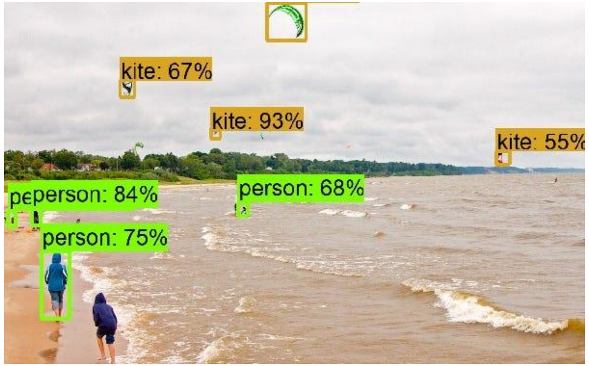
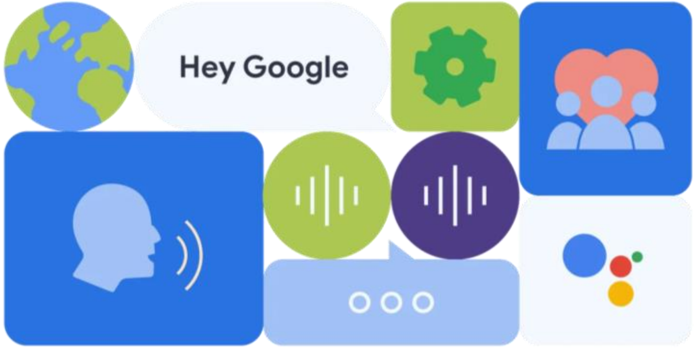
EcoEdgeInfer: Dynamically Optimizing Latency and Sustainability for Inference on Edge Devices

Sri Pramodh Rachuri, Nazeer Shaik, Mehul Choksi, Anshul Gandhi
PACE Lab, Stony Brook University

srachuri@cs.stonybrook.edu
pramodh.rachuri.dev

Motivation





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Motivation

- Deployments are usually inference servers
  - Light weight – resources, energy, processing time, memory etc
  - More frequent executions
    - Scale up in consumption
- User facing
  - Latency sensitive
  - Varying arrival rate

ChatGPT consumes 6-10X more energy than a Google Search - Goldman Sachs

ChatGPT's Energy Consumption
for Responding to Prompts and Its Cost in the U.S.

Time Period	Number of prompts	Energy Consumption	Cost
Day	214,285,714	621,429 kWh	$81,407
Week	1,500,000,000	4,350,000 kWh	$569,850
Month	6,517,860,000	18,901,794 kWh	$2,476,135
Year	78,214,350,000	226,821,615 kWh	$29,713,632

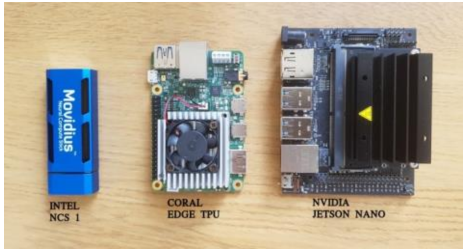
Data sources: U.S. Energy Information Administration, Electric Power Research Institute (EPRI)
Calculations based on: 100 million weekly users, 15 weekly prompts per user, 0.0029 kWh of energy consumption per prompt, average U.S. commercial electricity rate of $0.131/kWh as of June 2024

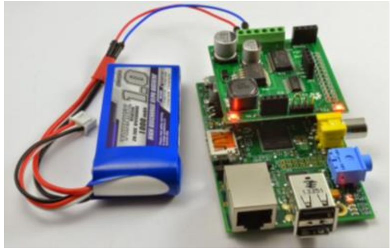
BestBrokers.com

Motivation

Edge for DNN inference

- Commercial products, Prior works
- Sits closer to the user
  - Low communication latency
- Local processing
  - Added privacy
- Possible remote locations
  - Limited energy supply
- Resource contention



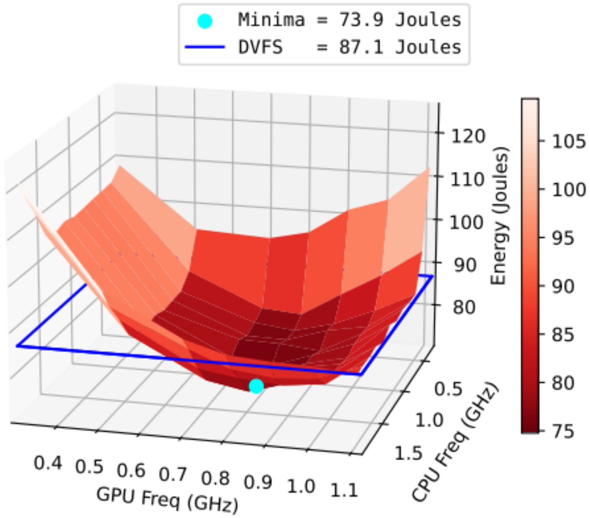


Problem Statement

Jointly optimize energy consumption and latency by tuning both hardware and software parameters under varying request arrival conditions of DNN inference workloads on Edge devices

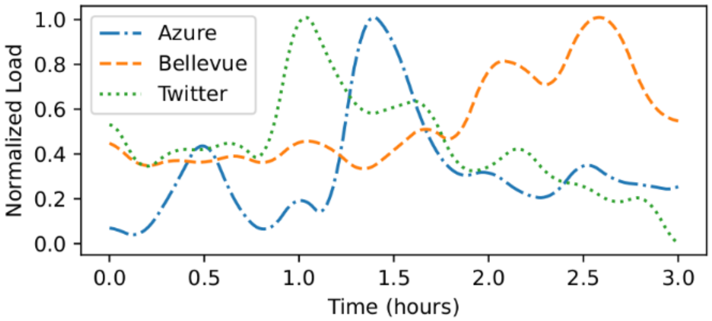
Challenges

- Knobs having non-linear affect on energy
  - CPU Frequency
  - GPU Frequency
- Knobs having complex interactions with latency
  - Batch Size
- Varying request arrival patterns complicates futher



[Source: Dutt et al., IGSC]

Challenges



- Too frequent arrivals ⇒ High load
  - Higher freqs for performance but energy inefficient
- Infrequent arrivals ⇒ Low load
  - Lower freqs for energy saving but higher latencies

- Batch Size
  - High batch size - better energy efficiency and throughput
  - Wait for batching - Increase latency
- Arrivals – Batch Size interaction

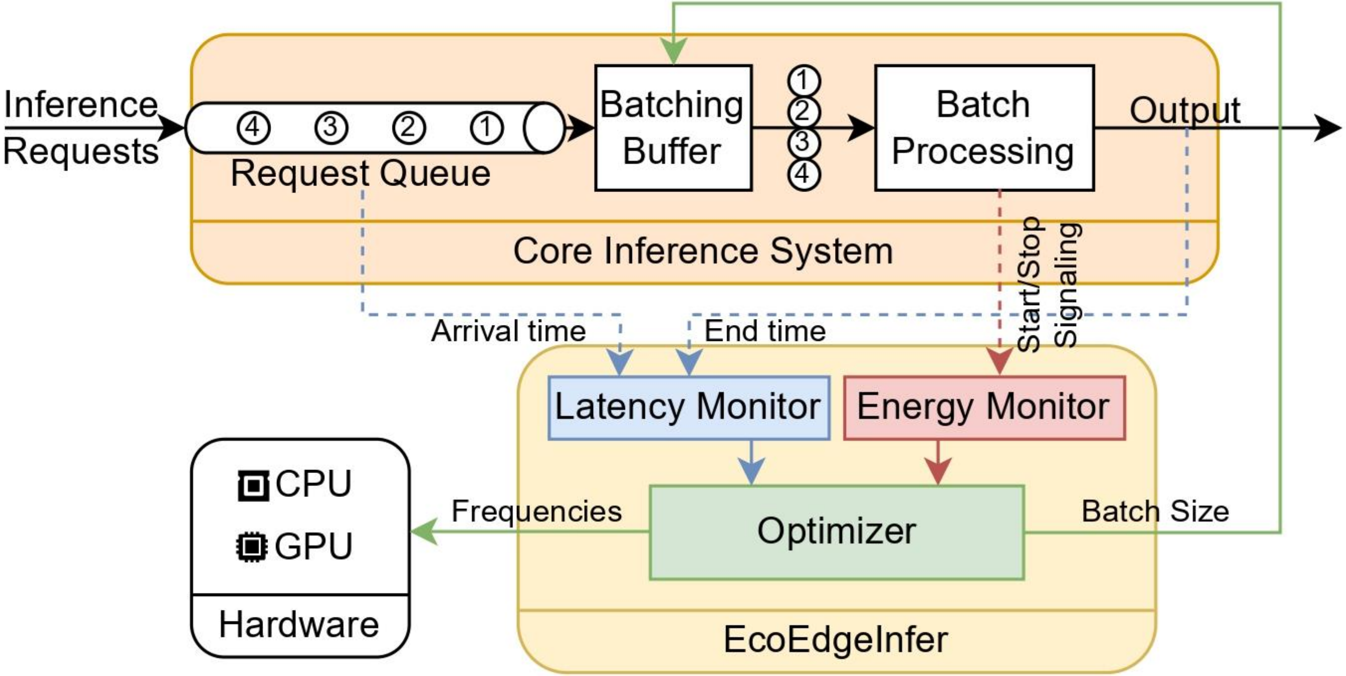
  Example- Consider batch size of 11
  - 100ms arrival interval ⇒ 1.1 s
  - 10ms arrival interval ⇒ 110 ms
  - Bursts of 10 every 100 ms

    ⇒ 200 ms!!!
    - Batch size = 10 ⇒ 100 ms

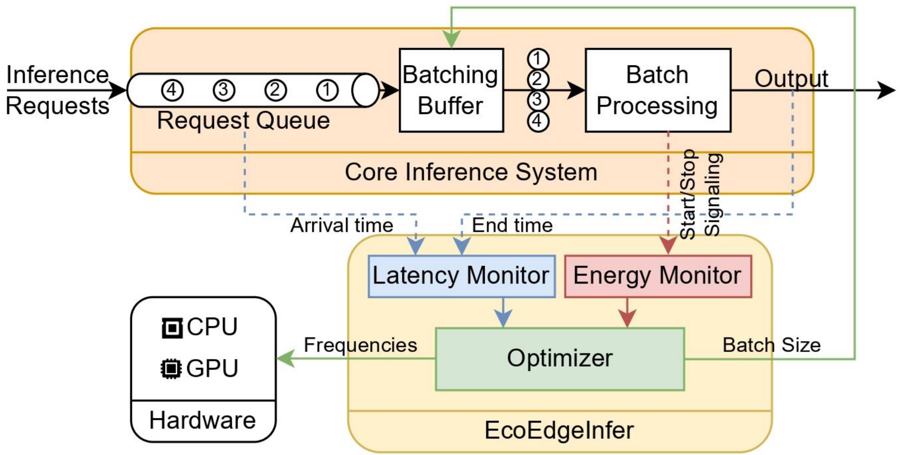
Outline

1. Motivation
2. Problem Statement
3. Challenges
4. **System Design**
5. Optimization Algorithm
6. Experimental Setup
7. Experimental Results
8. Conclusion

System Design

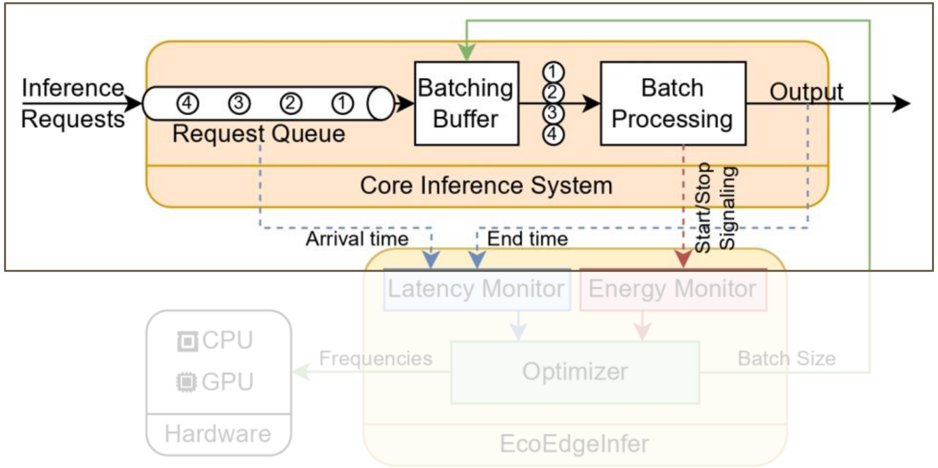


System Design



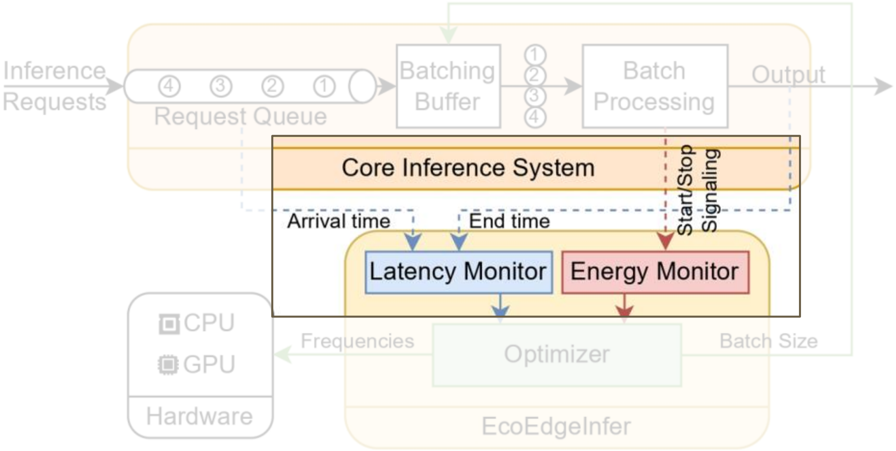
System Design

- Maintains a request queue
  - Store when busy
- Maintains a buffer of size = batch size
- Runs the DNN code provided by the developer
- Other signaling



