Dynamic GPGPU Power Management Using Adaptive Model Predictive Control

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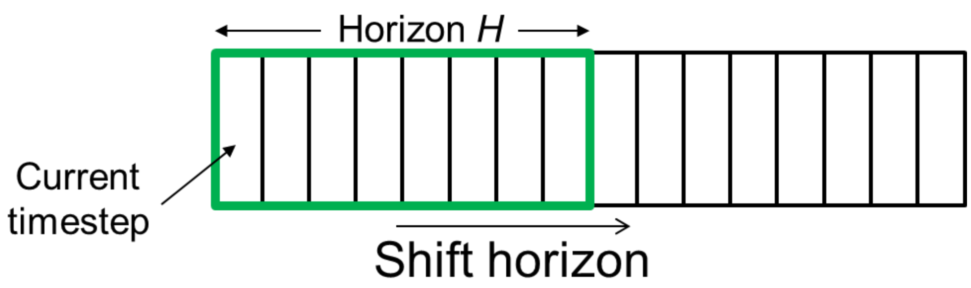
Model Predictive Control (MPC)

- Previous dynamic power management policies ignore future application behavior
  - Leads to performance loss or wasted energy
- MPC *looks into the future* to determine the best configuration for the current optimization time step

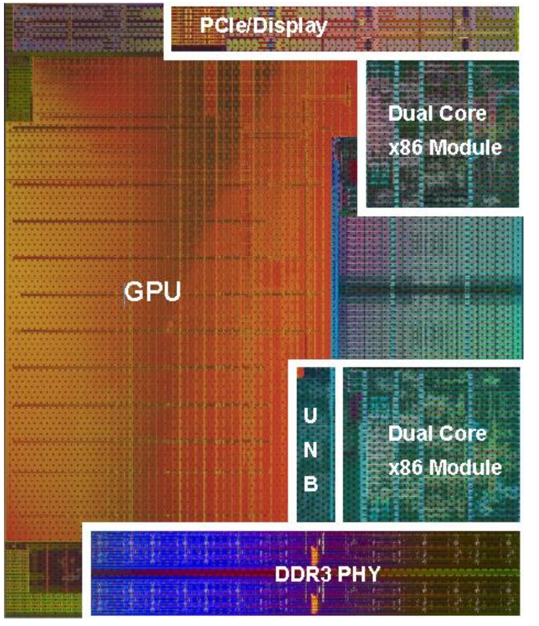


- Though effective in many domains, overheads far too high for short timescales of dynamic power management
- <u>Our approach</u>: An approximation of MPC that dramatically improves GPGPU energy-efficiency with orders of magnitude lower overhead

Dynamic GPGPU Power Management

- Attempts to maximize performance within power constraints

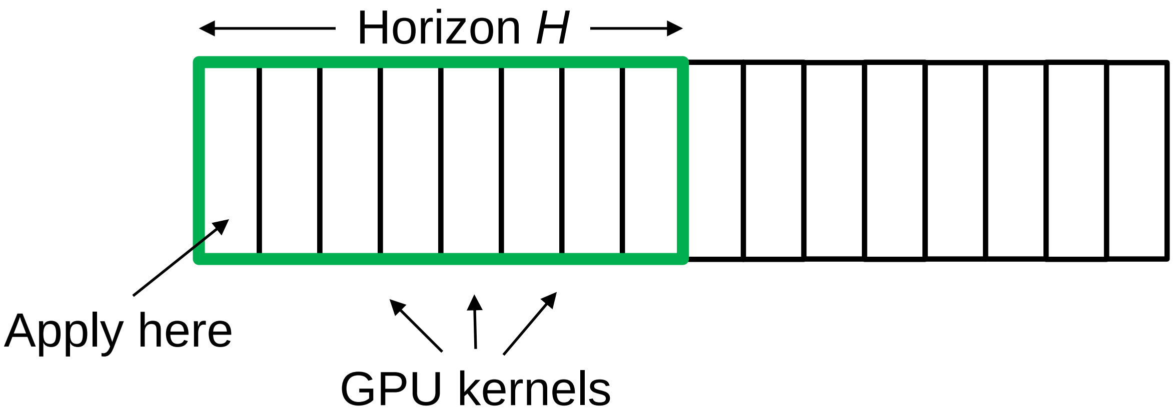
- Hardware knobs
  - Number of active GPU Compute Units
  - DVFS states



- <u>Goal</u>: Reduce the energy of the GPU application phases compared to the baseline power manager while matching its performance

Applying MPC to Dynamic Power Management

- General Idea



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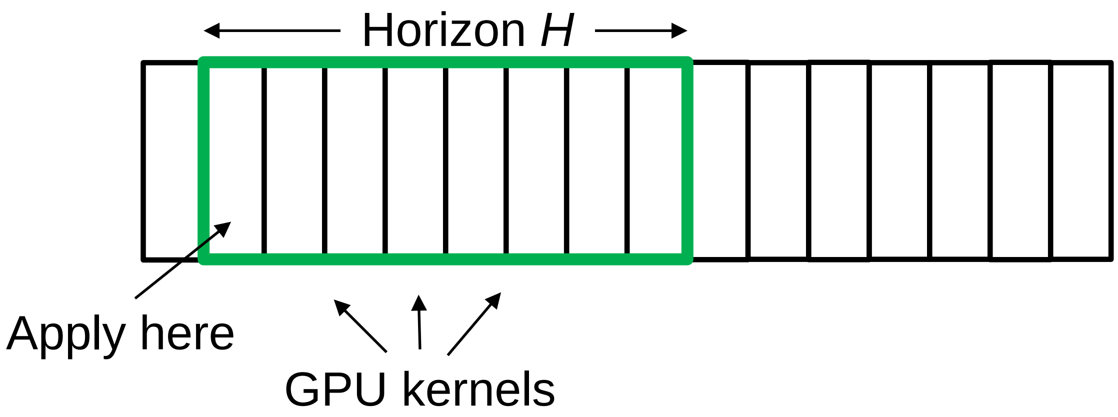

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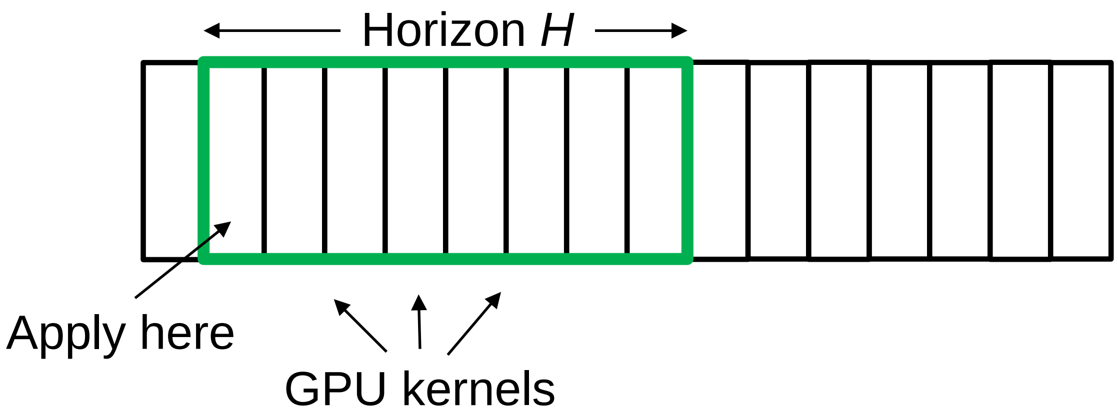


- MPC has high overhead
  - Complexity scales exponentially with *H*
  - Minimizing energy under performance cap with discrete HW settings is fundamentally NP-hard
  - Usually requires dedicated optimization solvers, such as CVX, lpsolve, etc.

