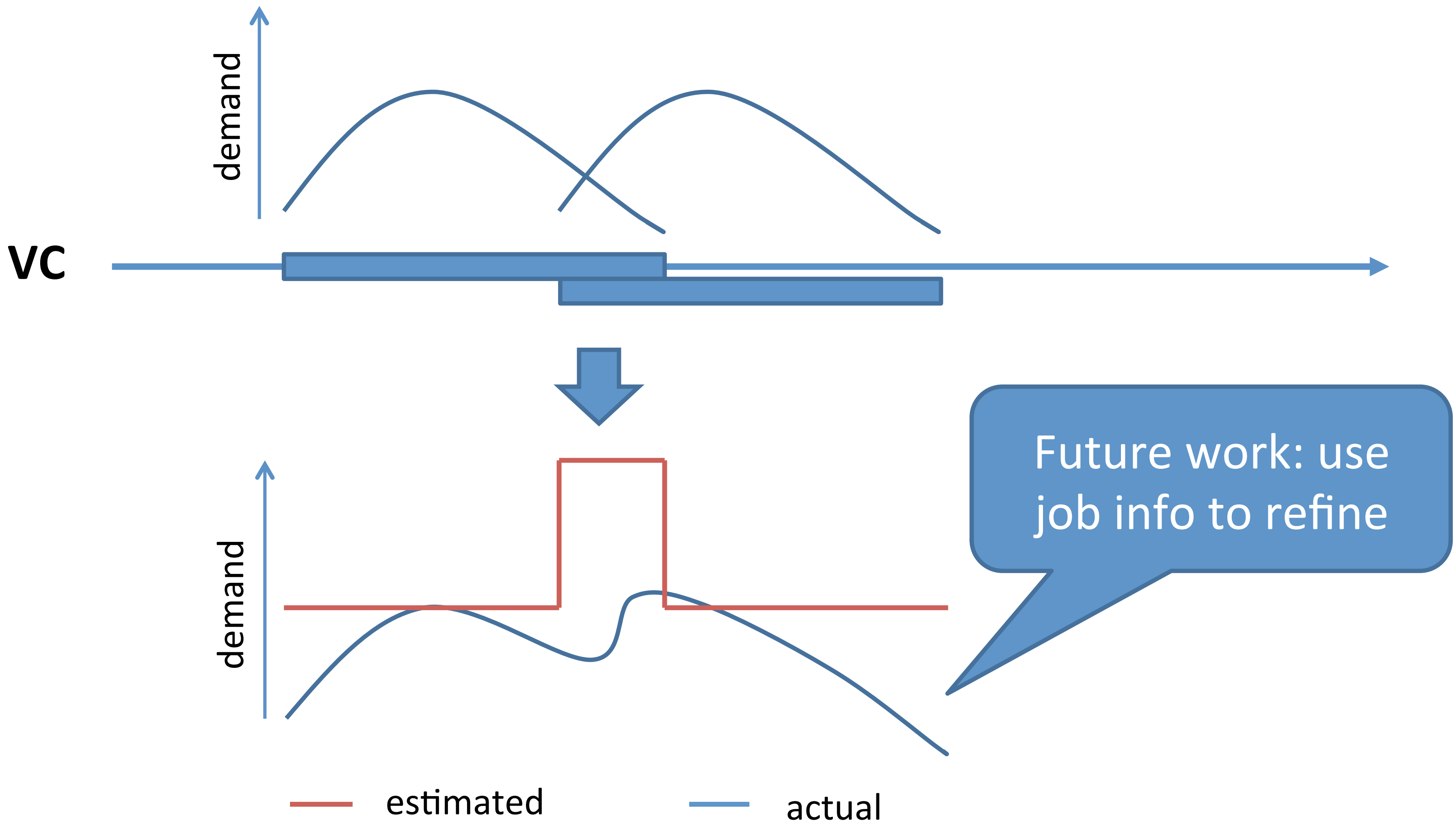
Backup

Parallelism estimation



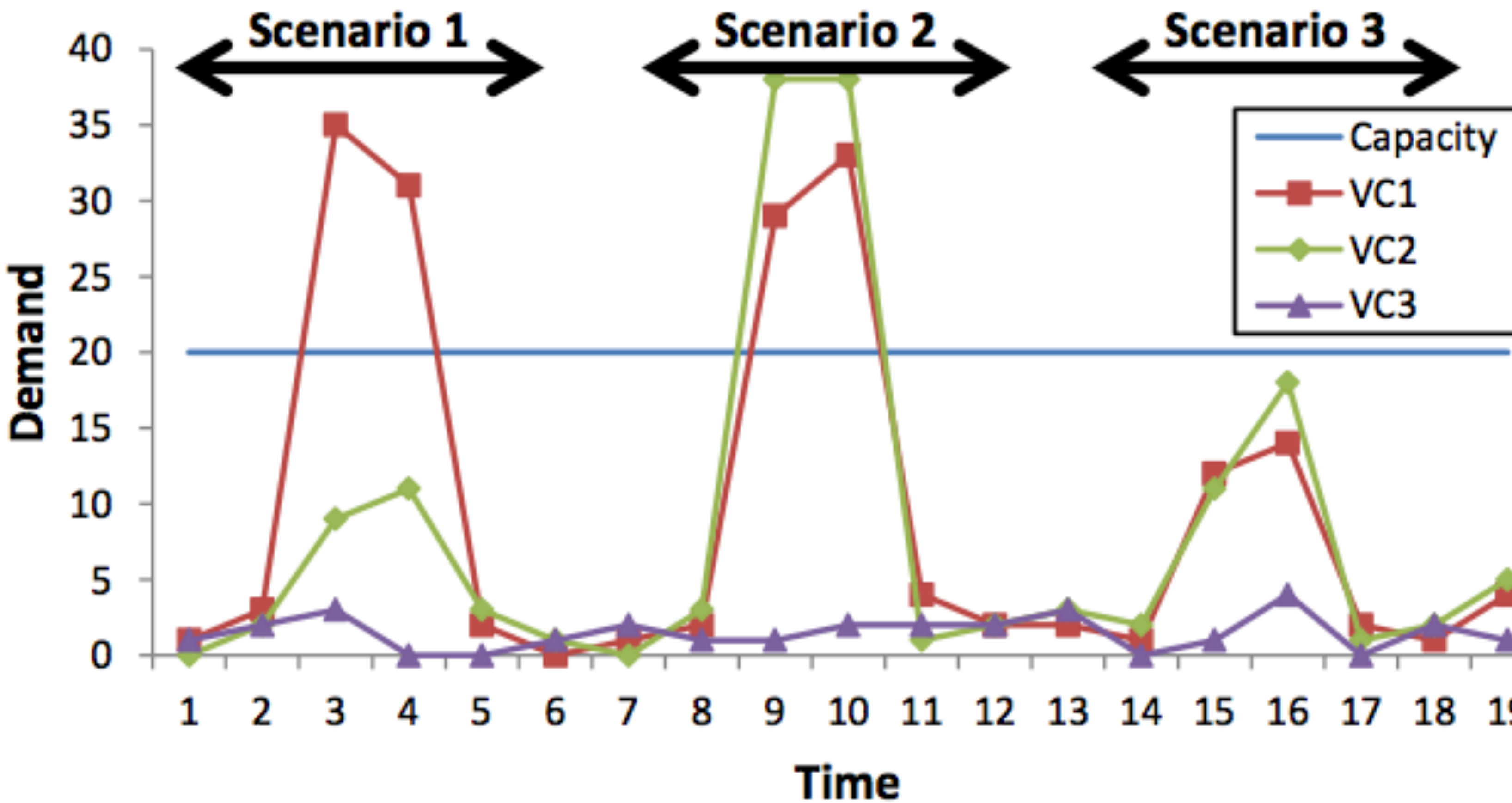
Short-term or long-term fairness

- MapReduce jobs are long (~hours), especially in large clusters like Cosmos
- Scheduling decisions are made on a minute basis
- Short-term fairness -> accumulated effects -> observe unfairness at job level

DRF scheduler

- Dominant Resource Fairness
  - Find the dominant resource type
  - Make MaxMin decision on that type (still only at a given time point)

Challenges



More credits lead to more allocation in the future

Burstiness impact

- MaxMin: If you peak meets others' peak you lose
- Ideal long term fairness: you will be treat better

Dynamic joining/leaving users