System Design

- Collects latency using timestamps from core inference system
  - All waiting times are also included
- Records energy consumed per batch
  - Uses Nvidia APIs through sysfs, I2C

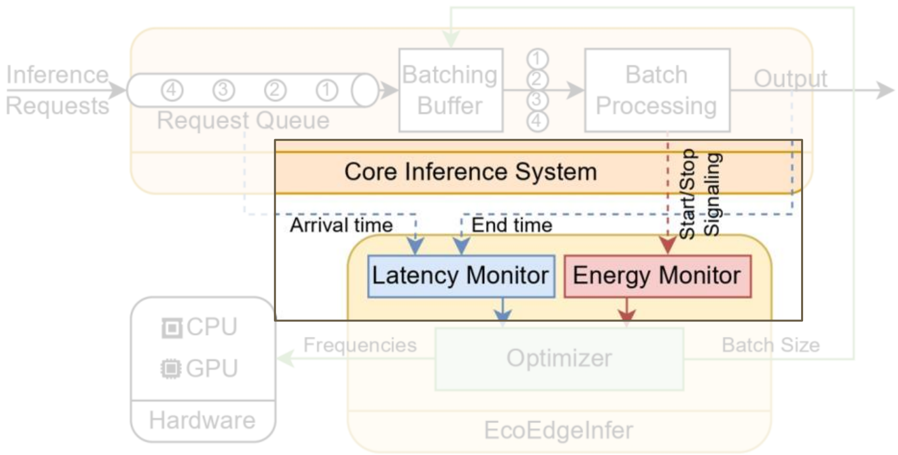


System Design

- Homogenize latency and energy of group of requests into cost

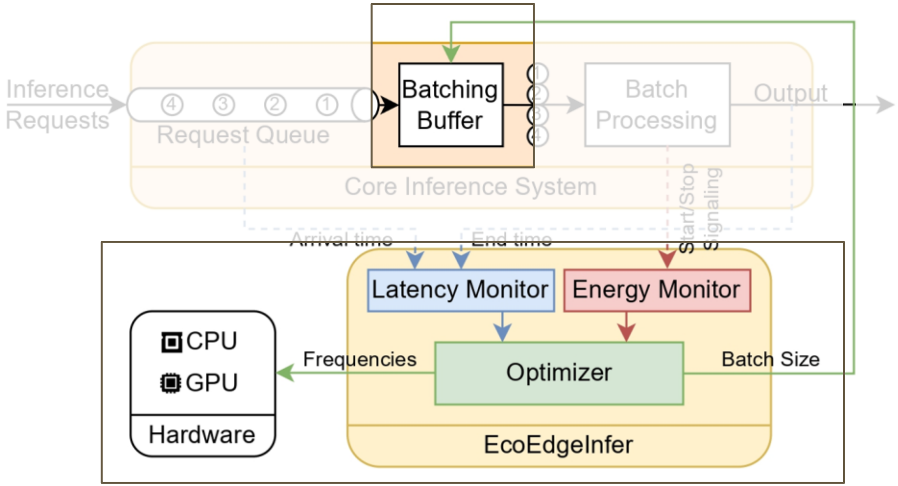
$$\text{Cost} = \frac{1}{2}\left(\frac{E}{E_o} + \frac{L}{L_o}\right)$$

E_0 and L_0 are measured when params are set to max



System Design

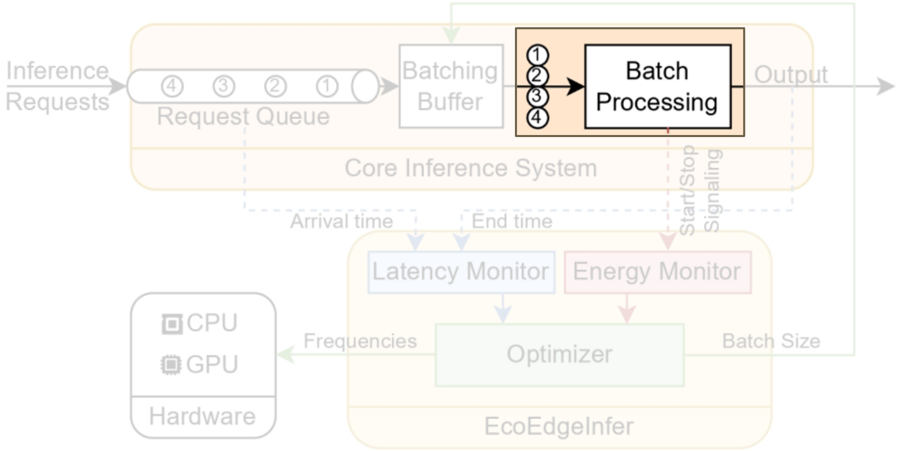
- Optimizer takes cost & predicts a config
- Output of optimizer
  - CPU - cpufrequtil
  - GPU - NVIDIA's devfreq framework
  - Batchsize - Batching buffer



System Design

Made to easily integrate with exiting PyTorch inference scripts using Python decorators

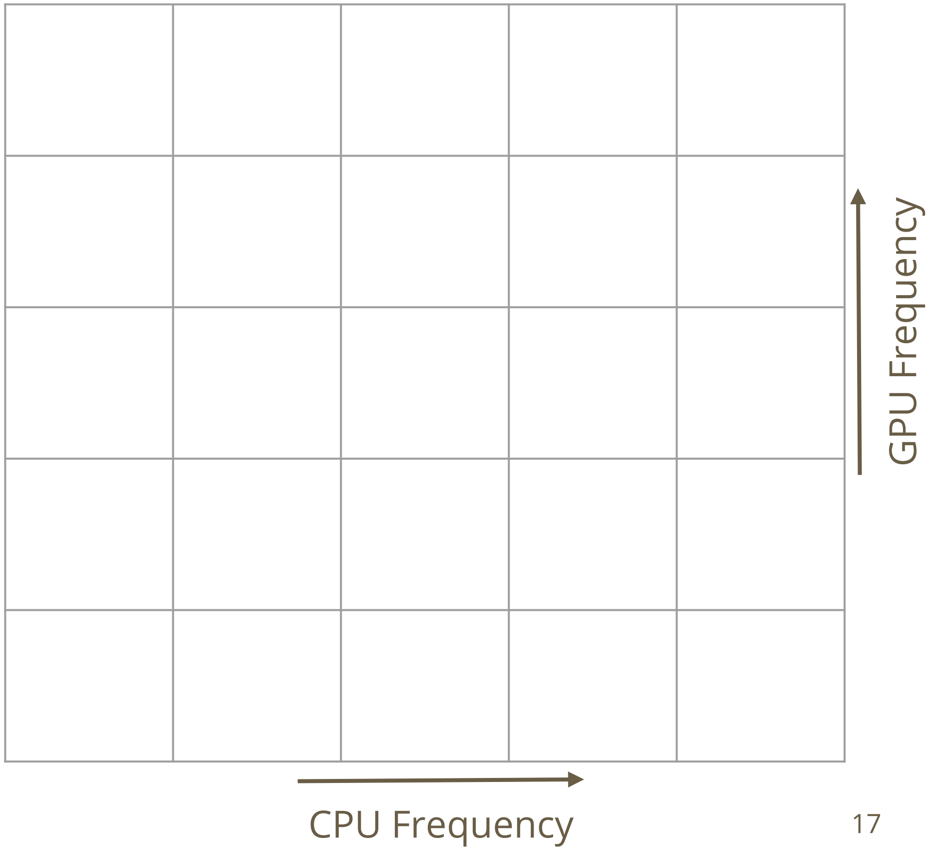
```
@eco_edge_infer.inference_method
def run_inference(input_data):
    output_data = model(input_data)
    output_handler(output_data)
run_inference(inference_request)
```



Outline

Optimization Algorithm: EcoGD

- Similar to Hill Climbing Local Search algorithm
  - Think of it as - gradient descent but only direction
- Cost is the objective function
- At every optimizer step, it either-
  - Explores 3D neighborhood
    - Only 6-neighborhood
  - Jumps to a better center
    - Loop detection
    - More loops than threshold ⇒ Jump outside 6-nbhrhood



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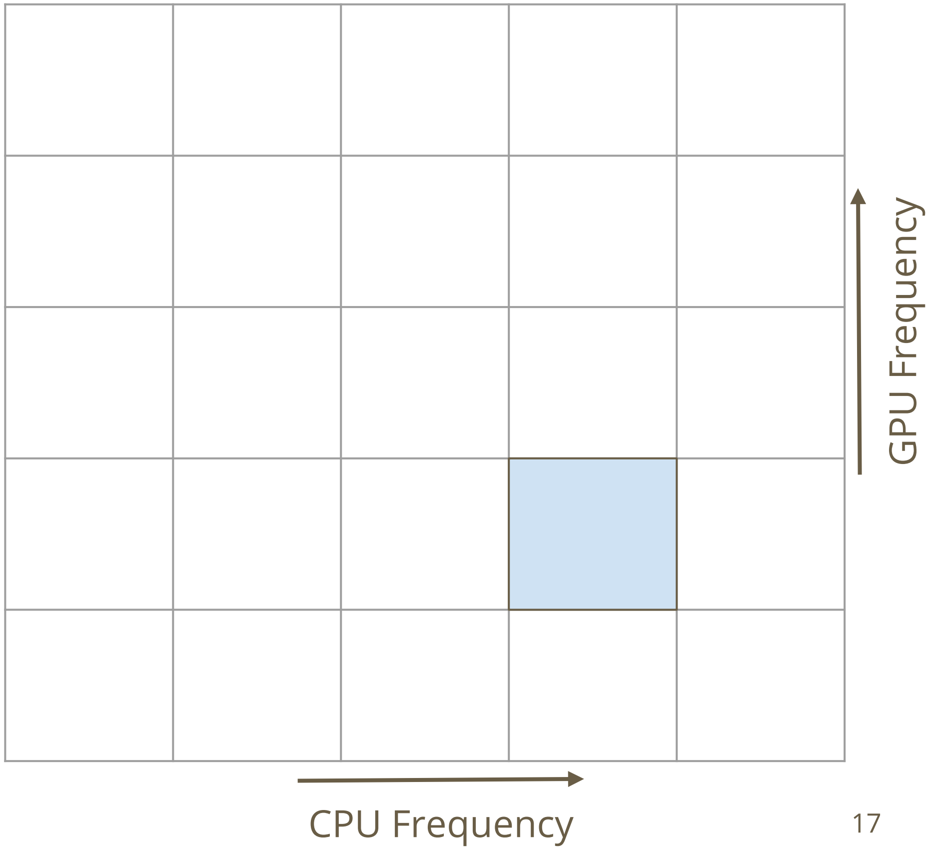

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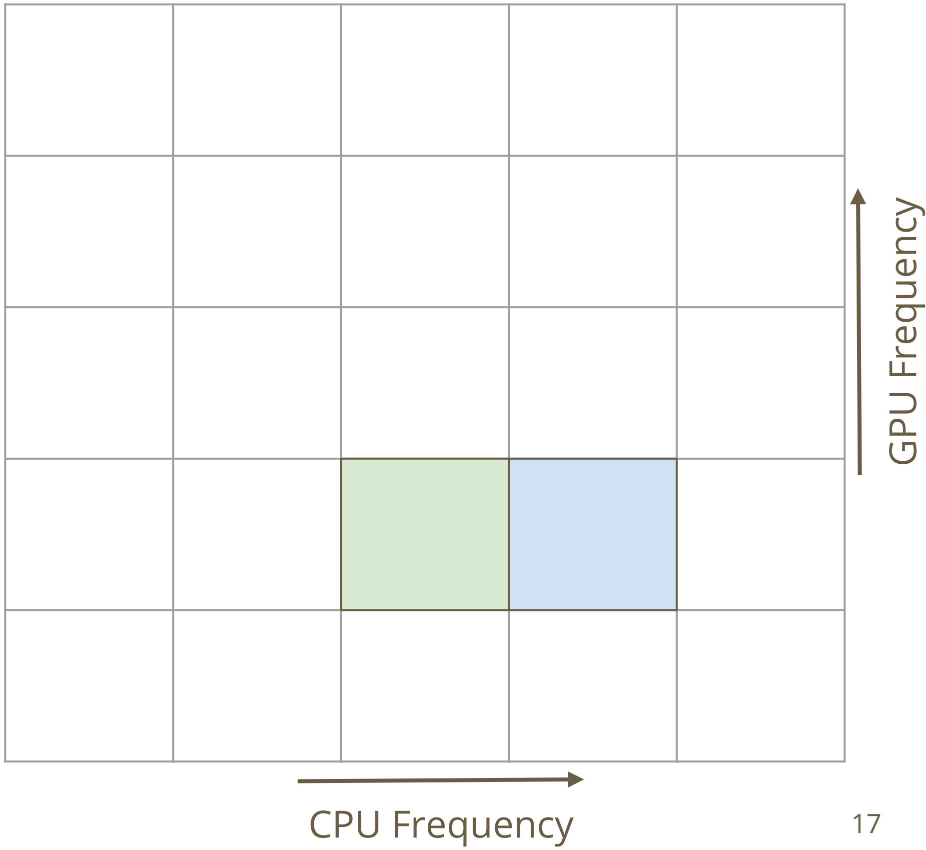