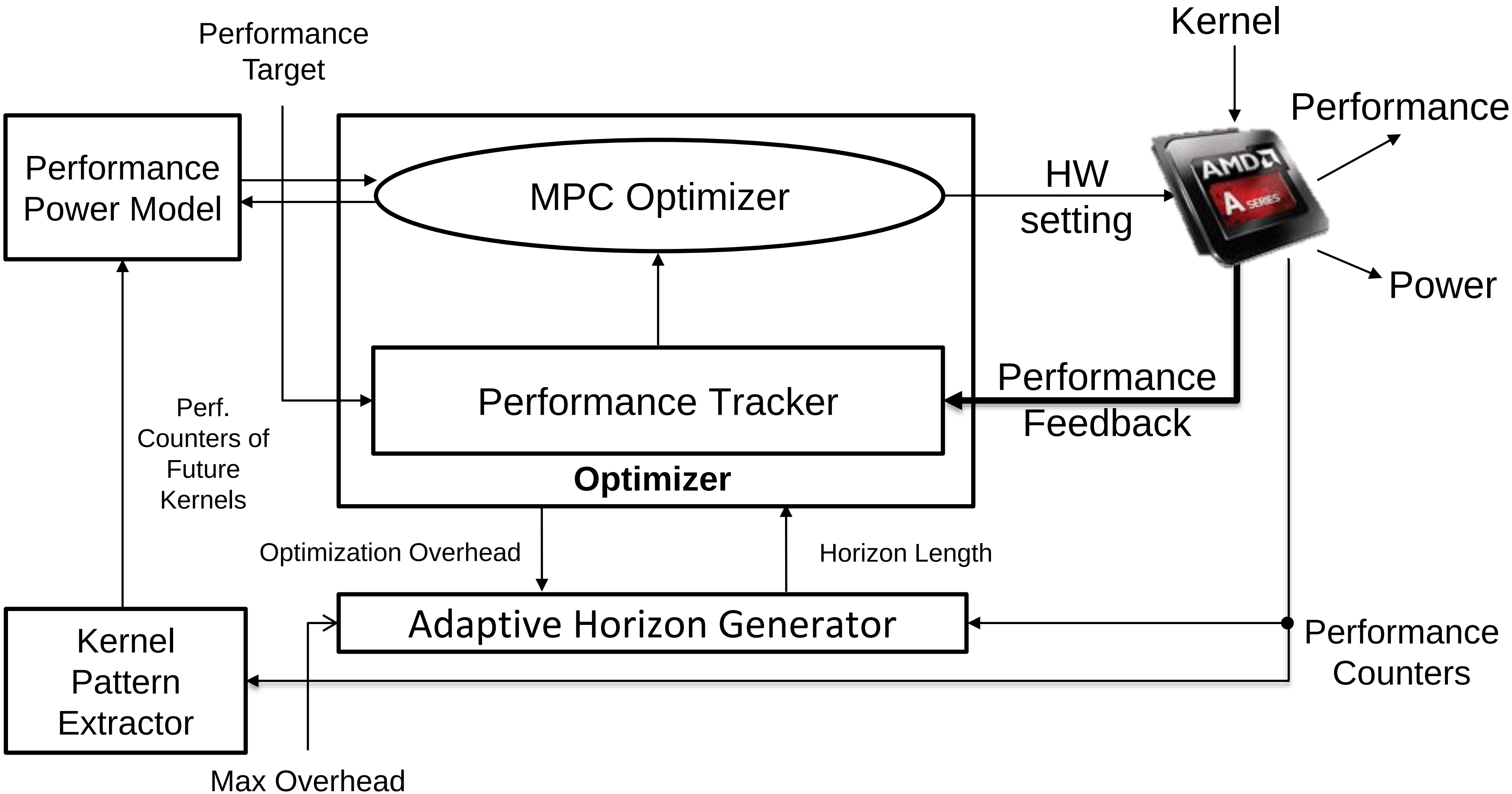
Approximations to MPC

- Greedy Hill Climbing to reduce the search space

- Static search order heuristic to make MPC optimization polynomial rather than exponential

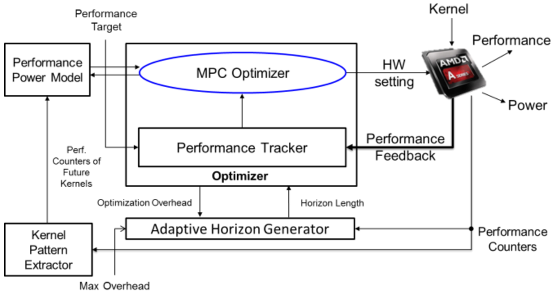
- Dynamically tuning of the horizon length *H* to limit the optimization overhead

MPC Power Manager Architecture



MPC Optimizer

- <u>Objective:</u> Find minimum energy HW setting for each kernel without impacting overall performance



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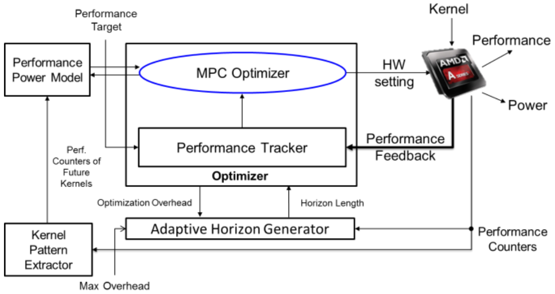
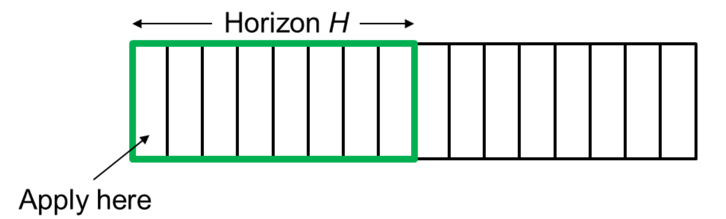


- Objective: Find minimum energy HW setting for each kernel without impacting overall performance
- Greedy Hill Climbing optimization
  - Select the HW knob with highest energy sensitivity
  - Search for the lowest energy configuration using hill climbing
- MPC Search Heuristic
  - Determines a static order without backtracking
  - Search cost becomes polynomial
  - Details in the paper
- 65X average reduction in total cost evaluations

Adaptive Horizon Generator

- Longer horizon improves savings but increases MPC optimization time



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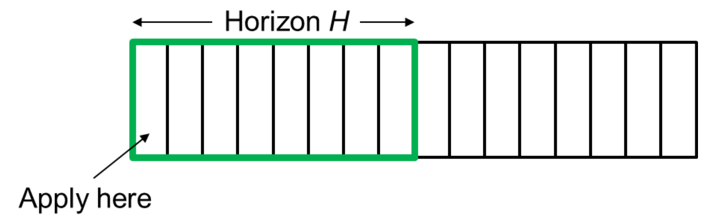

- Limit the overhead to a slowdown factor α by dynamically varying the horizon length

$$H_i \leq \frac{N}{\mathbb{N}} \frac{(1 + \alpha - \frac{1}{i})\frac{i \times T_{total}}{N} - \sum_{j=1}^{i-1}(T_j + T_{MPC,j})}{T_{PPK}}$$

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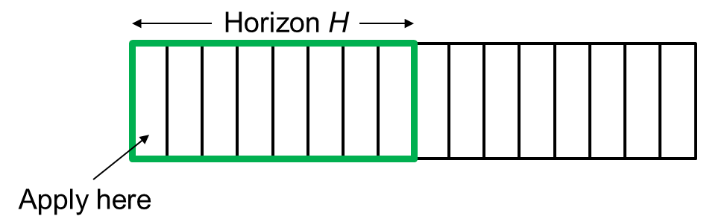

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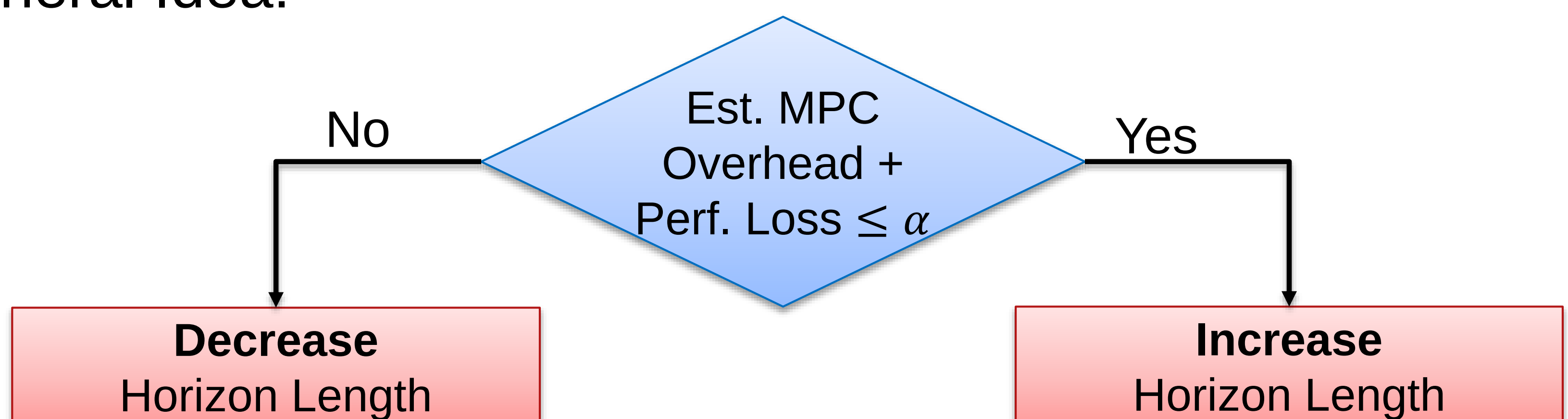
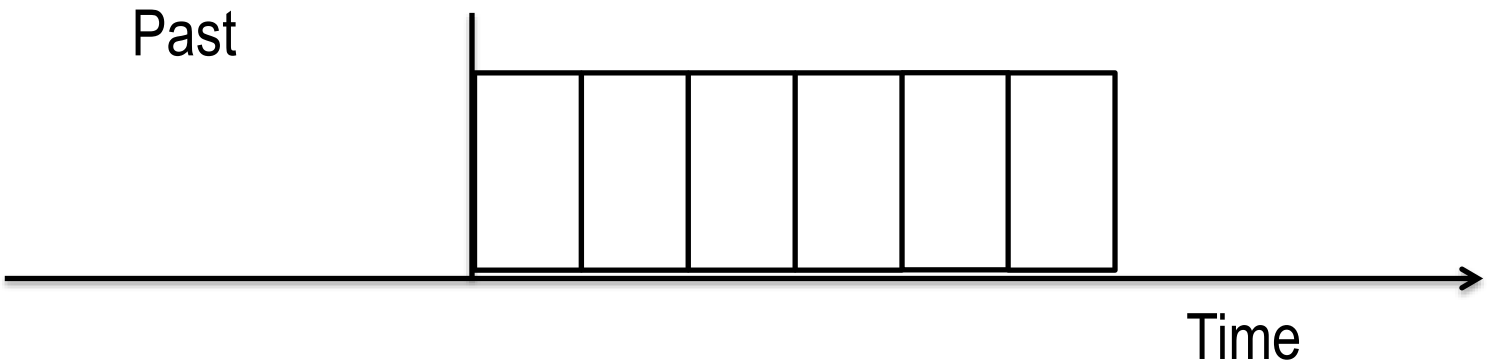
- General Idea:



