

Elastic HPC and AI Cloud Orchestration

Bridging Traditional HPC Workflows with Cloud-Native Kubernetes Infrastructure

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About Rajesh Narayanan

Rajesh Narayanan (Portland, OR): An engineering leader with 25+ years of experience across Cloud, HPC, AI Infrastructure, and Semiconductor Systems. Formerly an Engineering Manager at Intel, he specialized in scalable design and technical leadership for AI & HPC workloads.

Led the delivery of the **Aurora Supercomputer** at Argonne National Laboratory and the **Intel Tiber AI Developer Cloud**.

Connect

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Key Expertise

- Kubernetes orchestration
- Ansible automation
- Prometheus monitoring
- VoltDB analytics
- Slurm scheduling
- Embedded software development
- Telemetry systems

Project Highlights

- **Intel Tiber AI Cloud:** 25K+ user onboardings, hybrid GPU orchestration.
- **Aurora Supercomputer:** >1 ExaFLOPS, 10,624 nodes, 21,248 CPUs, 63,744 GPUs.
- **HPC Infrastructure:** Kubernetes orchestration, telemetry rollouts.
- **Telemetry System:** Prometheus + VoltDB, Rapid MQ, petabyte/year anomaly detection.

The Challenge: Traditional HPC Limitations

Lack of Elasticity

Traditional HPC clusters had fixed resource allocation, lacking dynamic scalability. Resources idled during low utilization; jobs queued during peak.

Poor Resource Efficiency

Static provisioning resulted in over- or underprovisioning, creating bottlenecks. Suboptimal GPU utilization meant expensive hardware was underutilized.

Integration Gaps

HPC and AI workloads were siloed, using separate orchestration systems. No unified platform connected traditional batch scheduling with cloud-native container orchestration.

Strategic Goal: Integrate HPC batch workloads and AI training jobs into a unified, elastic, cloud-native infrastructure that delivers both reliability and performance at scale.

Solution: Elastic Kubernetes Pods for HPC

Architecture Overview

Our solution introduces **Elastic Kubernetes Pods (EKP)** — a hybrid orchestration model that enables Slurm workload manager to dynamically provision Kubernetes pods as compute nodes. Instead of waiting for bare-metal or VM provisioning, Slurm launches containerized compute pods on-demand, executes jobs, and tears down resources automatically.

Key Innovation: This approach merges HPC-style batch scheduling with elastic, container-based resource management, delivering cloud-native benefits to traditional HPC workflows.