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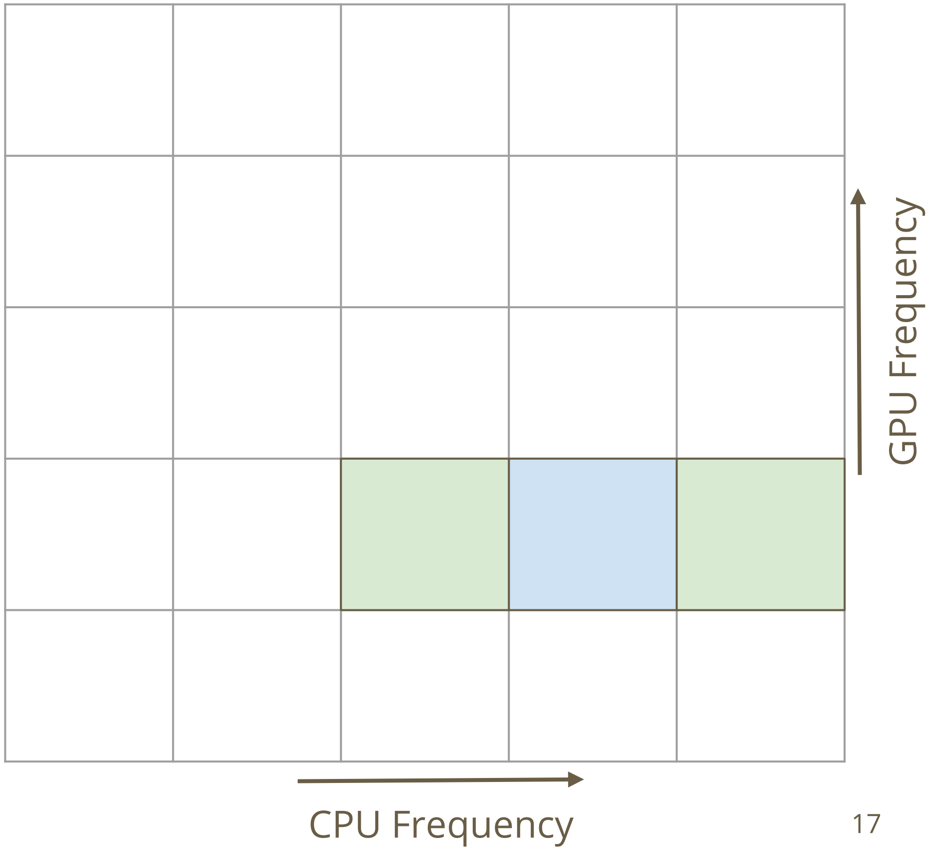

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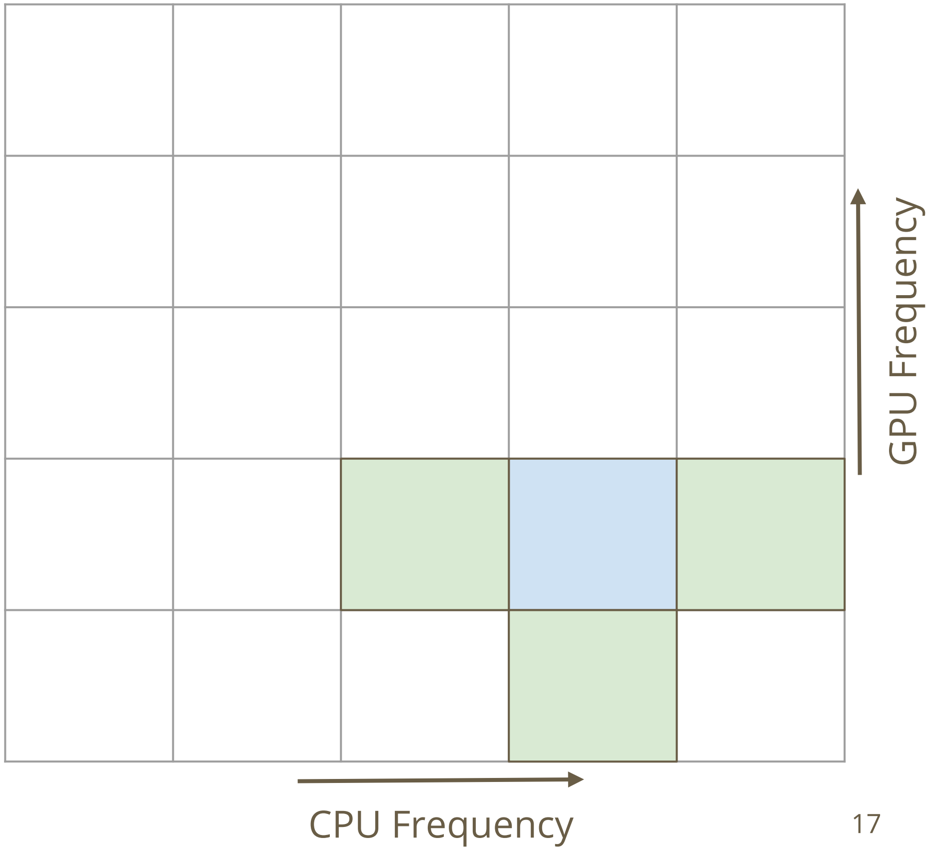

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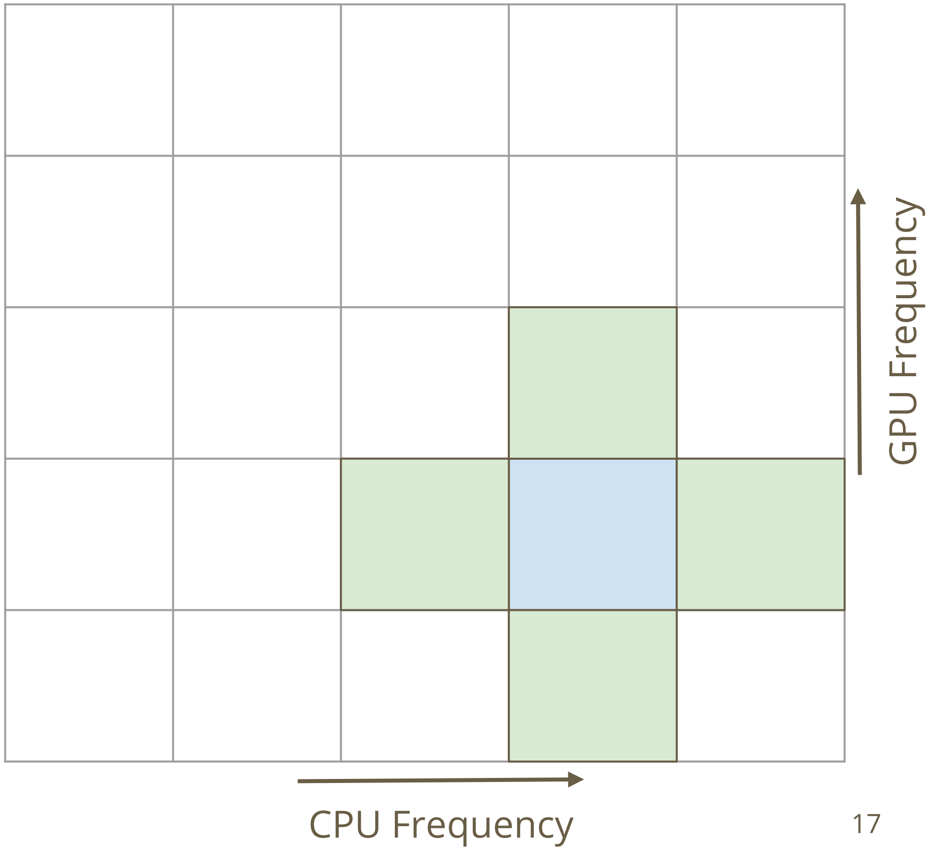

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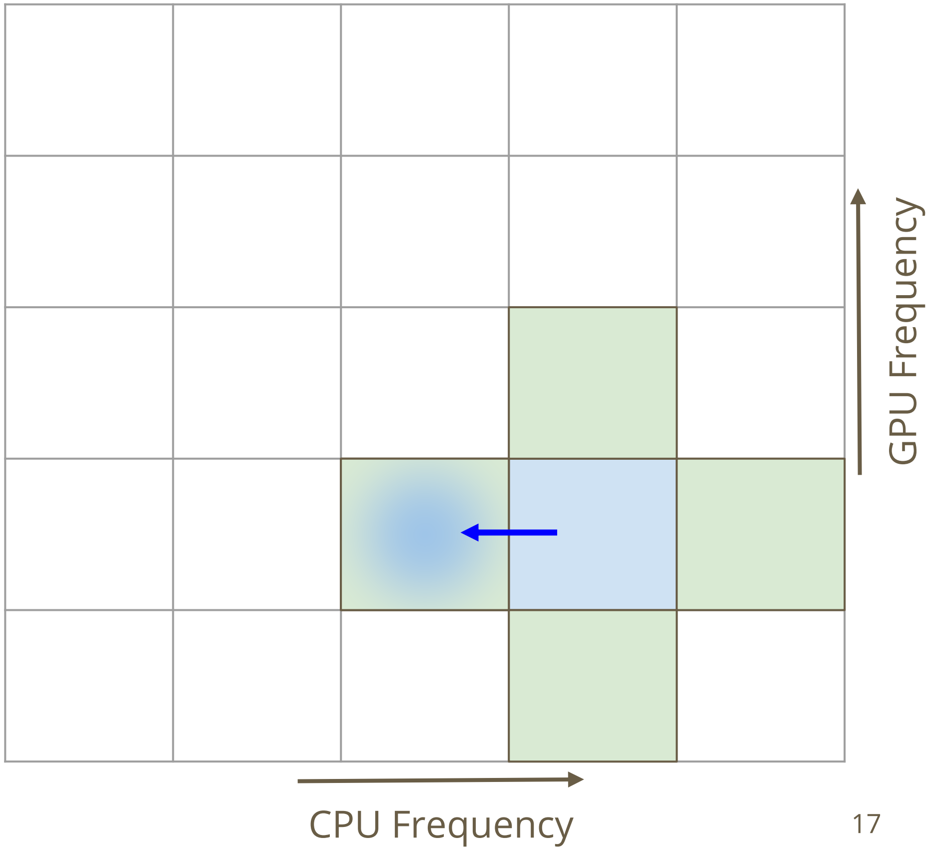

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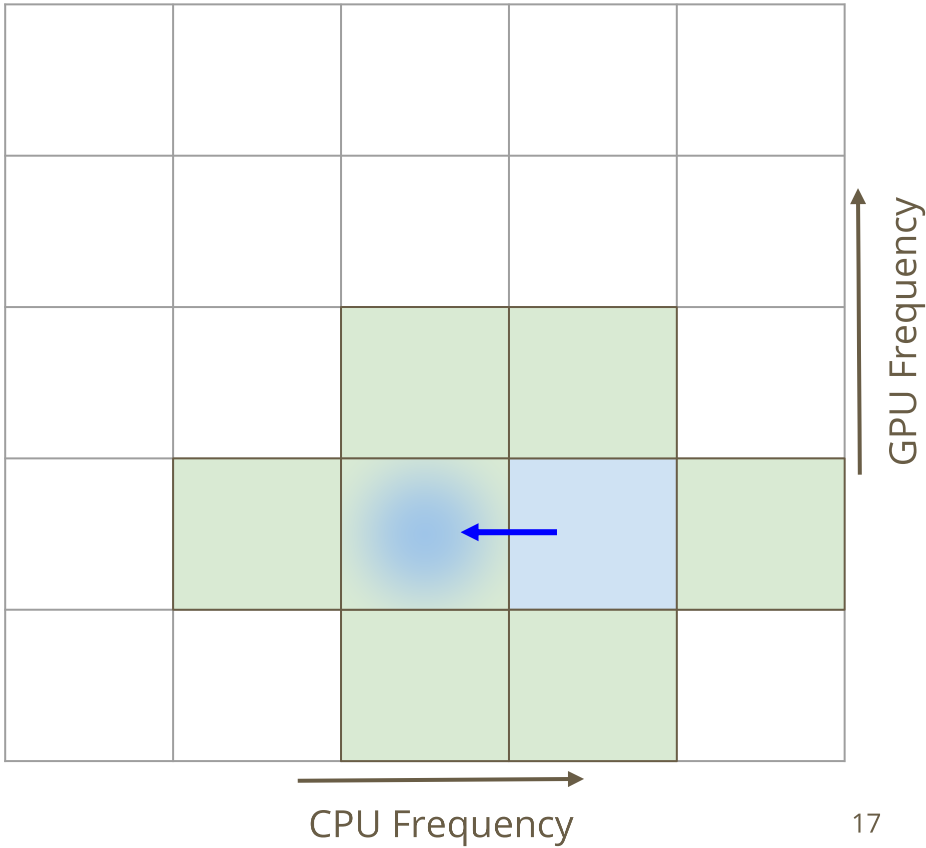

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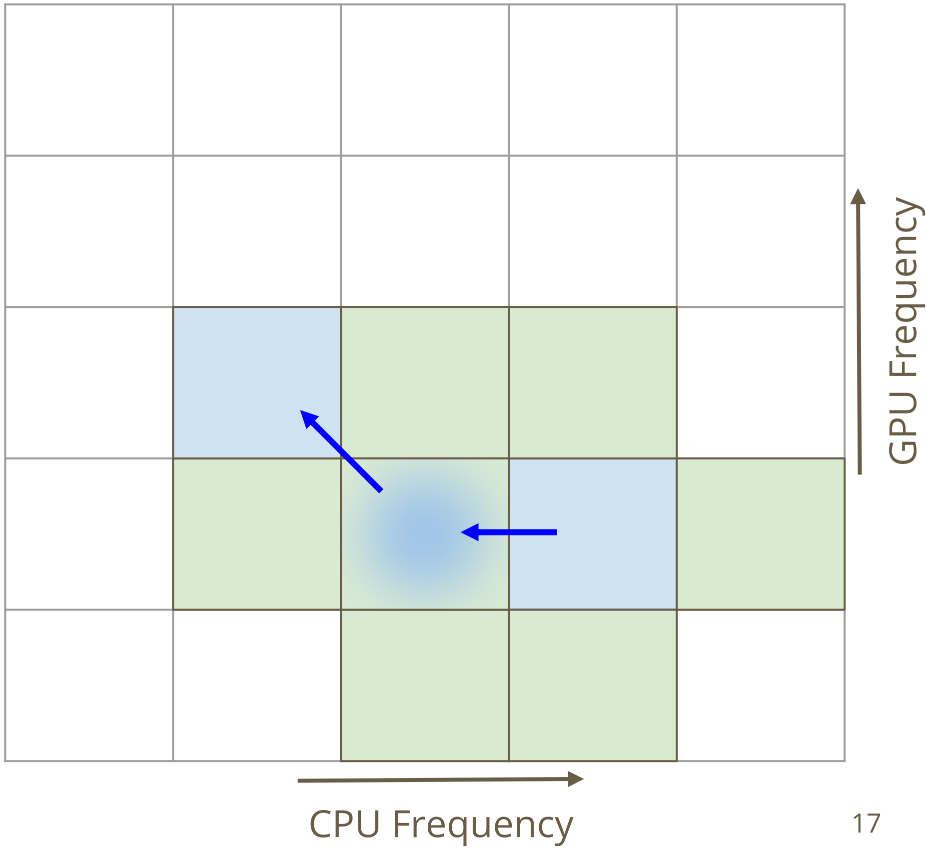