MPC in Action – An Example



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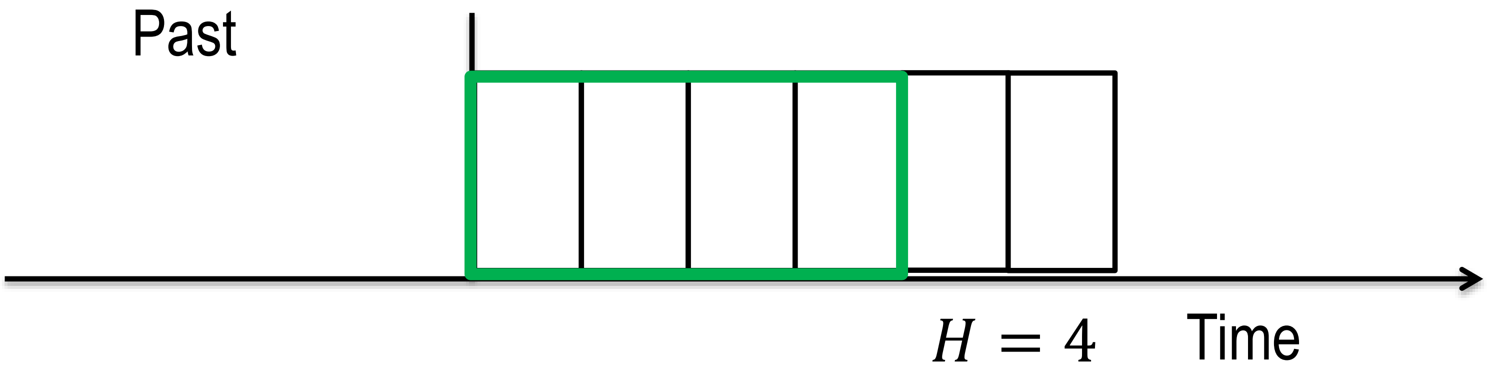

Search order

(2, 1, 4, 5, 3, 6)

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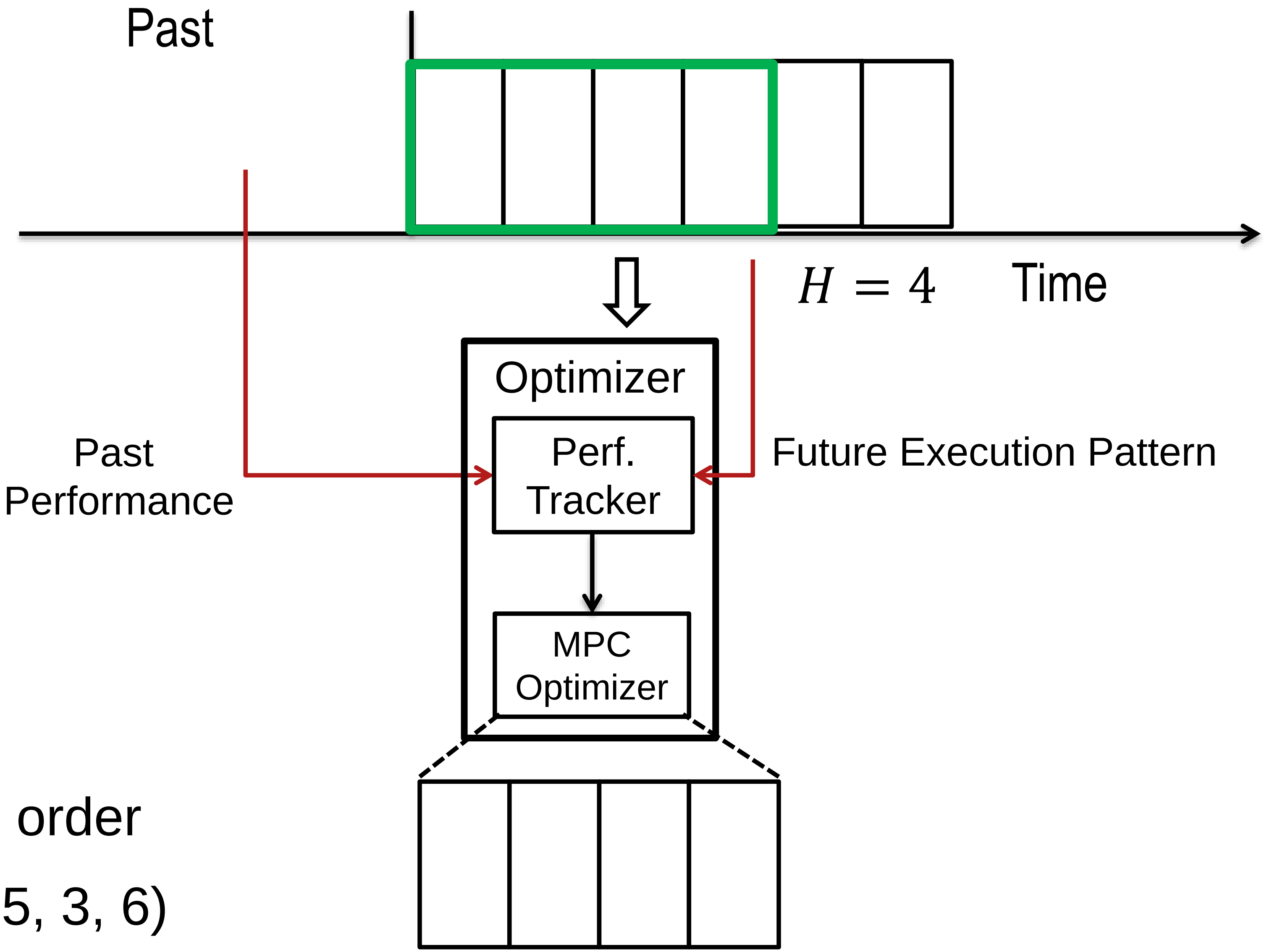

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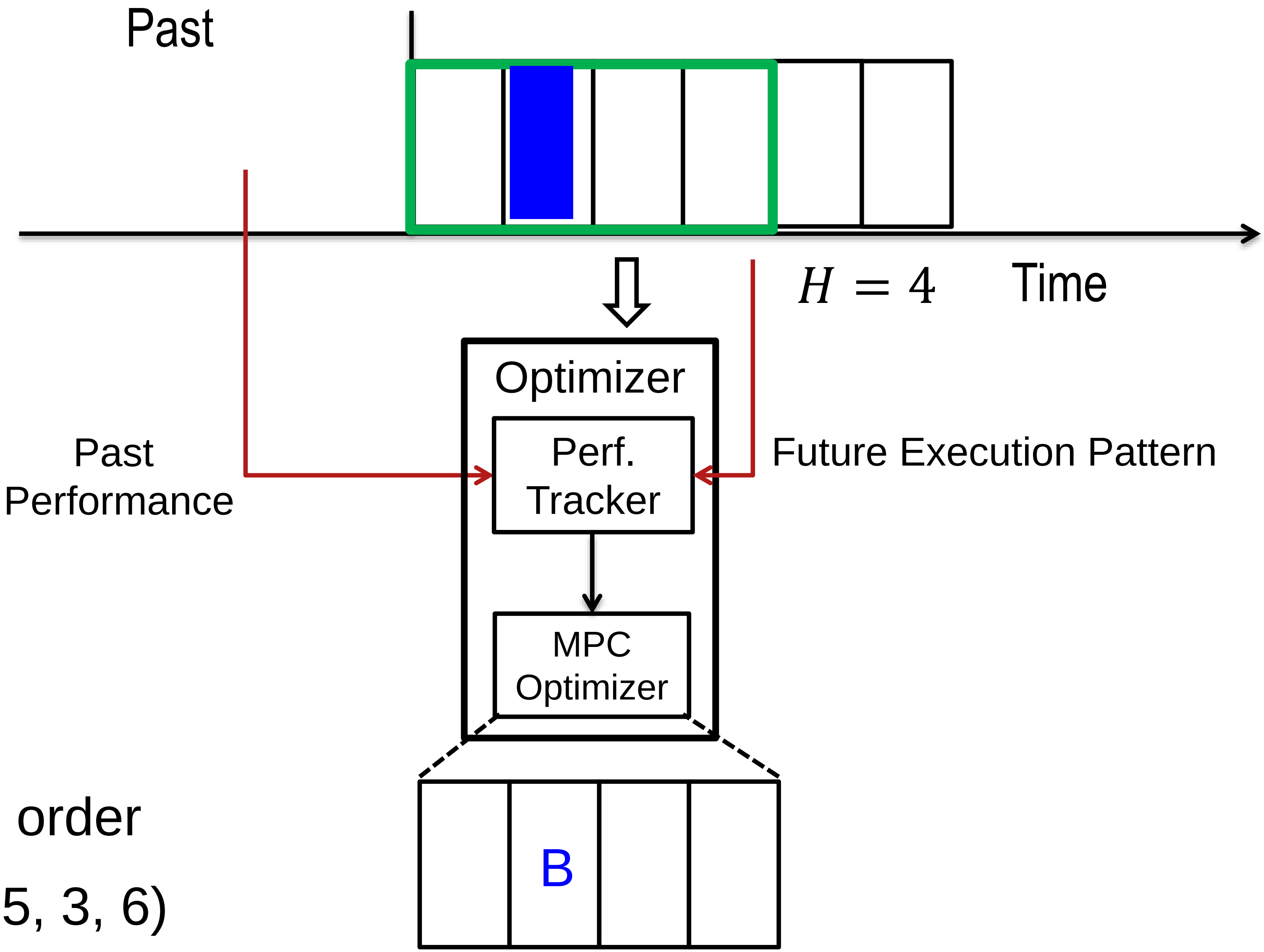