01

User submits job via Jupyter or CLI

02

Slurm Controller receives request

03

Kubernetes provisions compute pods

04

Pods execute workload with slurmd

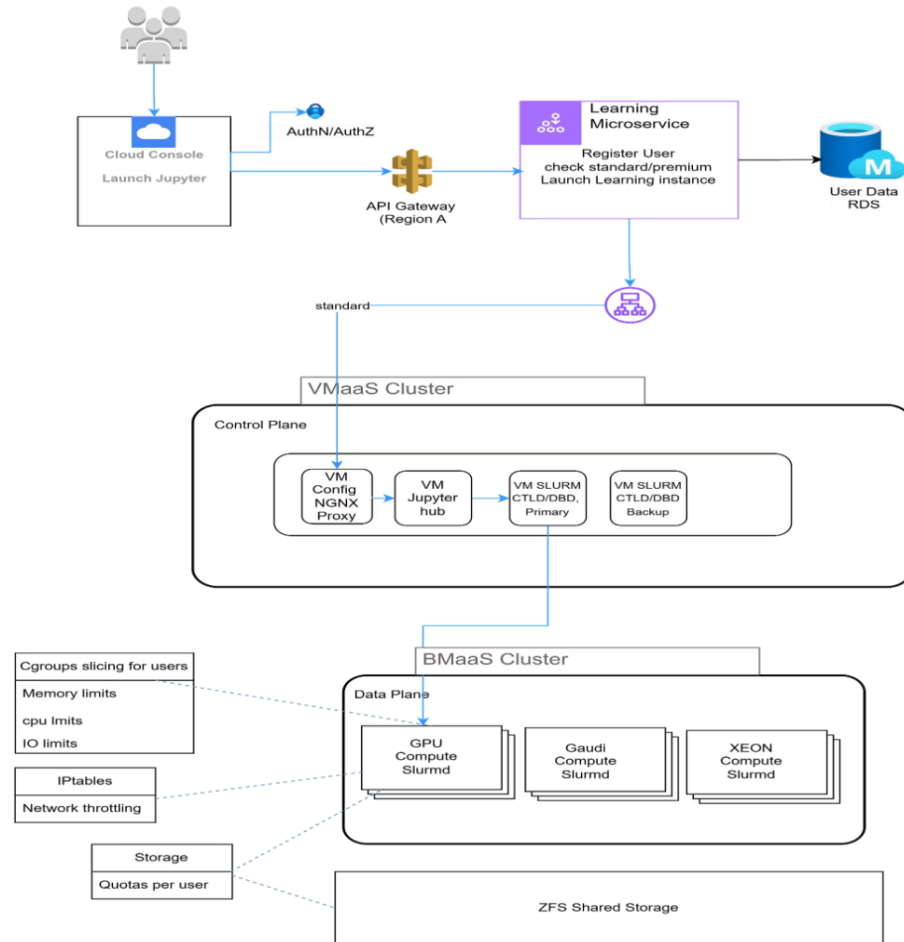
05

Resources terminate post-completion

Technical Specifications: 50 compute nodes | 400 GPUs | 200 Gbps network fabric | 1TB RAM per node | 128GB HBM per GPU | NFS/ZFS shared volumes | Support for 2 parallel jobs per GPU | 8 HPC parallel jobs per user