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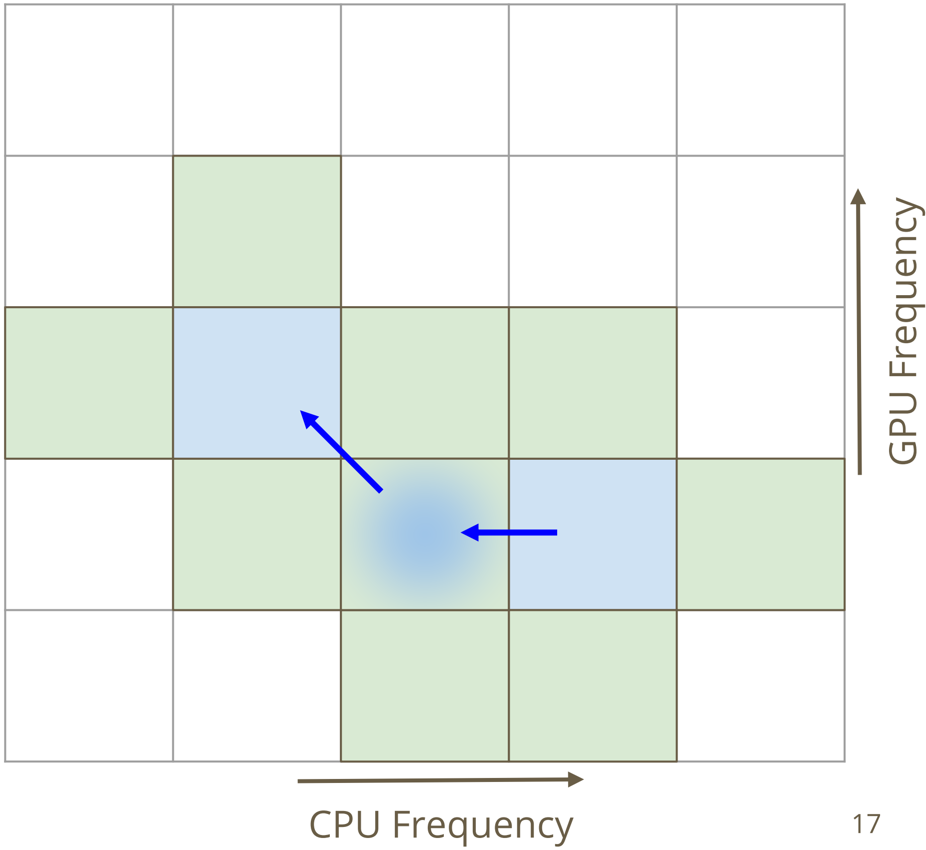

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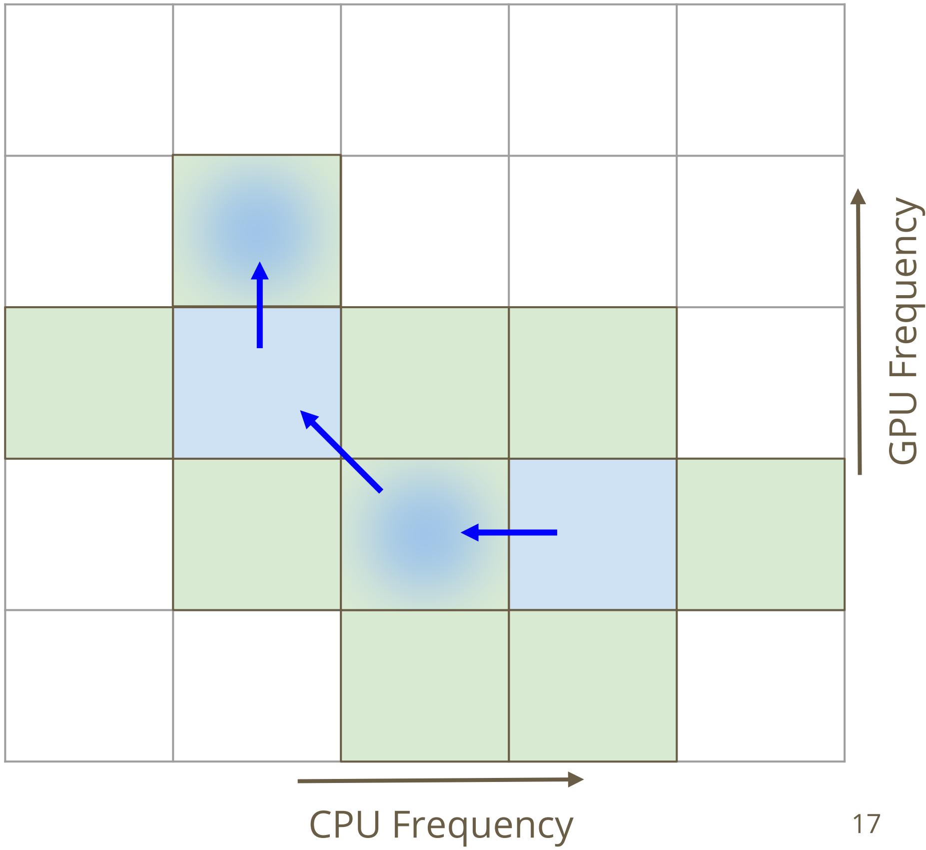
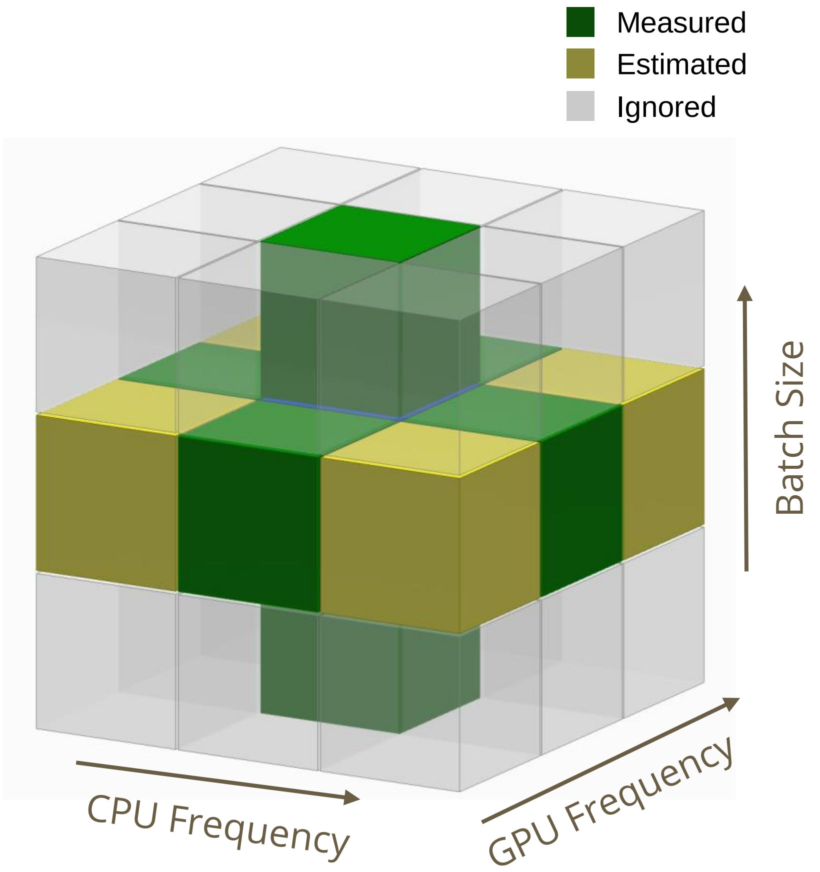


Optimization Algorithm: EcoGD

- Diagonal estimations
  - Data available - 6 Neighborhood
  - Diagonals in CPU – GPU plane can be estimated
  - Diagonals in planes involving Batchsize cannot be estimated
- What is a better center?
  - Lowest cost among 6+4 neighbors
- History trimming
  - Adapt to changing arrival rates
  - Saves memory



Outline

Evaluation Setup

- Nvidia Xavier NX
  - 25 CPU Frequencies
  - 15 GPU Frequencies
- Inference Workloads
  - Resnet 50, BERT-Tiny
  - Batch Sizes: 1-16
- Search Space
  - 25 X 15 X 16 = 6000

- 3 reruns
- Duration
  - Synthetic pattens – Till convergence
  - Traces – 3 hours

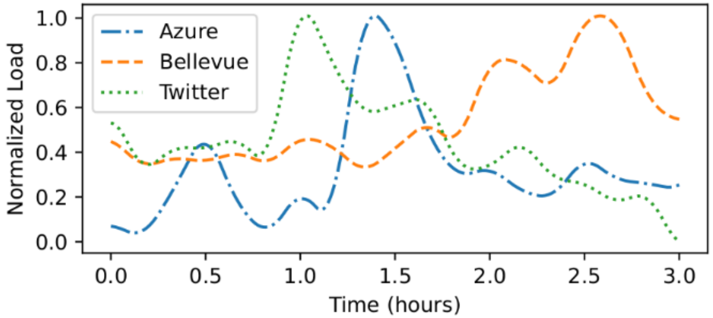
TECHNICAL SPECIFICATIONS OF NVIDIA XAVIER NX

Specification	Value
CPU	6-core Nvidia Carmel
CPU Freq. range	115 MHz – 1.9 GHz; 25 steps of 77 MHz
GPU	NVIDIA Volta
GPU Cores	384 CUDA Cores + 48 Tensor Cores
GPU Freq. range	114 MHz – 1.1 GHz; 15 steps of 90 MHz
Memory	8 GB LPDDR4x
Throughput	21 TOPs
Default Power Modes	10W, 15W, 20W
Jetpack version	5.1.3 [L4T v35.5.0]
Framework	PyTorch 2.1.0
Operating Sys. & Libraries	Ubuntu 20.04.6; CUDA 11.4 + cuDNN 8.6

Evaluation Setup

Request Arrival Pattern

- Fixed inter-arrival times between requests
  - 50 ms/90 ms
- Bursty arrivals
  - 10 requests arriving together every 500 ms/900 ms
- Bellevue Traffic Camera
  - Num of cars passing through
  - Proxy for Edge Traffic Video Analytics
- Twitter Stream Dataset
  - 1% sample of tweets in US East
  - Proxy for Edge content moderation
- Azure Functions Traces
  - Calls to azure serverless functions
  - Proxy to Serverless Edge Computing



Evaluation Setup

Comparison Baselines

- Grid Search
  - Brute force method. Tries all configurations
- Linear Search
  - Sweeps each dimension one by one
  - Keeps sweeping forever
- Dynamic Voltage Frequency Scaling (DVFS)
  - CPU - schedutil
  - GPU - nvhost_podgov
  - Batch Size - 8, 16
- Bayesian Optimization
- Multi-Armed Bandit (MAB)

In detail explanations and exact hyperparameters can be found in the paper.

Outline

Experimental Results: Fixed Loads

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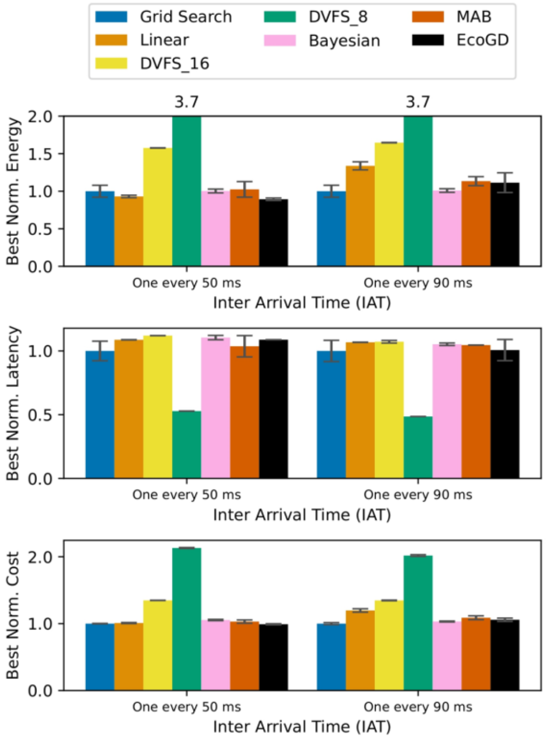
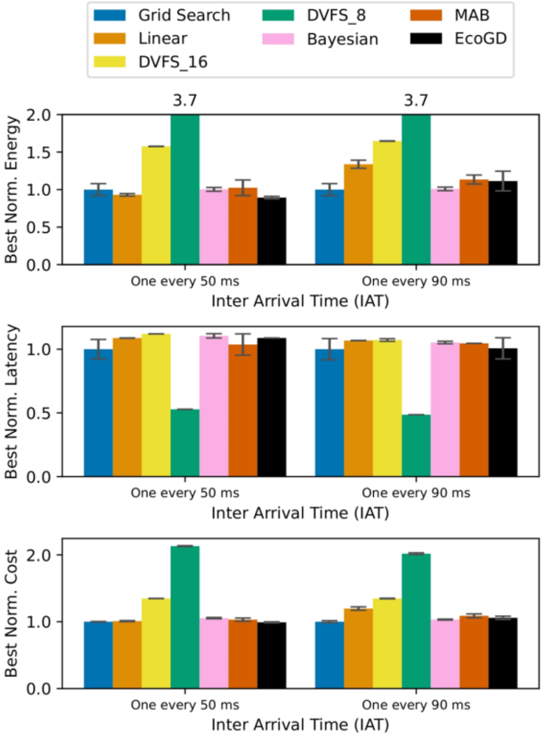