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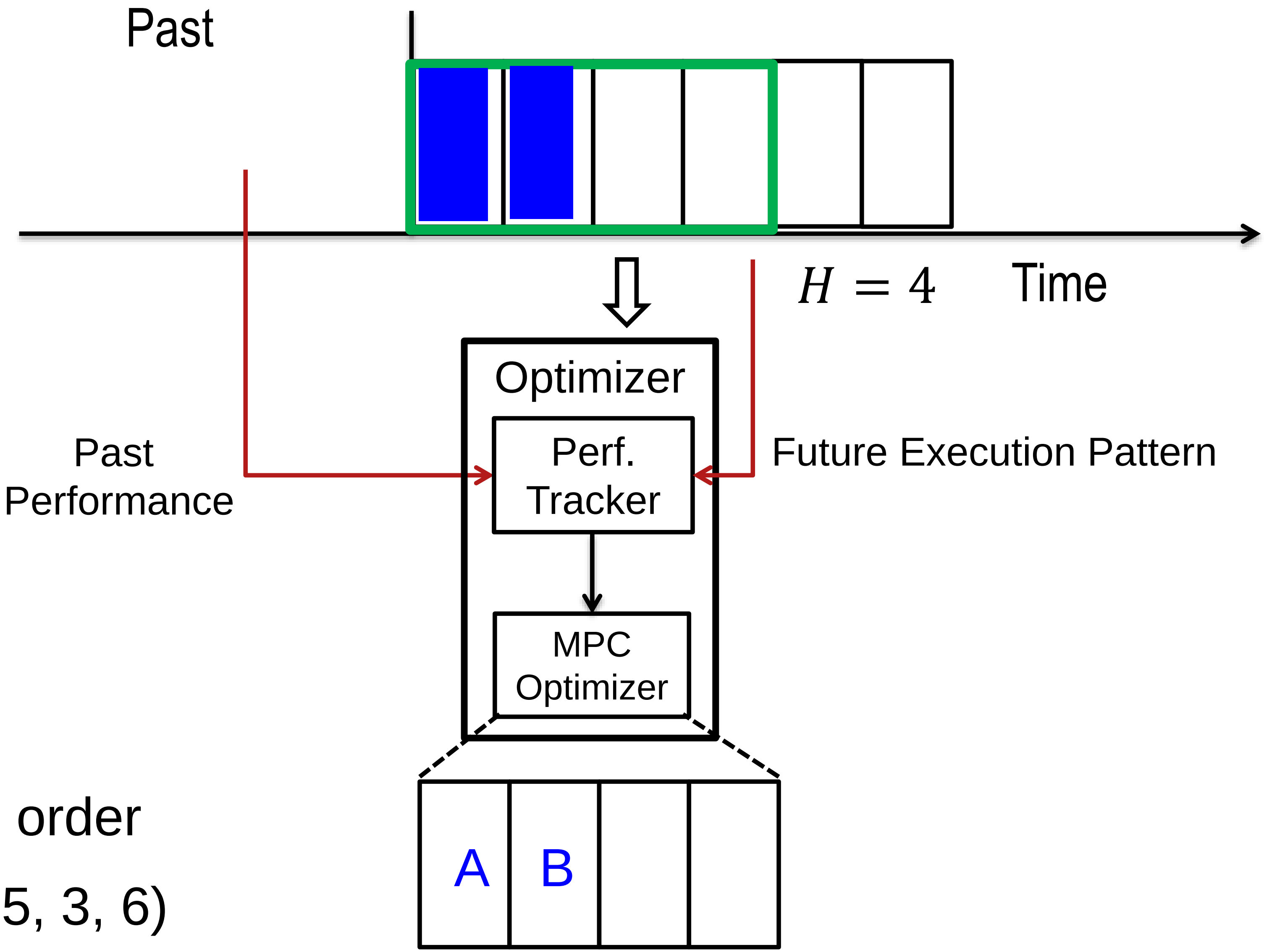

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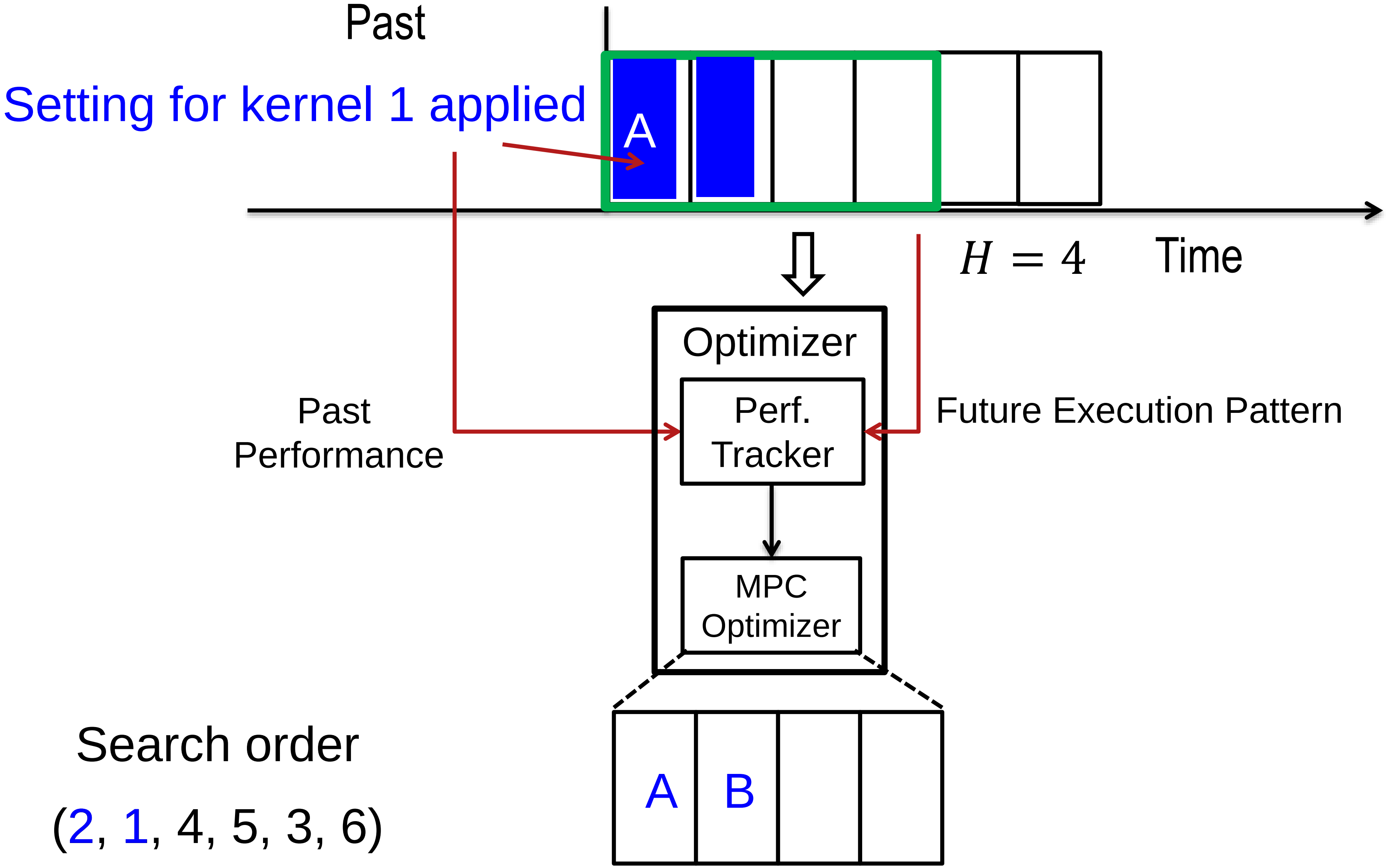