Architecture Evolution: From Bare Metal to Elastic Pods

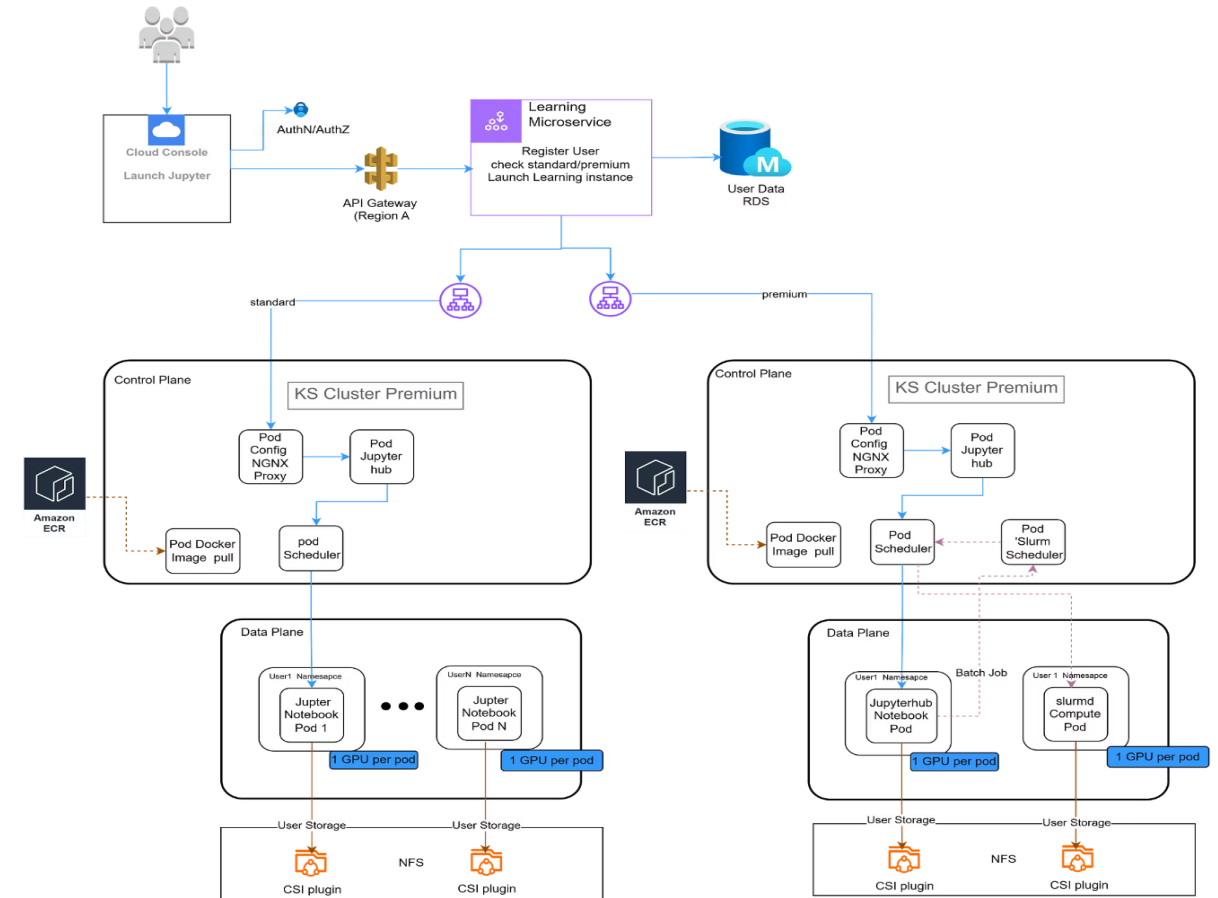
Previous State



Traditional architecture relied on bare-metal servers with static provisioning. Jobs waited in queue for physical resources to become available, leading to poor utilization and extended wait times.

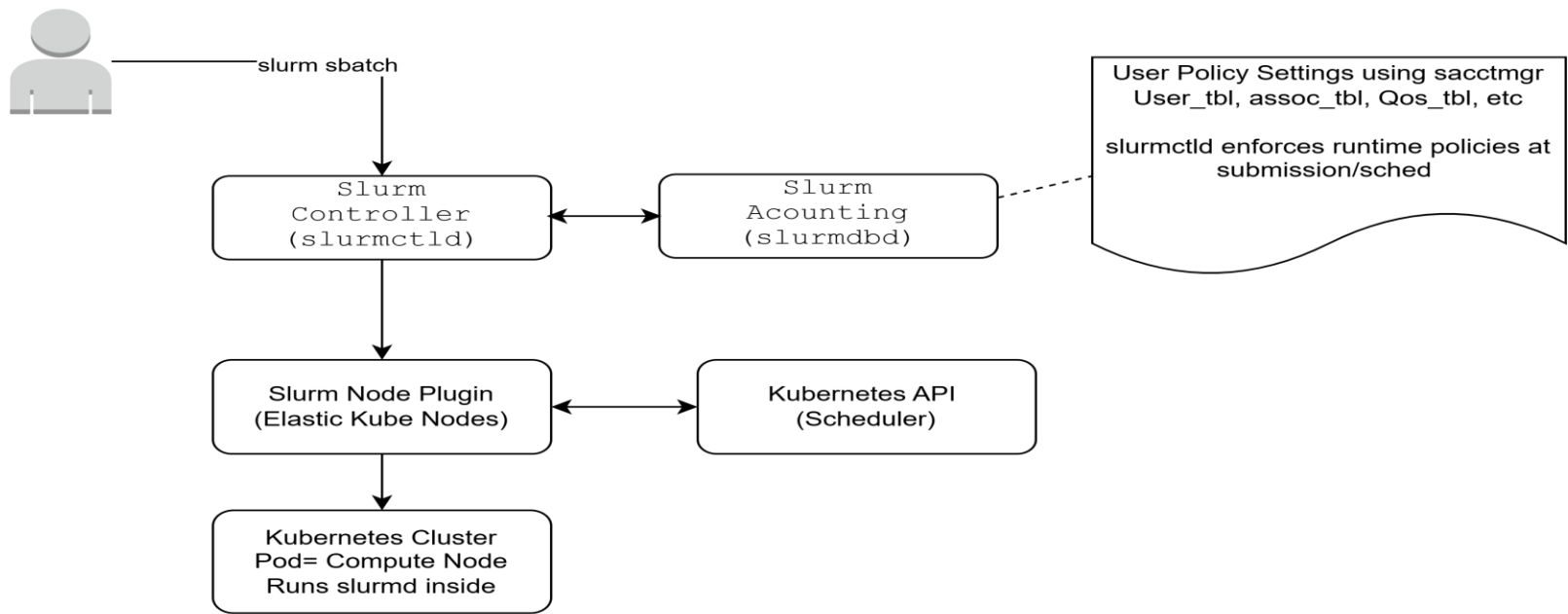
Transformation Impact: Migration from static bare-metal provisioning to dynamic pod orchestration reduced job start times by 50% while improving GPU utilization by 3×.