Metrics **after** convergence

Experimental Results: Fixed Loads



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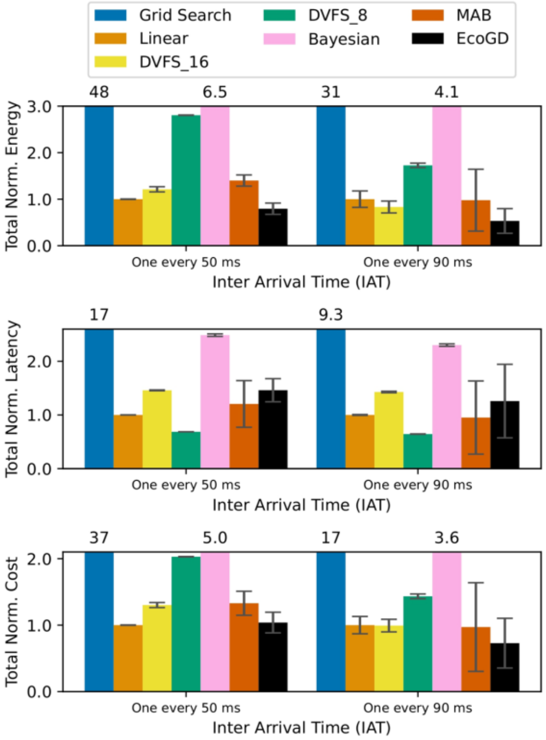
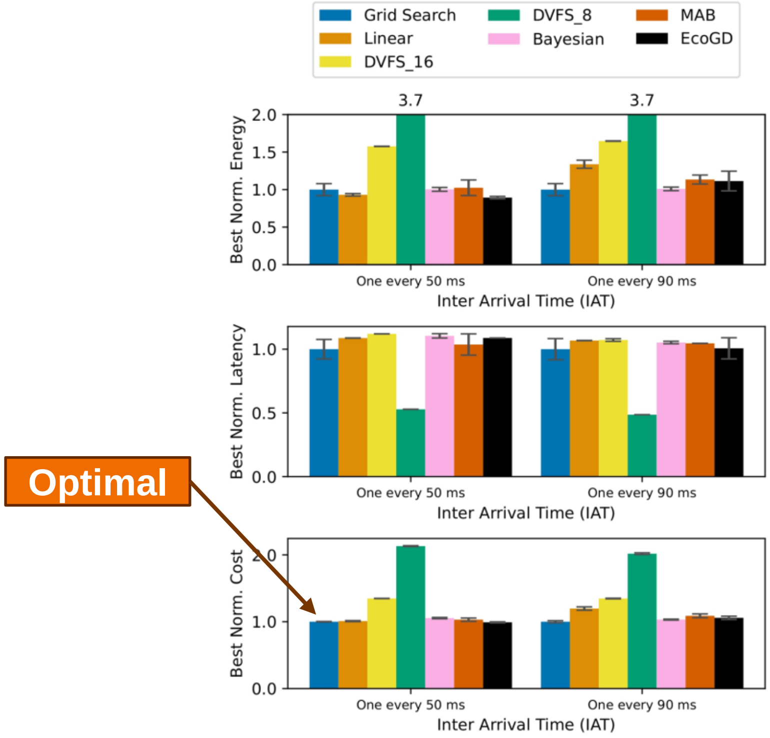


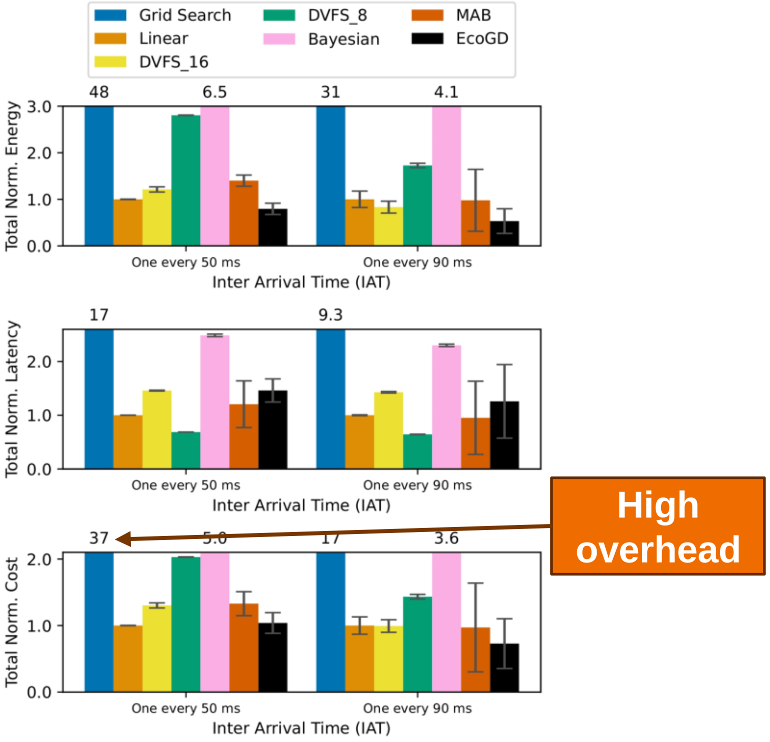
Metrics **during** convergence (overhead)

Experimental Results: Fixed Loads



Metrics **after** convergence

Grid Search



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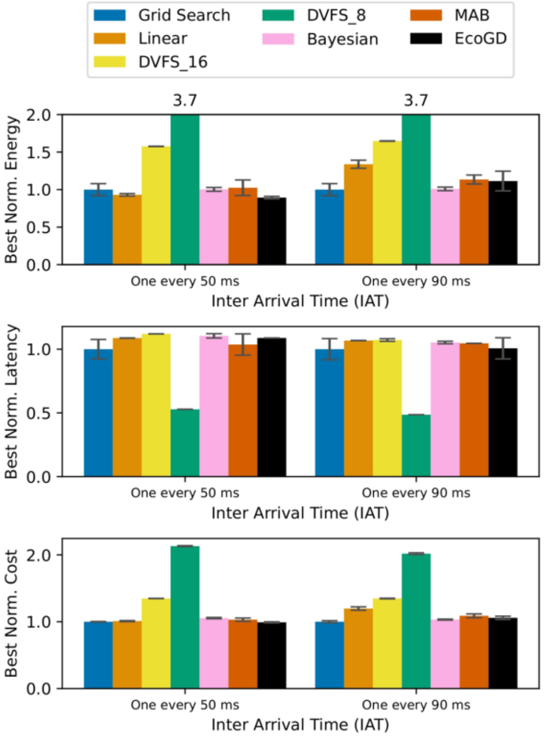
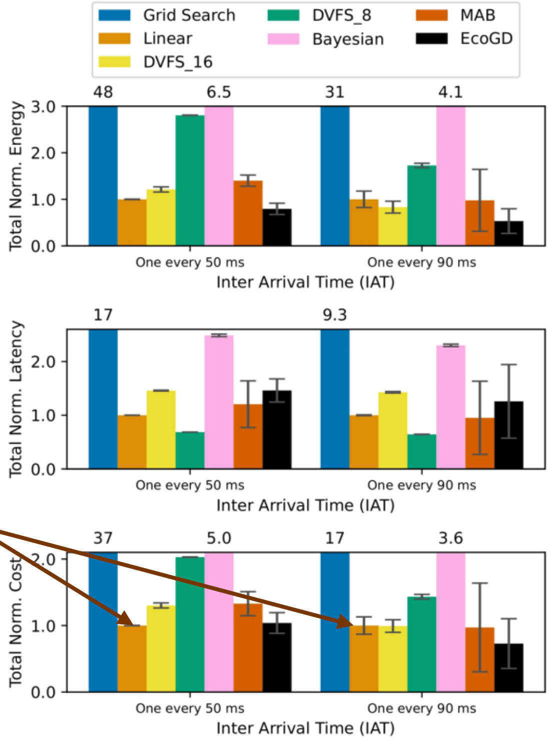


Metrics **after** convergence

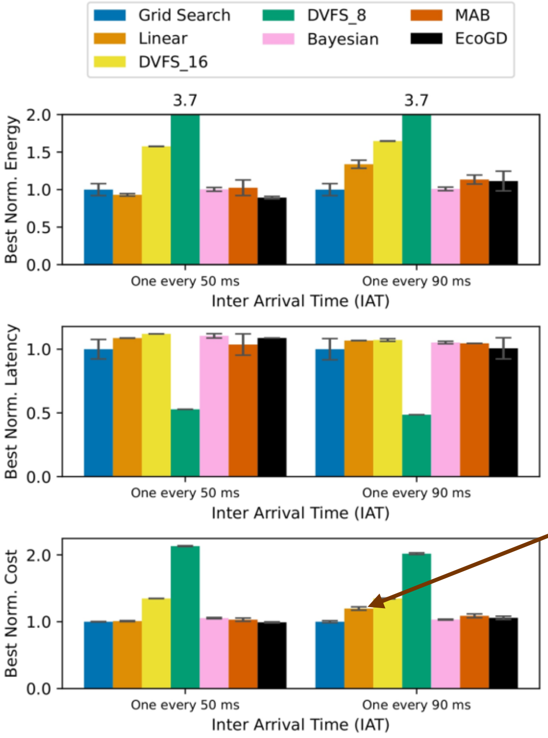
Linear Search

Low overhead but suboptimal



Metrics **during** convergence (overhead)

Experimental Results: Fixed Loads



Metrics **after** convergence

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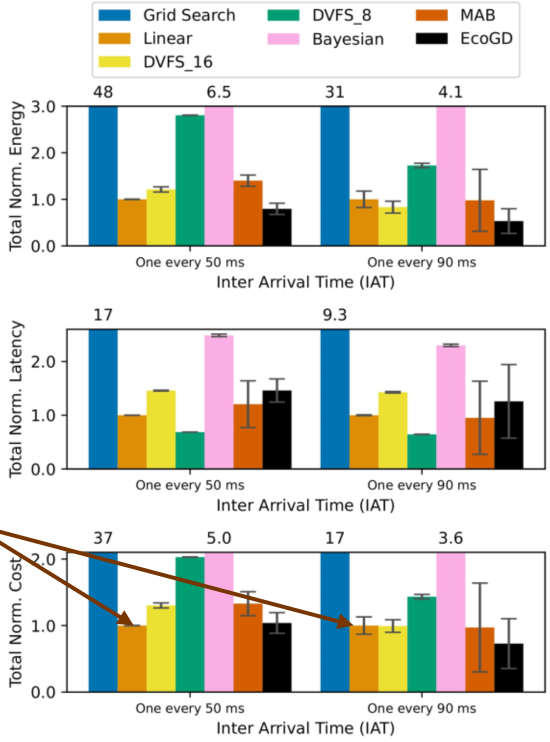
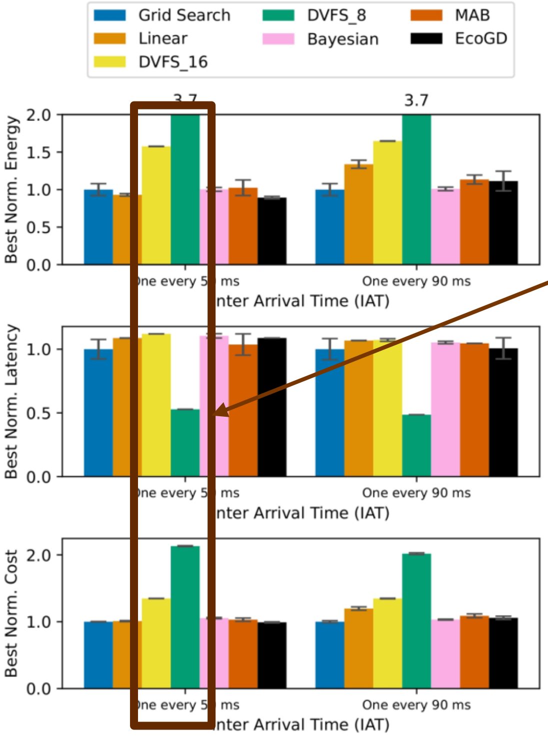


Metrics **during** convergence (overhead)

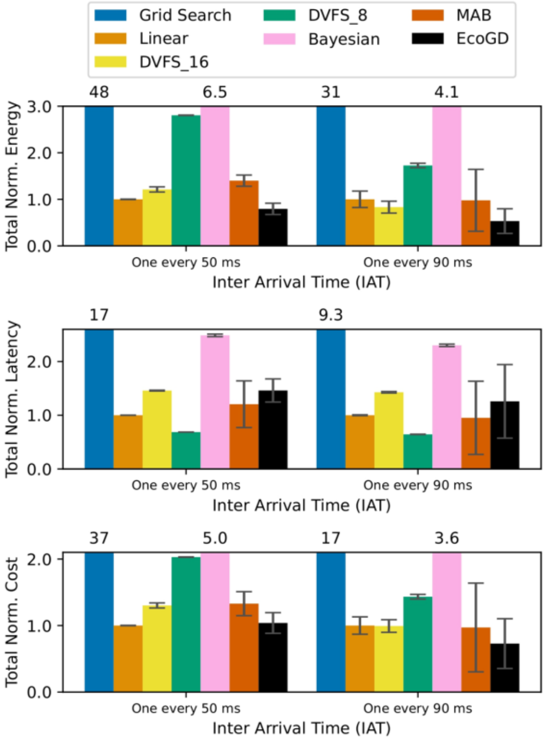
Experimental Results: Fixed Loads

DVFS



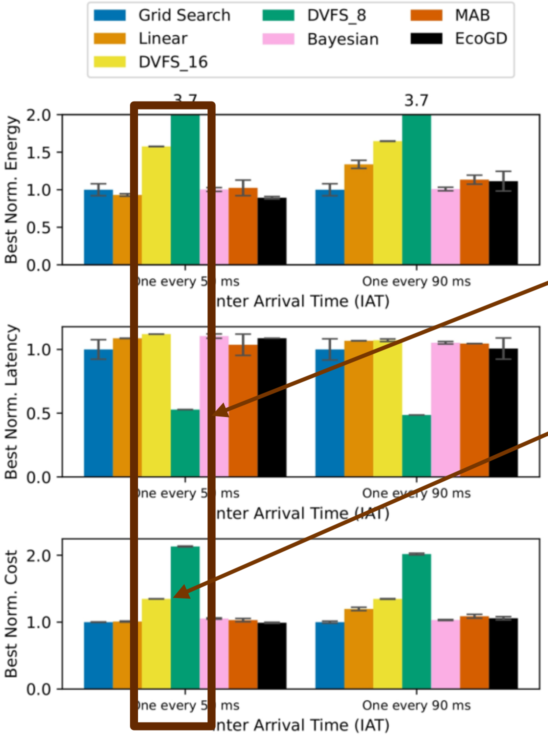
BS 16 w.r.t BS 8
Lower energy
Higher latency, cost