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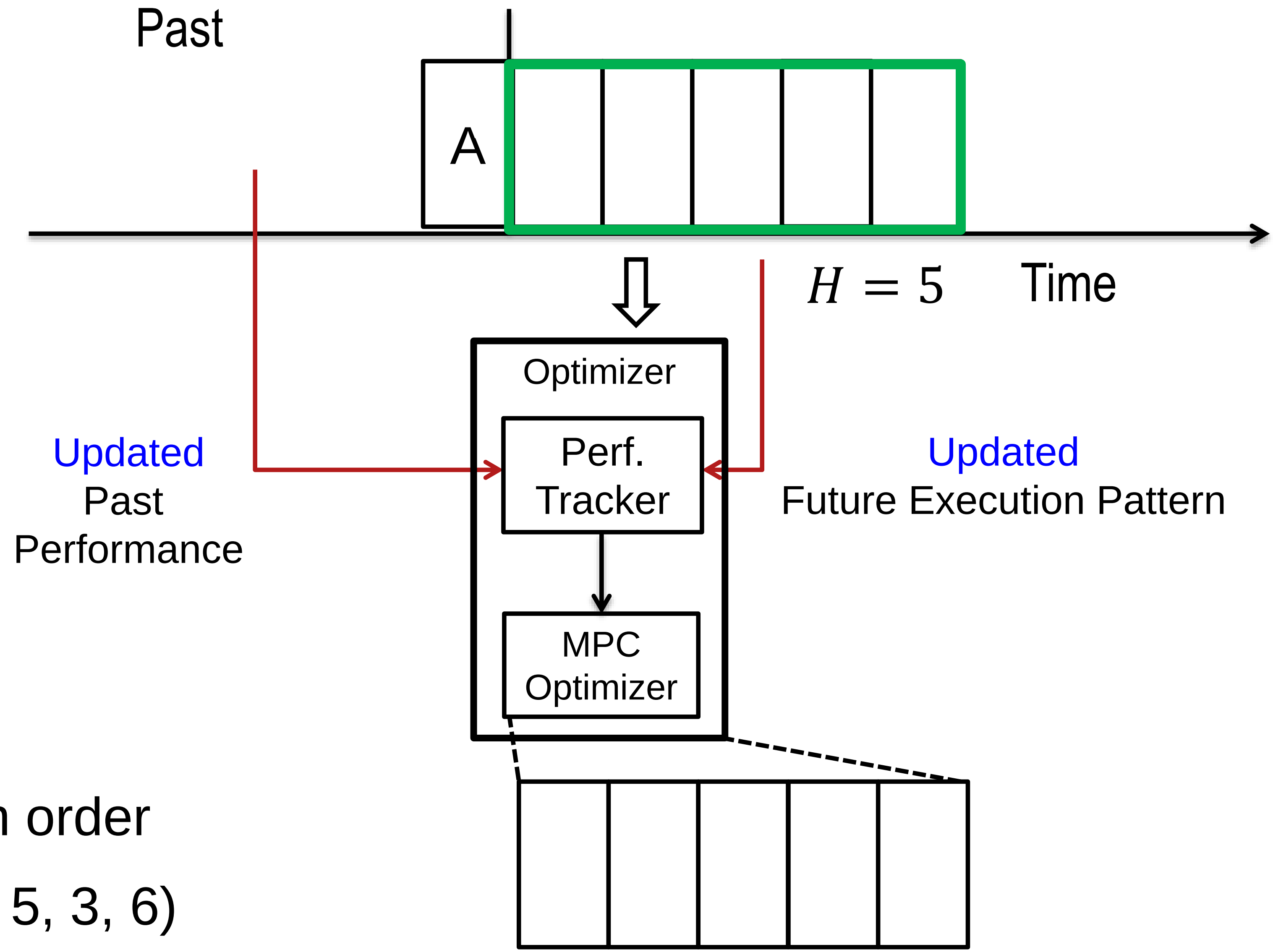

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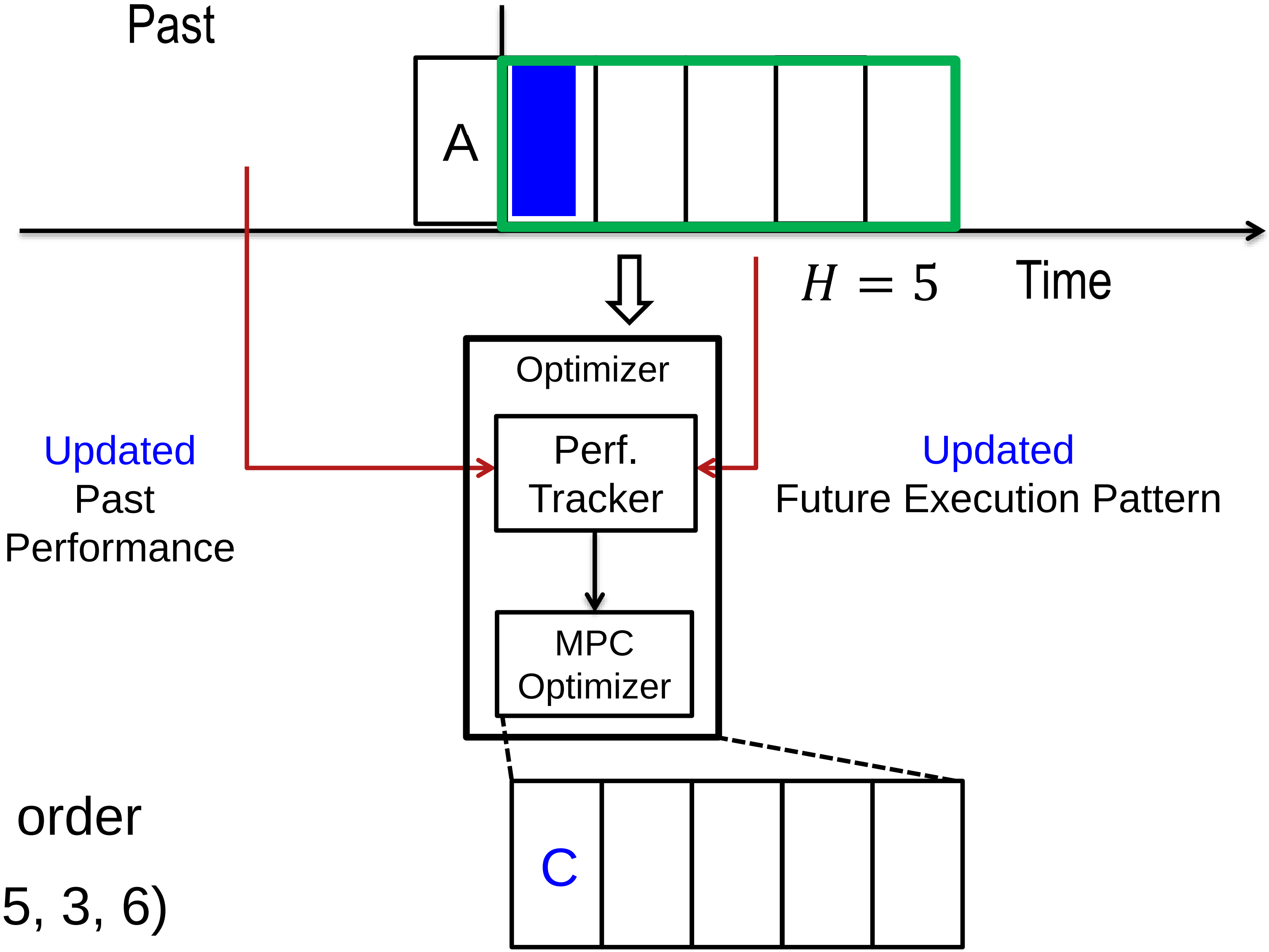