Current State with EKP



Modern elastic architecture leverages Kubernetes pod orchestration. Compute resources provision dynamically in seconds, scale based on demand, and terminate automatically, maximizing efficiency and throughput.

System Architecture: Component Interaction



Slurm Controller

Manages job queues, triggers elastic provisioning, communicates with Kubernetes, monitors jobs.



Kubernetes Cluster

Schedules compute pods, provides elastic scaling, manages pod lifecycle and cleanup.



Elastic Compute Pods

Run `slurmd` daemon, register as compute nodes, execute workloads, terminate post-job.

Each pod runs a lightweight **slurmd** daemon, dynamically joining the Slurm cluster as a compute node capable of executing MPI, GPU, and HPC workloads, terminating automatically post-job.

Implementation: Configuration Highlights

Step 1: Build or pull a Slurm Pod Image

Create container image with **slurmd**, **munge** authentication, and minimal dependencies. Store in ECR image repository for deployment. Configure **slurm.conf** to point to the controller.

Step 2: Create Kubernetes Service Account and RBAC

Give Slurm permission to create pods using the following Kubernetes YAML configurations:

```
apiVersion: rbac.authorization.k8s.io/v1
kind: Role
metadata:
  name: slurm-elastic

rules:
- apiGroups: [""]
  resources: ["pods"]
  verbs: ["create", "delete", "list", "get"]
---
apiVersion: rbac.authorization.k8s.io/v1
kind: RoleBinding
metadata:
  name: slurm-elastic-binding
roleRef:
  kind: Role
  name: slurm-elastic
  apiGroup: rbac.authorization.k8s.io
subjects:
- kind: ServiceAccount
  name: slurm
  namespace: default
```

Step 3: Configure slurm.conf for Elastic Nodes

Update **slurm.conf** with elastic node definitions. Add the following example snippet:

```
# slurm.conf snippet for elastic nodes
NodeName=elastic[1-100] State=CLOUD
PartitionName=ekp Nodes=elastic[1-100] Default=YES
MaxTime=INFINITE State=UP
```

Step 4: Add Slurm Prolog Plugin

Configure **slurm.conf** to use a Prolog script for dynamic pod provisioning. Example:

```
# slurm.conf snippet for prologProlog=/etc/slurm/prolog.sh
```

Example **prolog.sh** script (simplified):

```
#!/bin/bash# Example prolog.sh scriptNODELIST=$SLURM_JOB_NODELIST# Logic to call kubectl
to provision pods for NODELIST# e.g., kubectl apply -f pod-template.yaml --
selector=slurm.node=$NODELIST
```

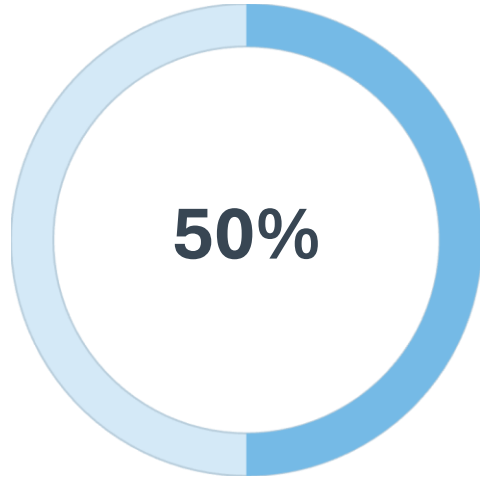
Step 5: Test Job Submission

Submit a test job via **sbatch** and verify successful execution on elastic nodes.

```
# Example sbatch commandsbatch --nodes=2 --wrap="hostname"
```