Metrics **after** convergence



Metrics **during** convergence (overhead)

Experimental Results: Fixed Loads

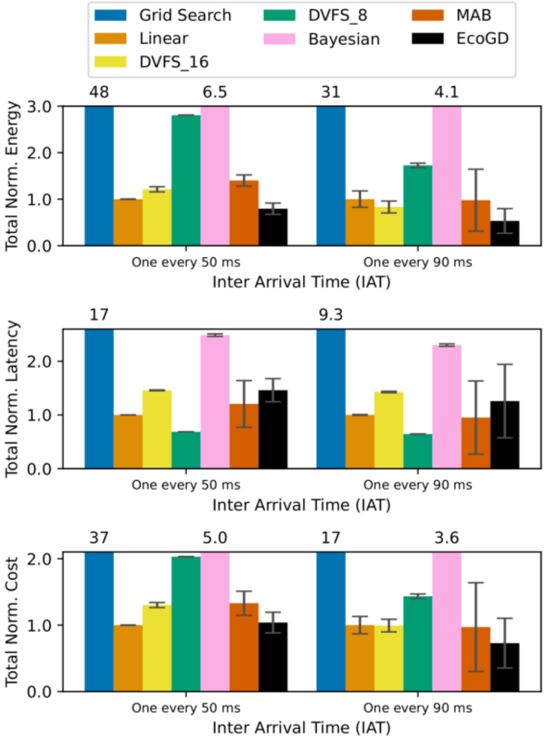


Metrics **after** convergence

DVFS

BS 16 w.r.t BS 8
Lower energy
Higher latency, cost

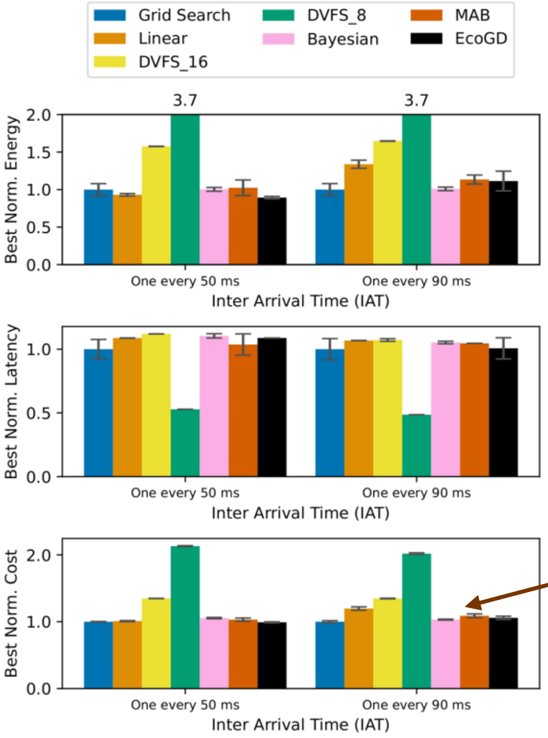
Both BS 8, 16 suboptimal



Metrics **during** convergence (overhead)

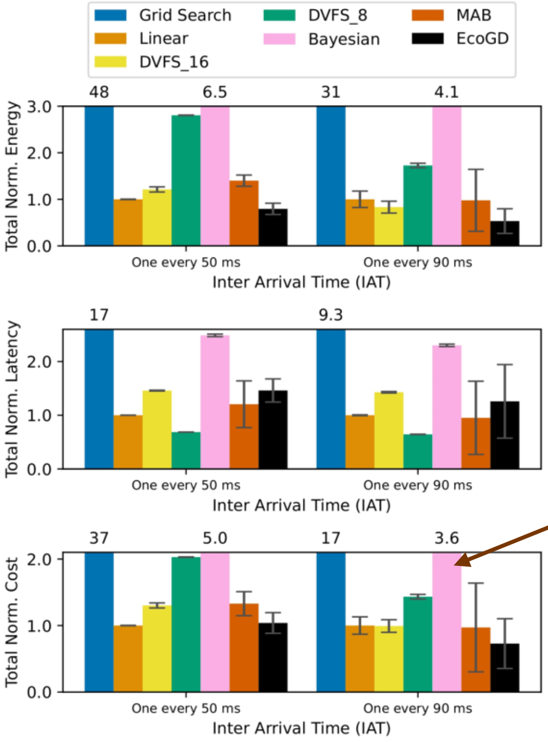
Experimental Results: Fixed Loads

Bayesian



~Optimal

Metrics **<u>after</u>** convergence

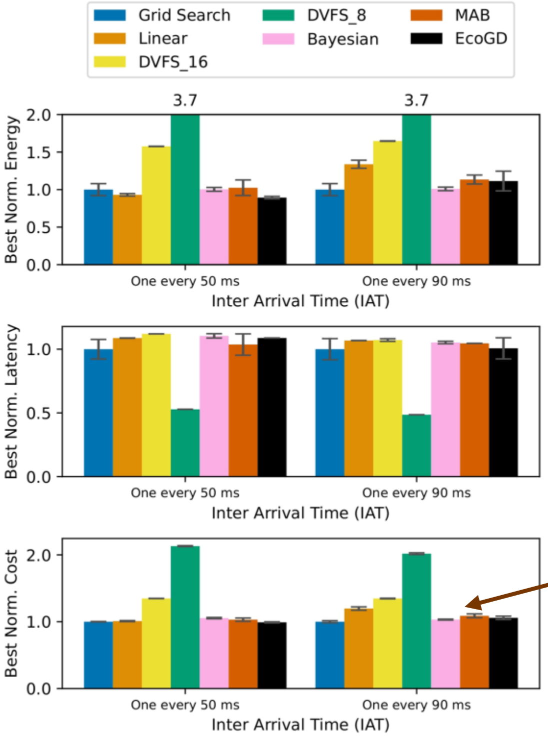


High overhead

Metrics **<u>during</u>** convergence (overhead)

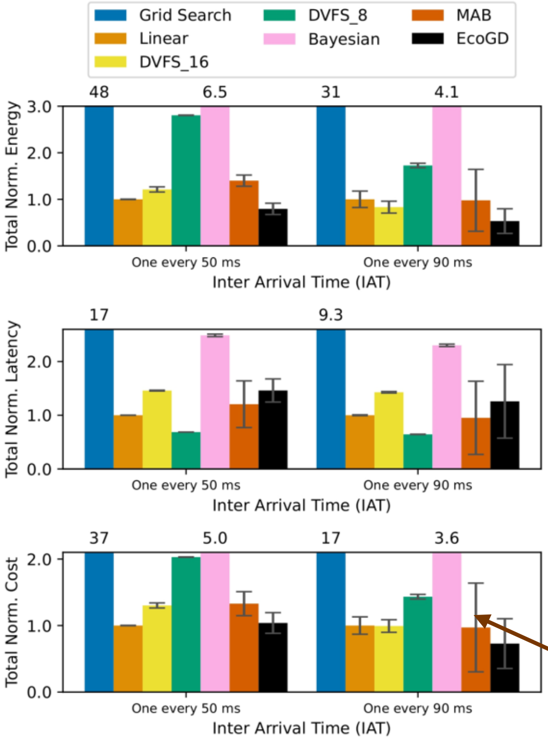
Experimental Results: Fixed Loads

MAB



~Optimal

Metrics **after** convergence

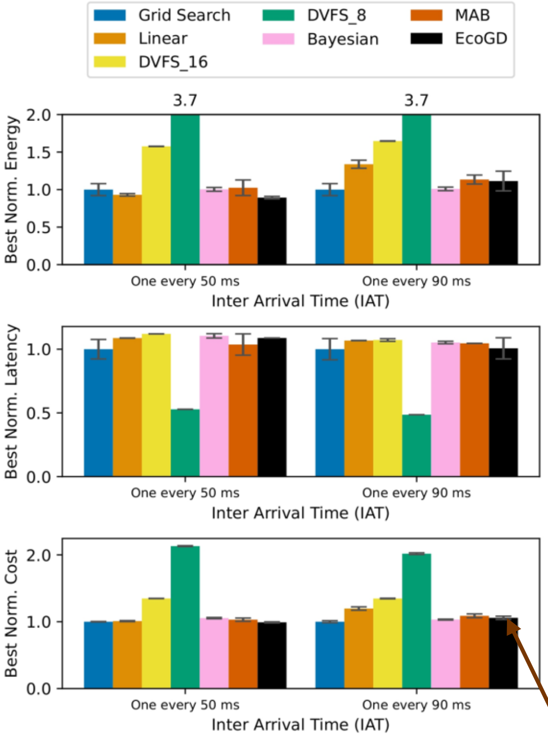


High variance

Metrics **during** convergence (overhead)

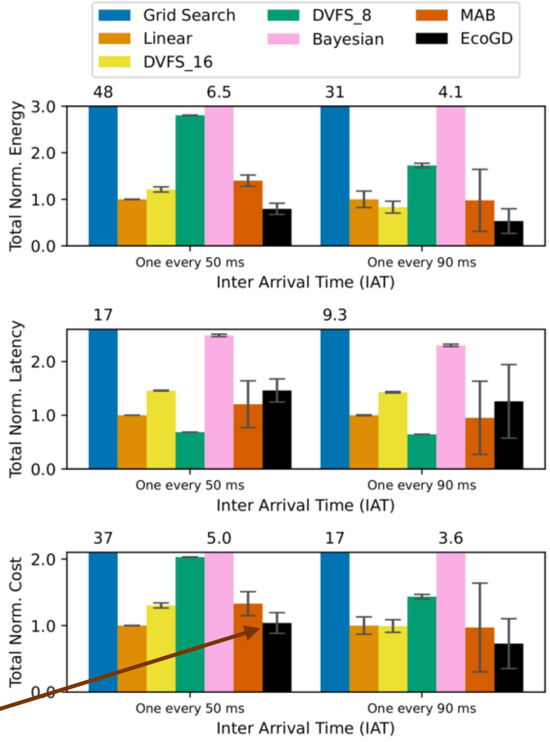
Experimental Results: Fixed Loads

EcoGD



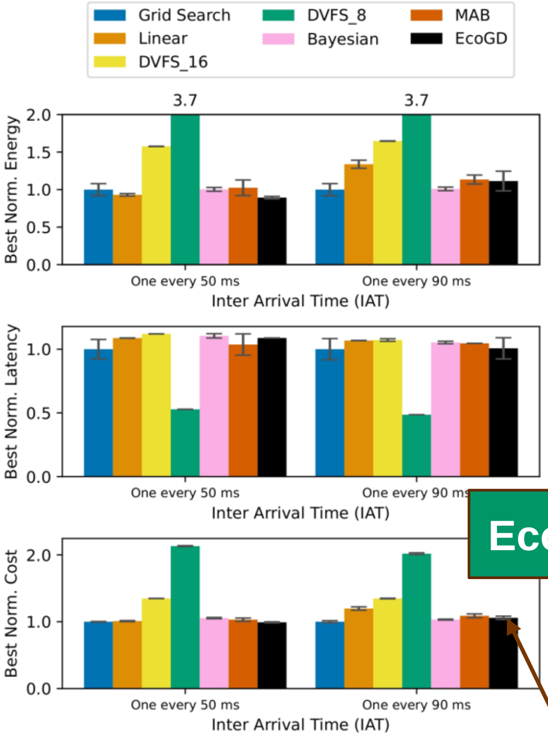
Metrics **after** convergence

~ Optimal and low overhead



Metrics **during** convergence (overhead)

Experimental Results: Fixed Loads

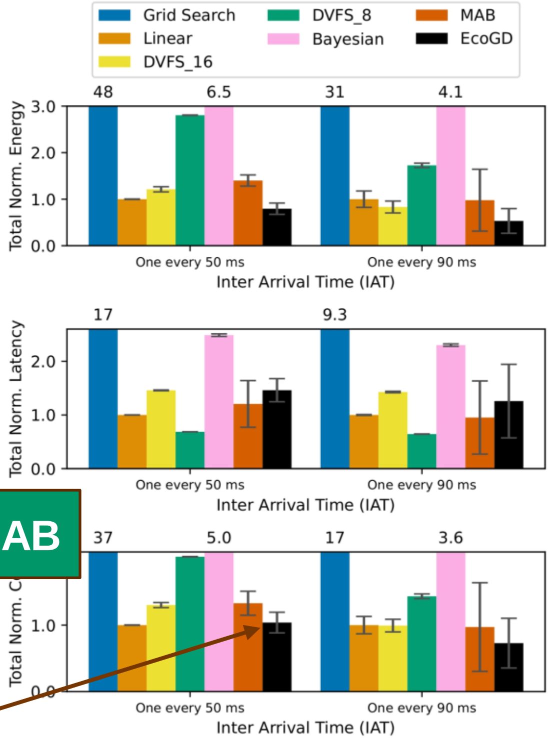


Metrics **after** convergence

EcoGD

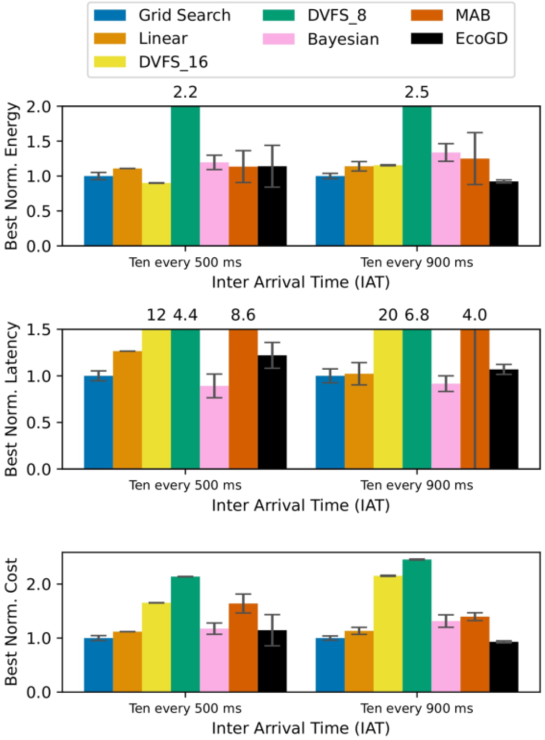
EcoGD better than MAB

~ Optimal and low overhead

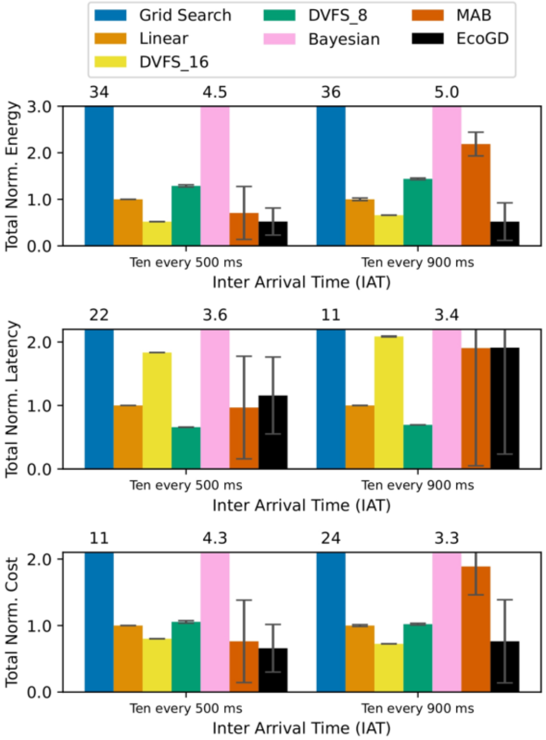


Metrics **during** convergence (overhead)