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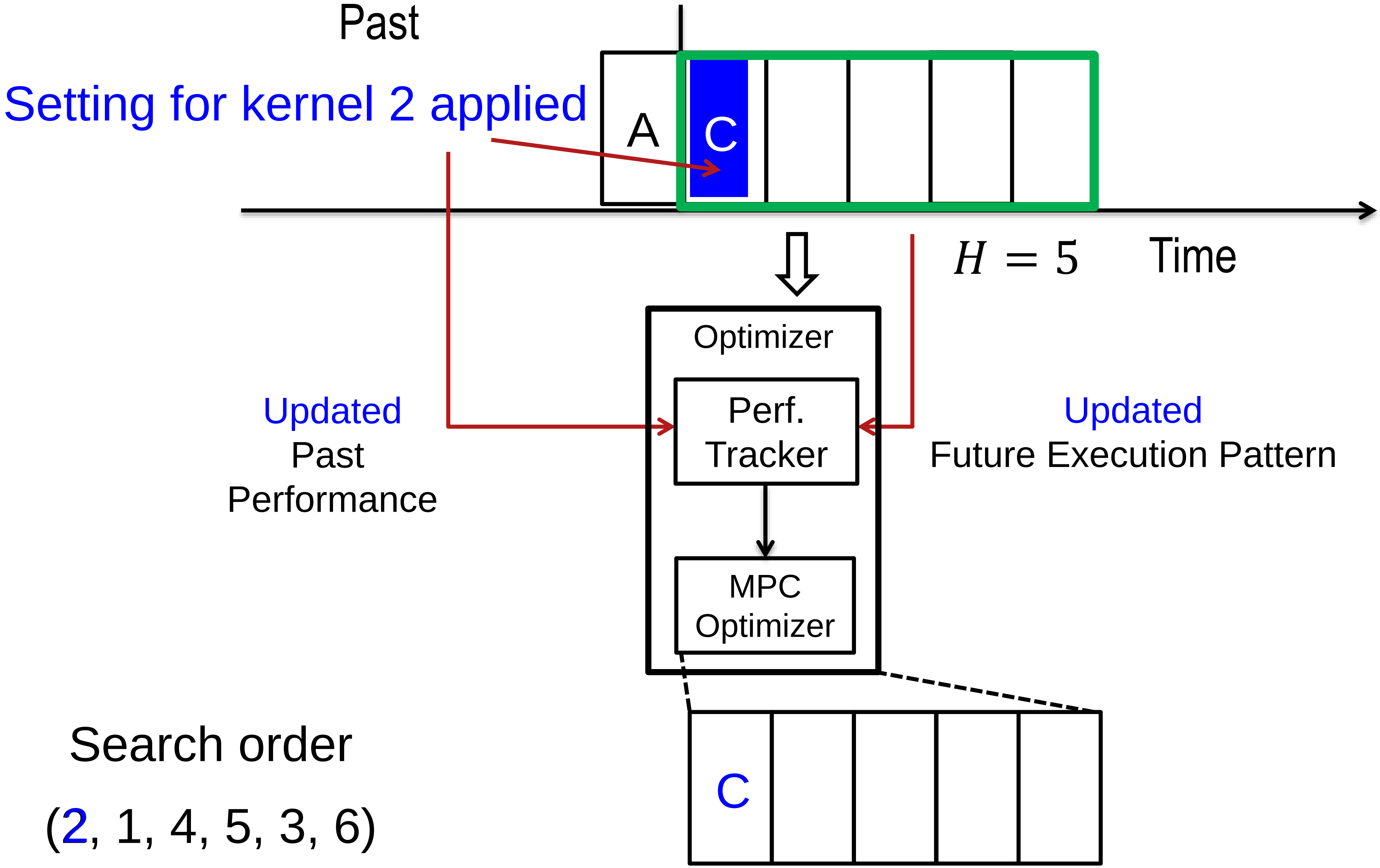

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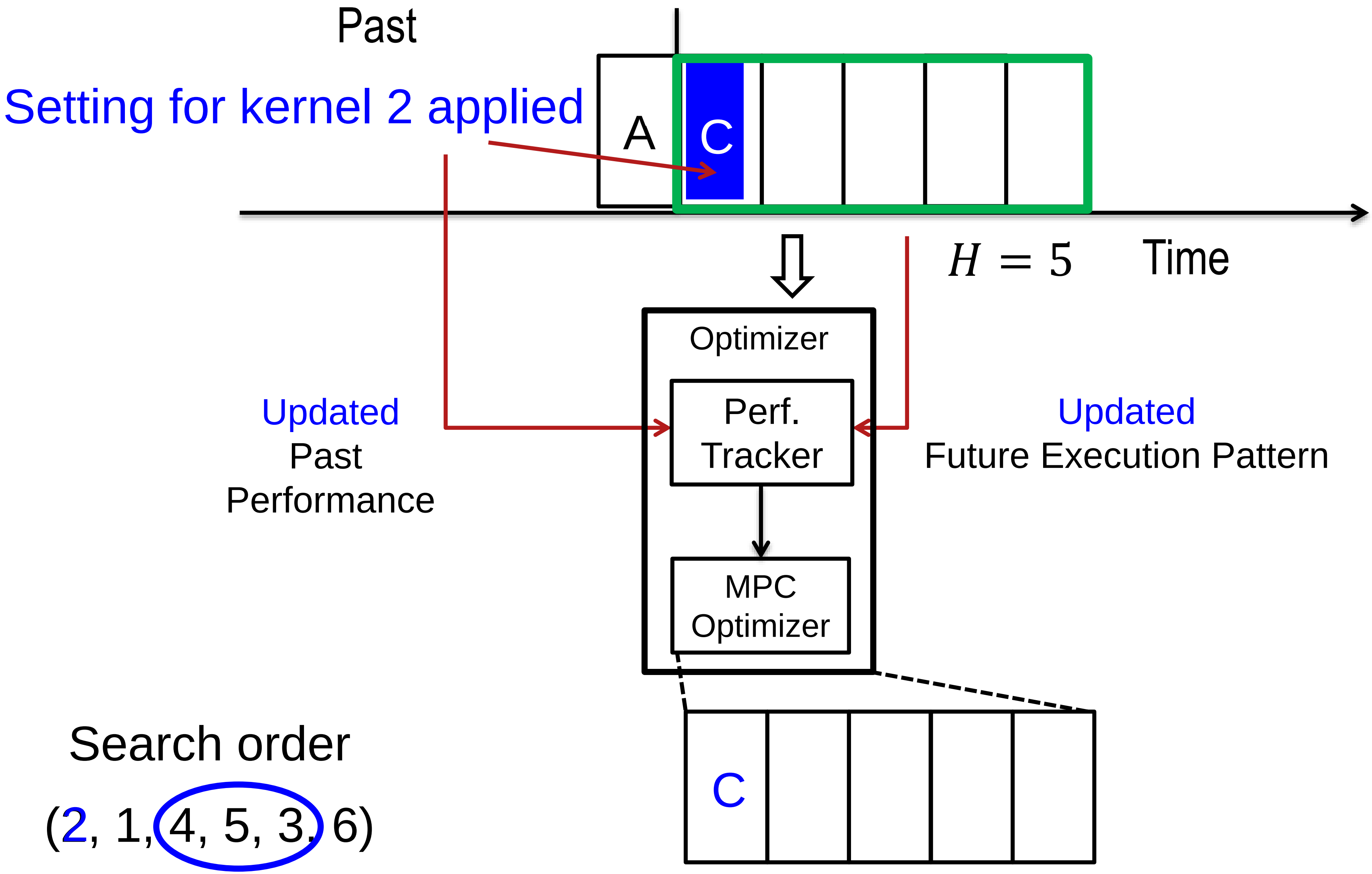

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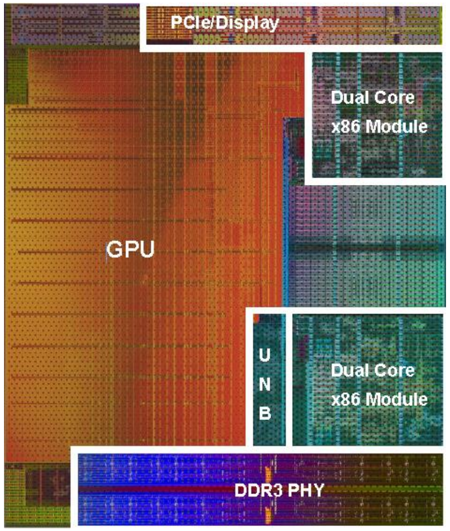
Experimental Testbed

- AMD A10-7850K APU
  - 2 out-of-order dual core CPUs
  - GPU contains 512 processing elements (8 CUs) at 720 MHz



- DVFS states

CPU P States	Voltage (V)	Freq (GHz)
P1	1.325	3.9
P2	1.3125	3.8
P3	1.2625	3.7
P4	1.225	3.5
P5	1.0625	3
P6	0.975	2.4
P7	0.8875	1.7

NB P States	Freq (GHz)	Memory Freq (MHz)
NB0	1.8	800
NB1	1.6	800
NB2	1.4	800
NB3	1.1	333

GPU P States	Voltage (V)	Freq (GHz)
DPM0	0.95	351
DPM1	1.05	450
DPM2	1.125	553
DPM3	1.1875	654
DPM4	1.225	720