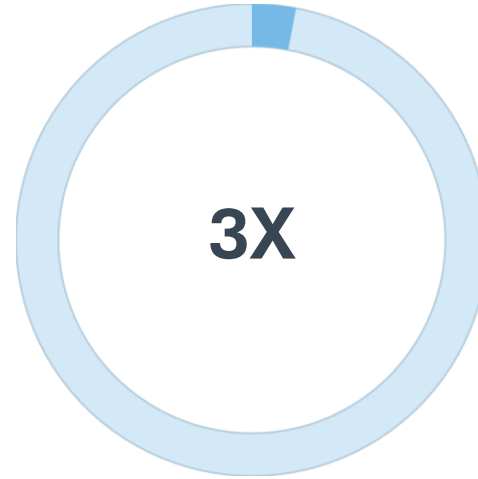
Verify pod creation in Kubernetes, **slurmd** registration, workload execution, and automatic pod termination after job completion.

Results and Business Impact



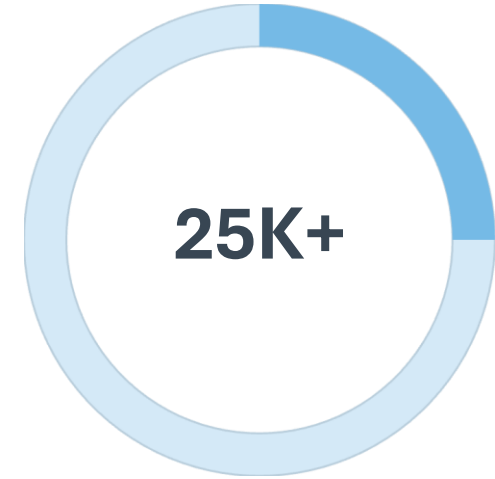
Faster Job Start

Reduced provisioning time from minutes to seconds
with dynamic pod creation



GPU Utilization

Improved resource efficiency through elastic scaling
and auto-termination



Active Users

Successfully scaled Intel Tiber AI Cloud to support
enterprise workloads

Technical Achievements

- Unified orchestration for HPC batch jobs and AI training workloads
- Auto-scaling compute infrastructure based on real-time demand
- Hybrid cloud capabilities enabling multi-region deployments
- Seamless integration with existing Slurm-based workflows

Operational Benefits

- Reduced infrastructure costs through efficient resource utilization
- Improved time-to-science for researchers and data scientists
- Enhanced system reliability with container-based isolation
- Simplified operations with Kubernetes-native tooling

Alternative Approach: Native Slurm Operator

Kubernetes-Native Slurm Deployment

An alternative architecture involves running Slurm entirely inside Kubernetes using the [SchedMD Slurm Operator](#). This approach handles the complete lifecycle of controllers and compute pods through Kubernetes Custom Resource Definitions (CRDs).

Advantages: Simpler for new deployments, leverages Kubernetes-native constructs, reduces external dependencies, provides declarative job definitions.

Trade-offs: Locks architecture to Slurm scheduler, limiting future flexibility to adopt alternative schedulers. Less suitable for organizations with existing Slurm infrastructure requiring gradual migration.

```
apiVersion: slurm.schedmd.com/v1alpha1kind:SlurmJobmetadata: name: mpi-testspec: partition: default tasks:4 image: ghcr.io/schedmd/slurm:latest command: ["mpirun","hostname"]
```

Best Use Case: Greenfield deployments starting fresh with Kubernetes-first architecture and no legacy Slurm infrastructure to maintain.

Case Study: Aurora Supercomputer at Argonne

System Architecture

Exascale compute system delivered through Intel + HPE + DOE partnership, achieving breakthrough performance milestones for scientific research and national security applications.

10.6K

Compute Nodes

63.7K

GPUs

1.012

ExaFLOPS

FP64 Linpack

Advanced Capabilities

- **Power Management:** GEOPM framework for power-aware scheduling under 20 MW budget with real-time energy calculations
- **Storage Innovation:** DAOS Object Store with burst buffers and pre-fetching libraries for extreme I/O performance
- **Multi-OS Architecture:** Hybrid kernel design (fat + lightweight) optimized for extreme-scale computing workloads
- **Telemetry System:** Prometheus + VoltDB infrastructure sampling every 10 minutes (716KB/node, ~1.6 PB over 4 years)
- **Predictive Analytics:** Health modeling and reliability optimization using machine learning on telemetry data