Experimental Results: Bursty Loads

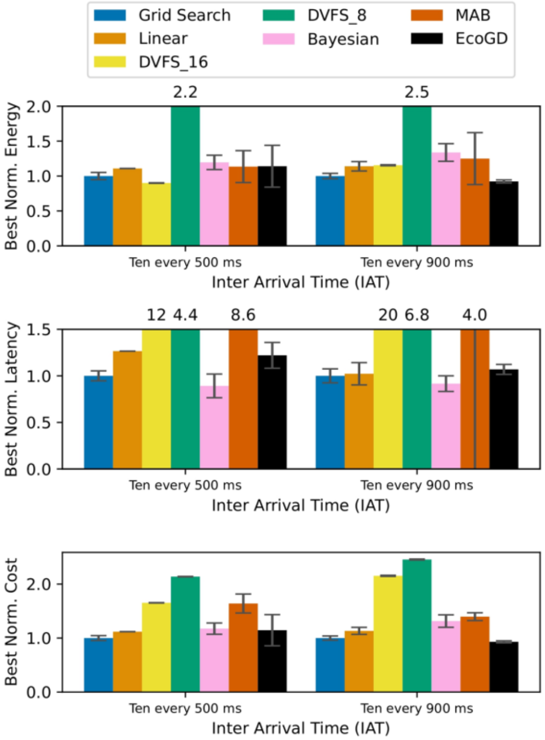


Metrics after convergence



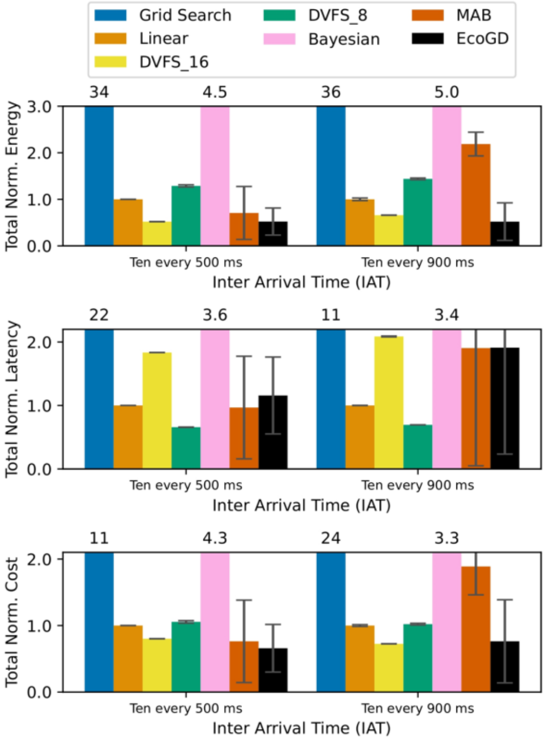
Metrics during convergence (overhead)

Experimental Results: Bursty Loads



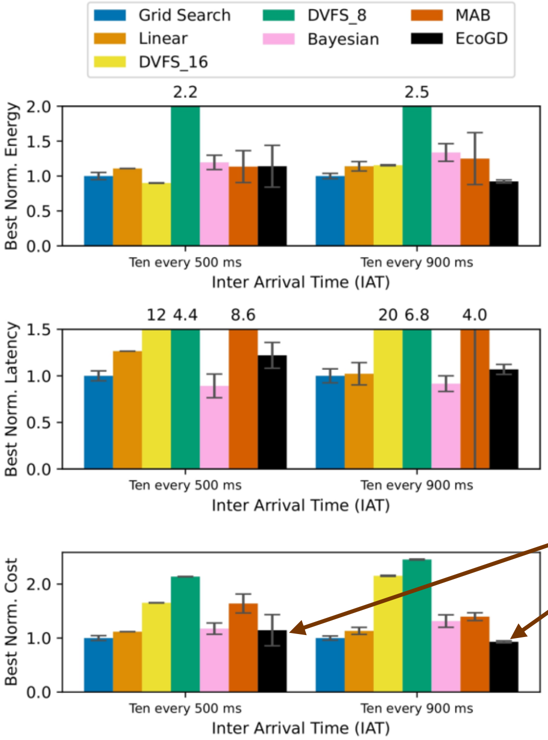
Metrics after convergence

Similar Observations



Metrics during convergence (overhead)

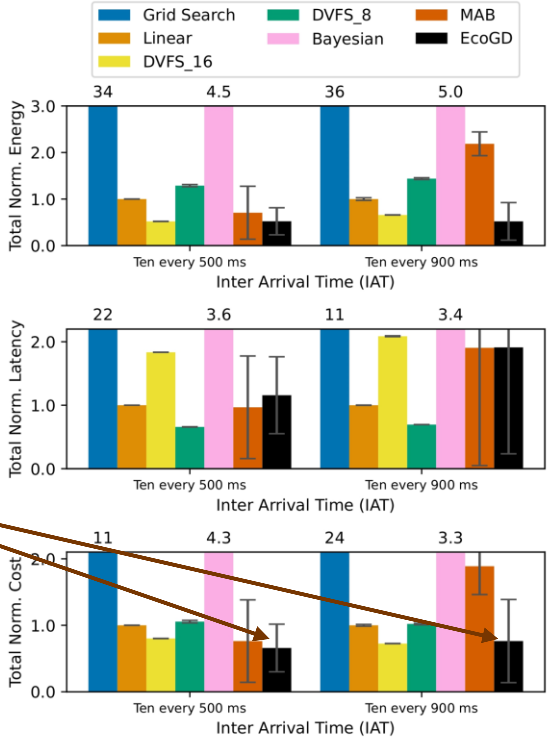
Experimental Results: Bursty Loads



Metrics after convergence

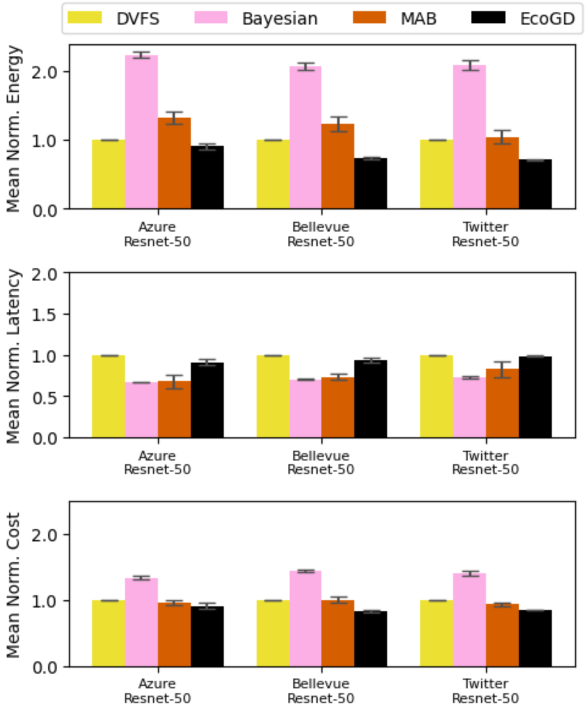
Similar Observations

EcoGD good in both convergence and overhead

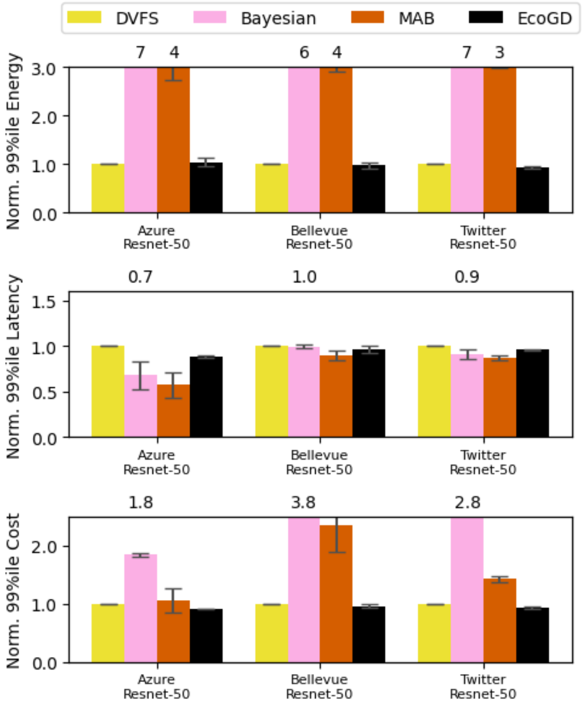


Metrics during convergence (overhead)