NB and GPU share the same voltage rail

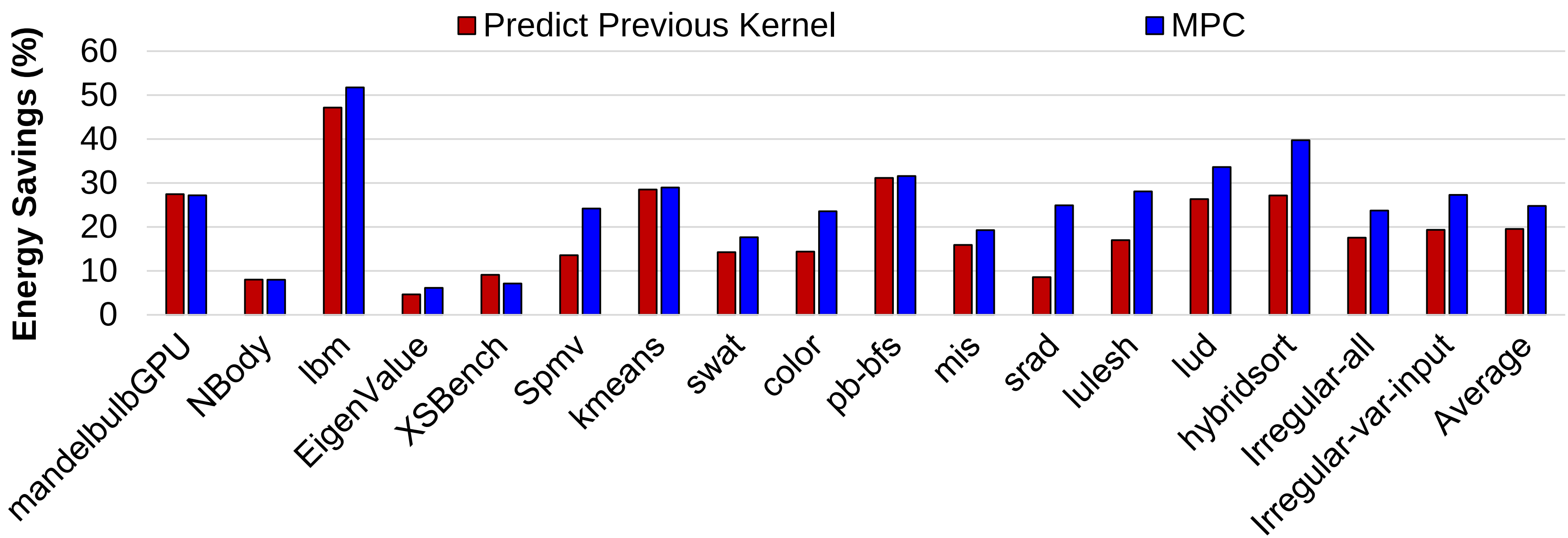
- Total HW configuration: 336

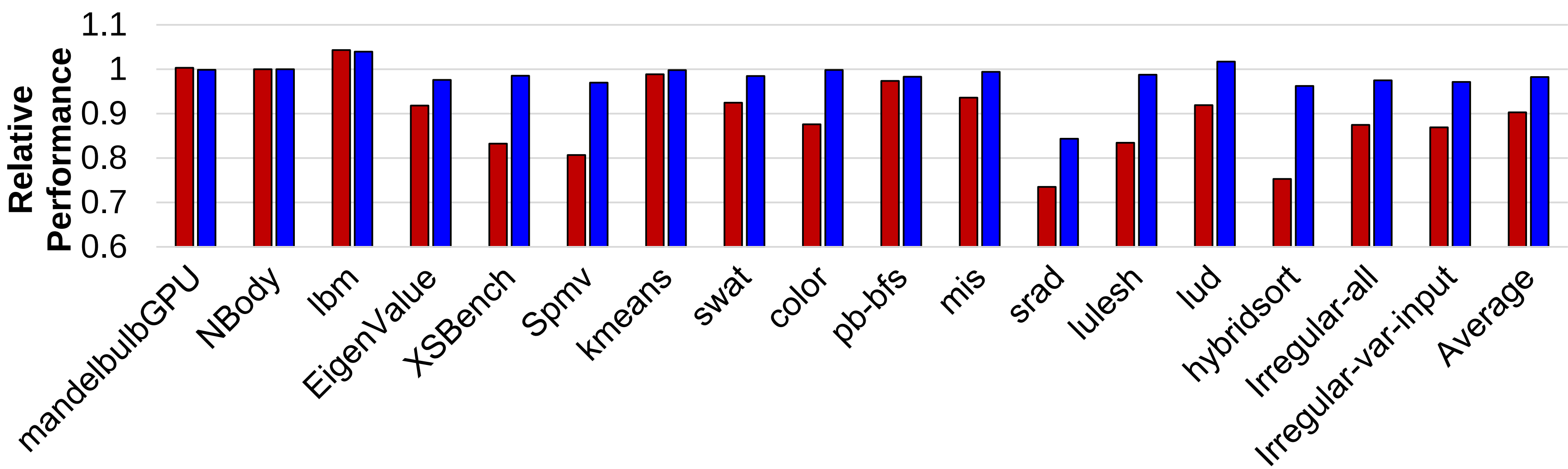
Experimental Setup

- 15 GPGPU Benchmarks
- Baseline scheme
  - AMD Turbo Core
- Predict Previous Kernel (PPK)
  - Assume last kernel repeats
  - State-of-the-art: Harmonia ISCA'15, McLaughlin et al. ASBD'14
- Maximum overhead α = 5%

Category	**Benchmarks**	**Benchmark Suite**	**Regular Expression**
Regular	mandelbulbGPU	Phoronix	A^{20}
	Nbody	AMD APP SDK	A^{10}
	juliaGPU	Phoronix	A^{10}
Irregular with repetitive pattern	EigenValue	AMD APP SDK	$(AB)^{5}$
	XSBench	Exascale	$(ABC)^{2}$
Irregular with non-repetitive pattern	Spmv	SHOC	$A^{10}B^{10}C^{10}$
	Kmeans	Rodinia	AB^{20}
Irregular with kernels varying with input	swat	OpenDwarfs	Complex pattern
	color	Pannotia	
	pb-bfs	Parboil	
	mis	Pannotia	
	srad	Rodinia	
	lulesh	Exascale	
	lud	Rodinia	
	hybridsort	Rodinia	

Energy-Performance Gains





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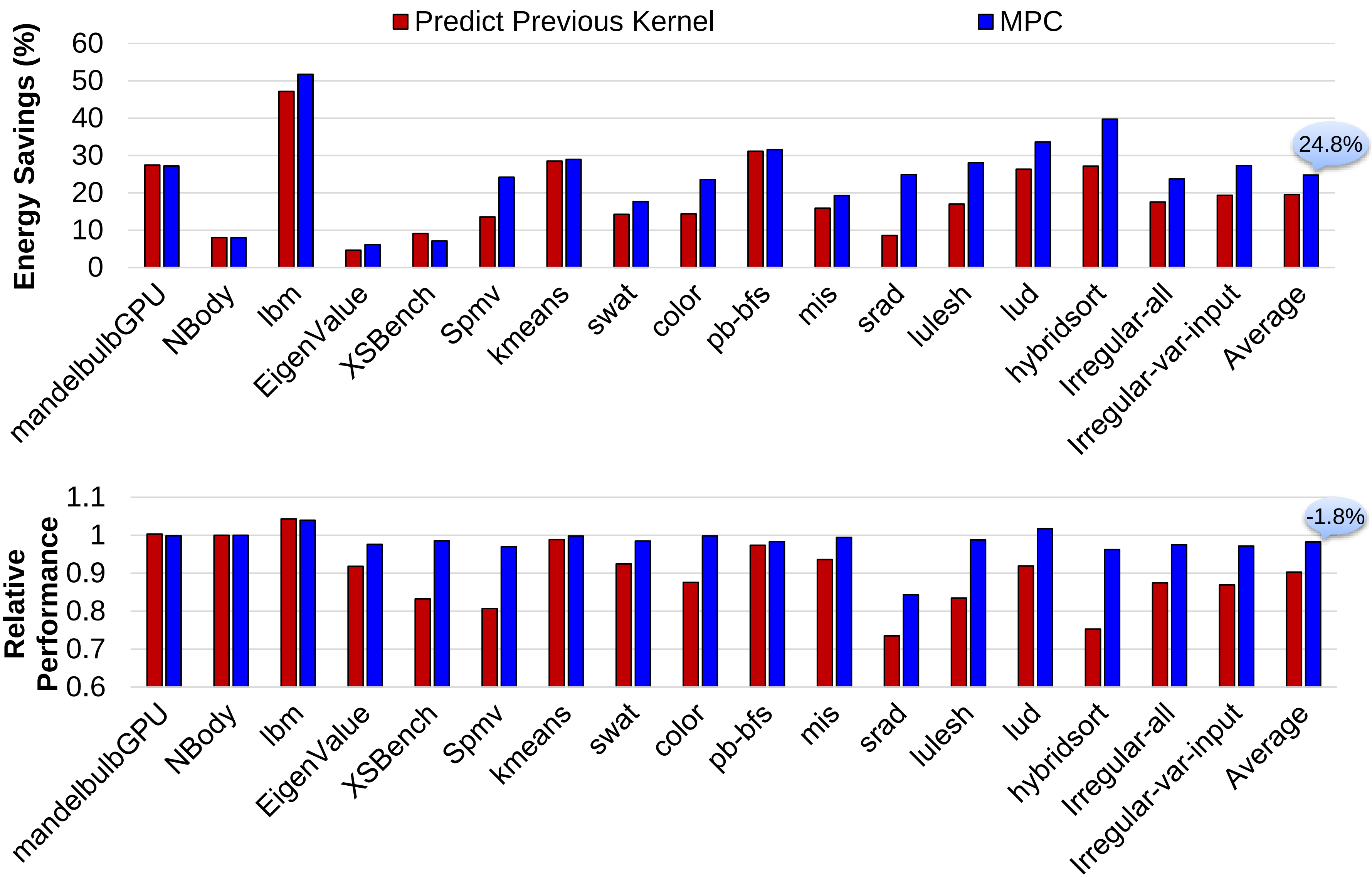