Experimental Results: Real-World Traces

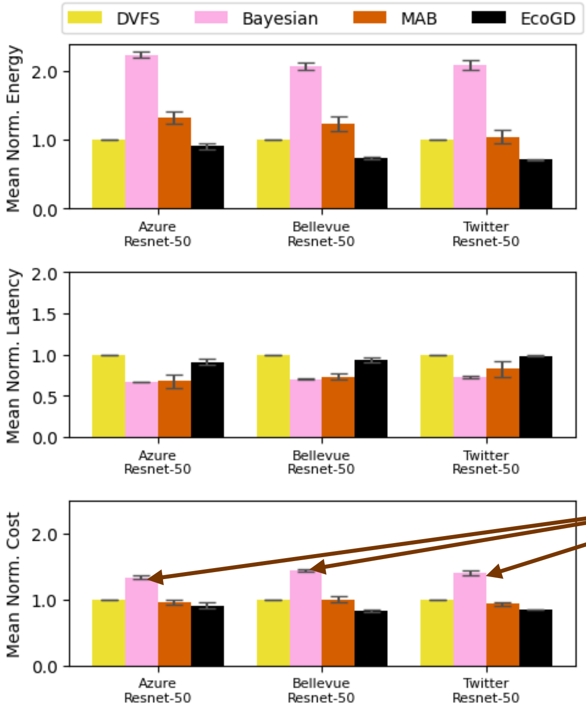


Metrics after convergence



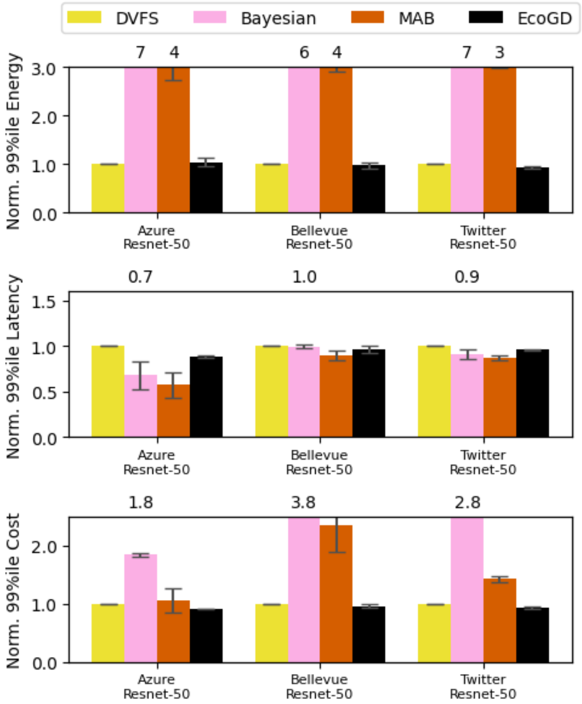
Tail metrics

Experimental Results: Real-World Traces



Bayesian

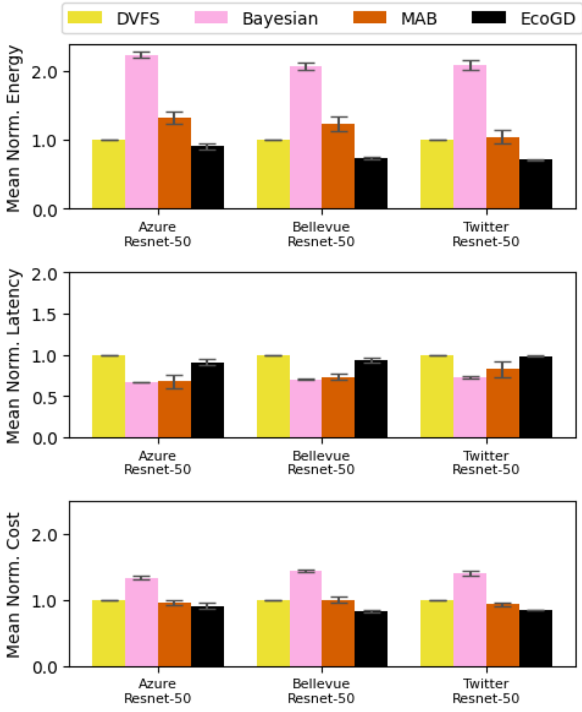
Not Optimal



Metrics after convergence

Tail metrics

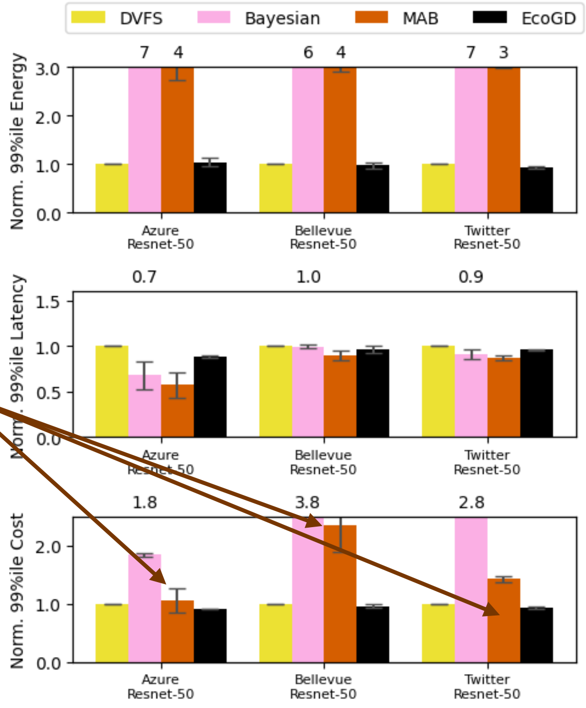
Experimental Results: Real-World Traces



Metrics after convergence

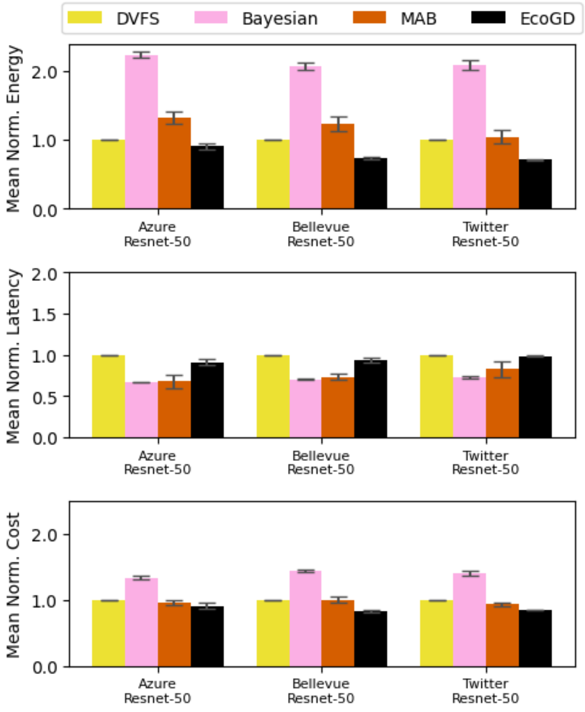
MAB

Higher tail metrics



Tail metrics

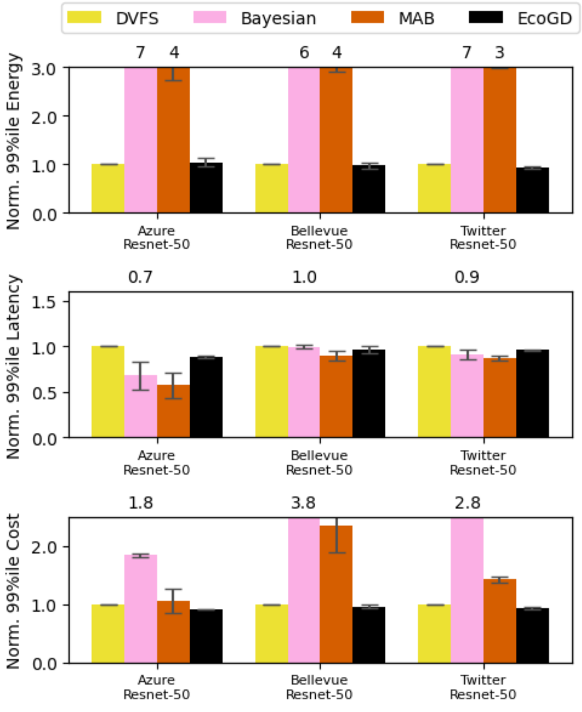
Experimental Results: Real-World Traces



Metrics after convergence

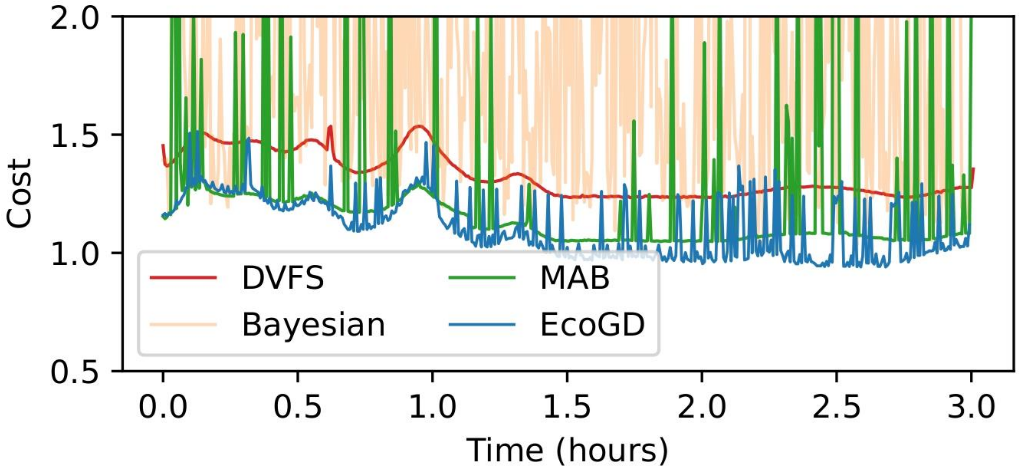
EcoGD

EcoGD gives the best performance



Tail metrics

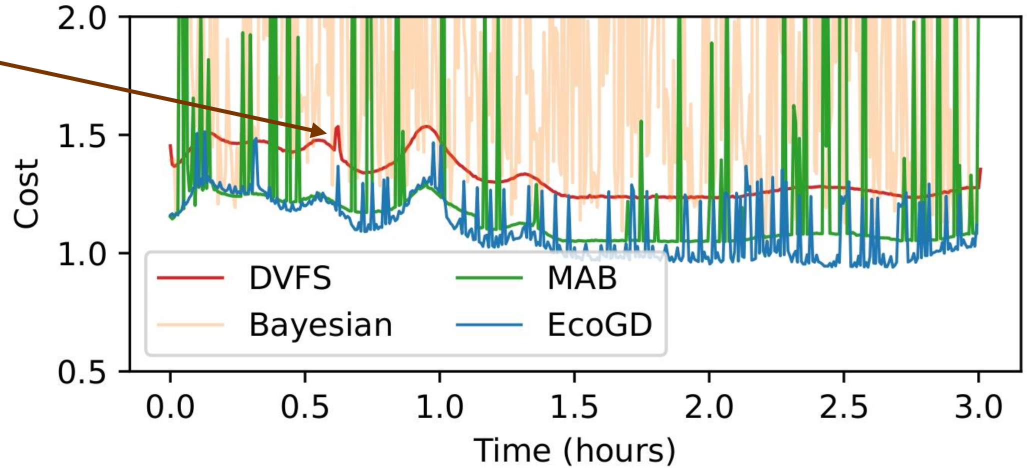
Experimental Results: Real-World Traces



Time series of cost of algorithms while running Bellevue trace with Resnet50

Experimental Results: Real-World Traces

DVFS > MAB, EcoGD

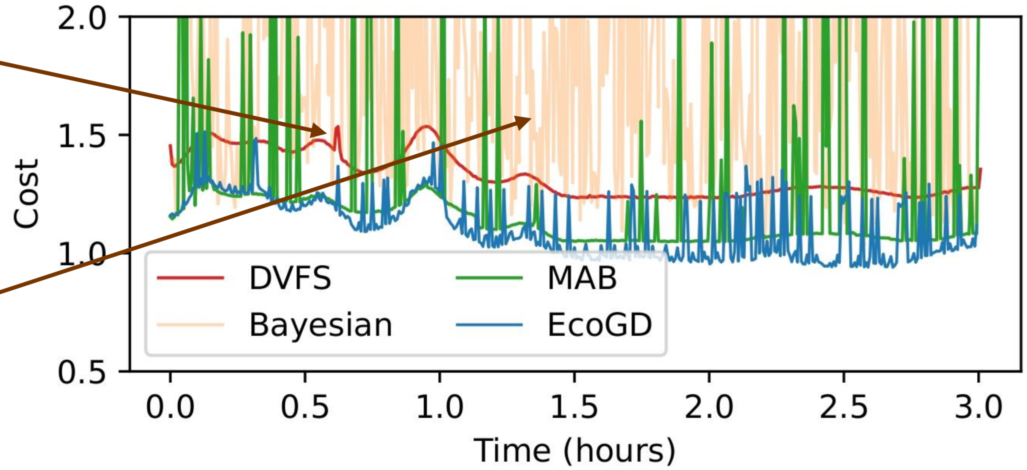


Time series of cost of algorithms while running Bellevue trace with Resnet50

Experimental Results: Real-World Traces

DVFS > MAB, EcoGD

Bayesian – high and keeps jumping



Time series of cost of algorithms while running Bellevue trace with Resnet50

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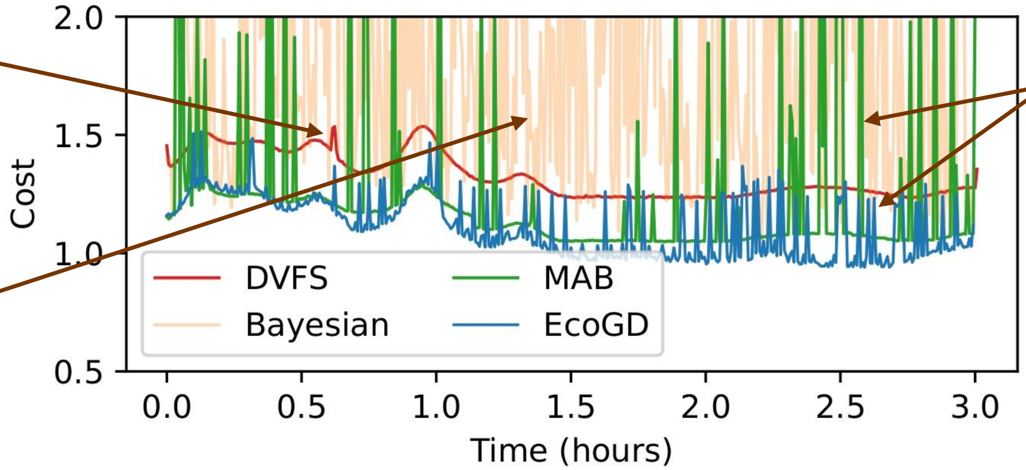
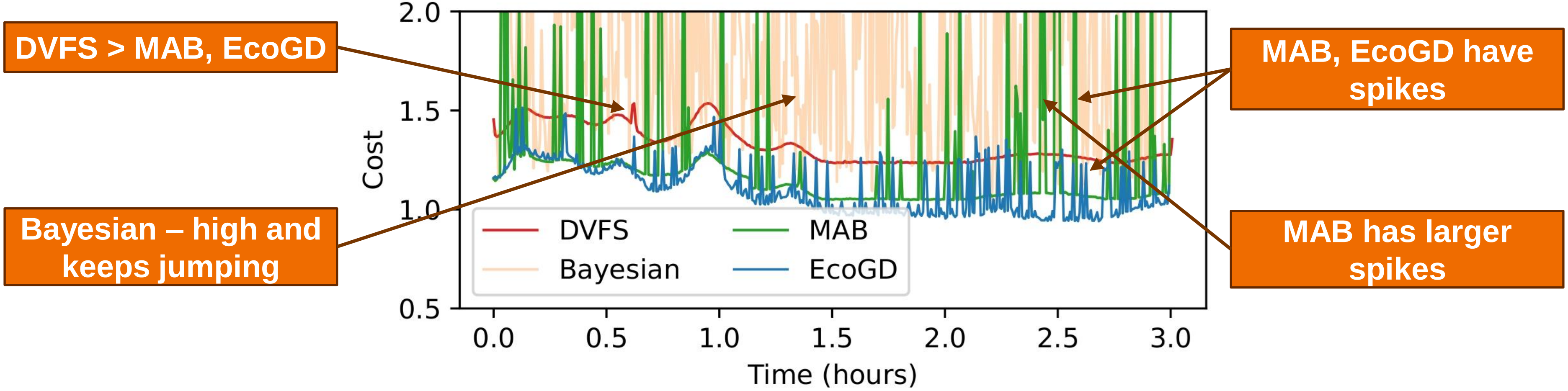


MAB, EcoGD have spikes

Time series of cost of algorithms while running Bellevue trace with Resnet50

Experimental Results: Real-World Traces



Time series of cost of algorithms while running Bellevue trace with Resnet50

Conclusion

- **Trade-offs** exist between energy consumption and latency
- **Time varying workloads** need dynamic and adaptive solutions
- **EcoEdgeInfer** - easy to use framework for tuning Frequencies and Batch Size
- **EcoGD** - algorithm to optimize for latency and energy
  - Mean cost reduction as much as 55% (19% average reduction)
  - Tail cost reduction as much as 90% (36% average reduction)
- **Wide applicability** with easy to use python APIs and opensourced code

- Future directions include
  - **More devices** with accelerators like TPUs and server grade hardware
  - **Mobile devices** with Tensor core – iPhones, Pixels etc
  - **Custom objectives** like SLOs, cost-effectiveness
  - **Load balancing** for heterogenous multi-device setup

Thanks for your attention

Any Questions?

GitHub Repo

Key Points-

- Trade-offs: energy/latency
- Time varying workloads
- EcoEdgeInfer framework
- EcoGD algorithm
- Wide Applicability