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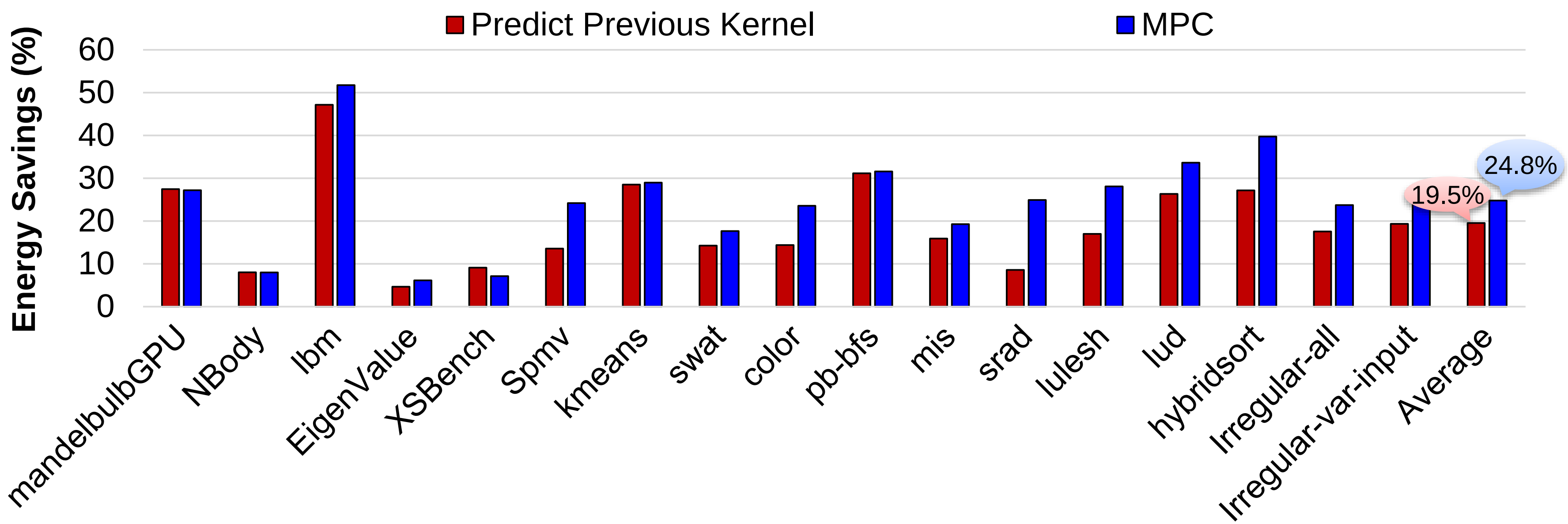
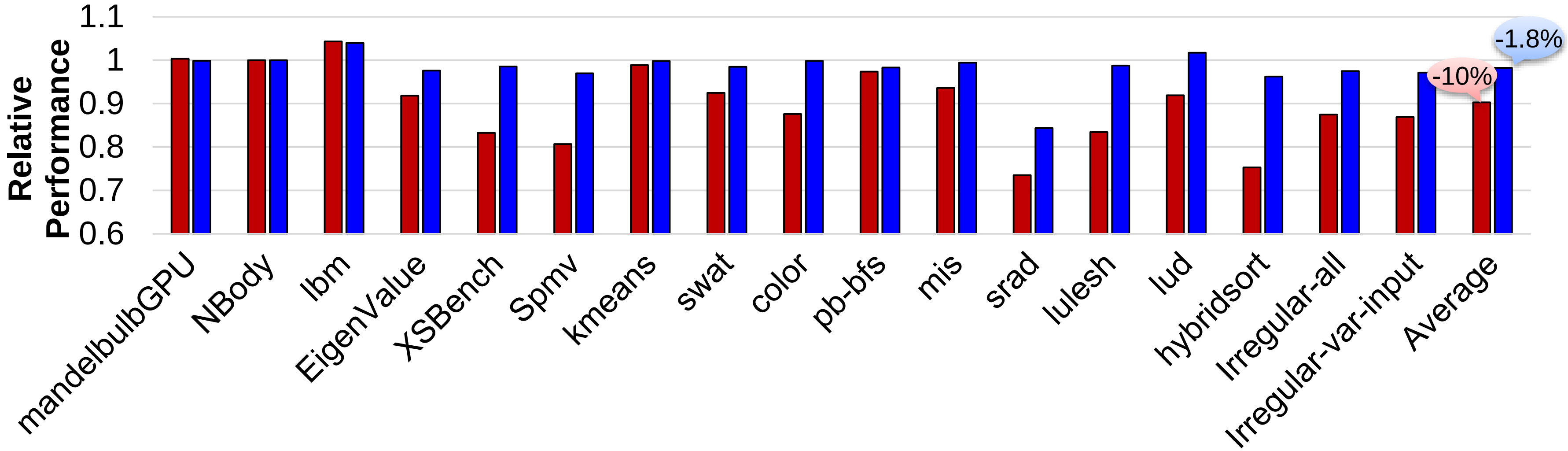
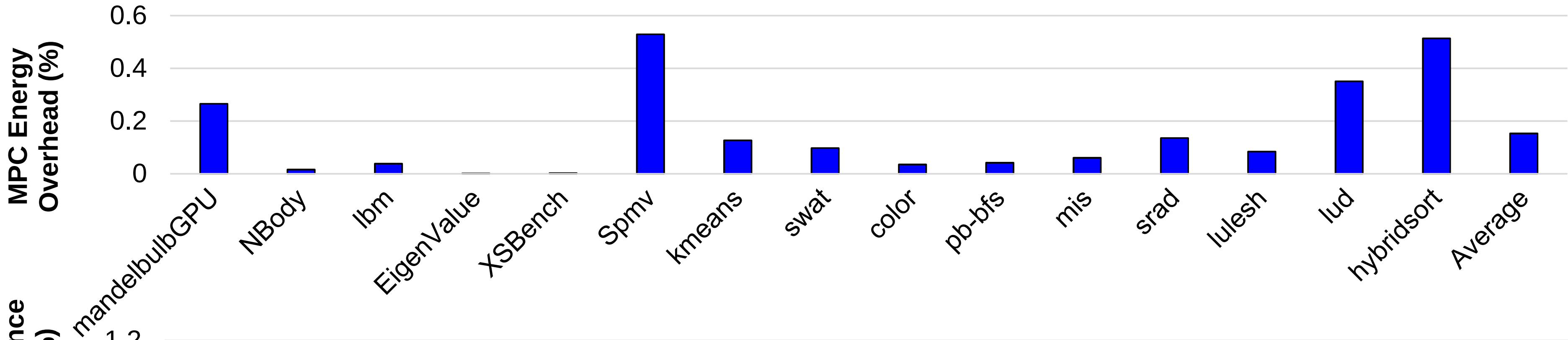
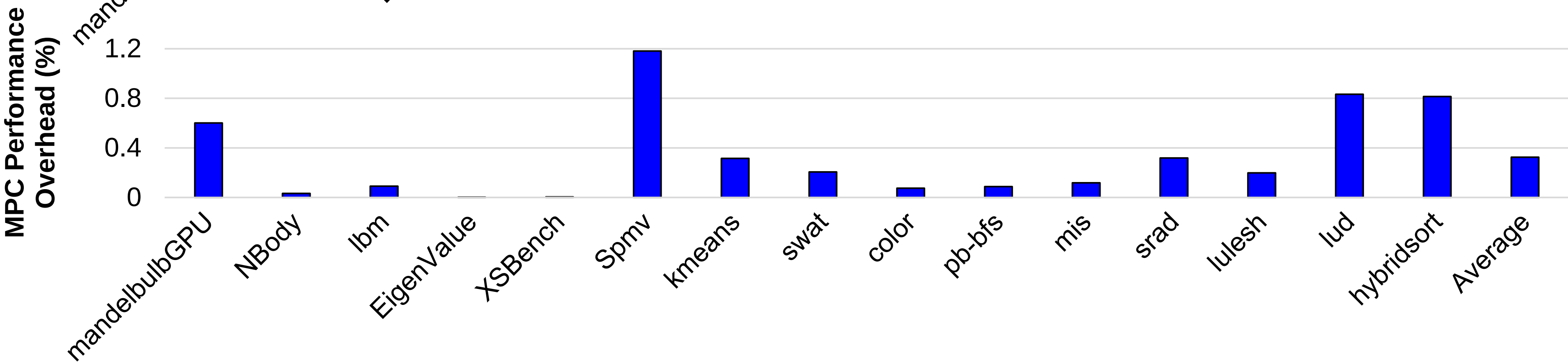
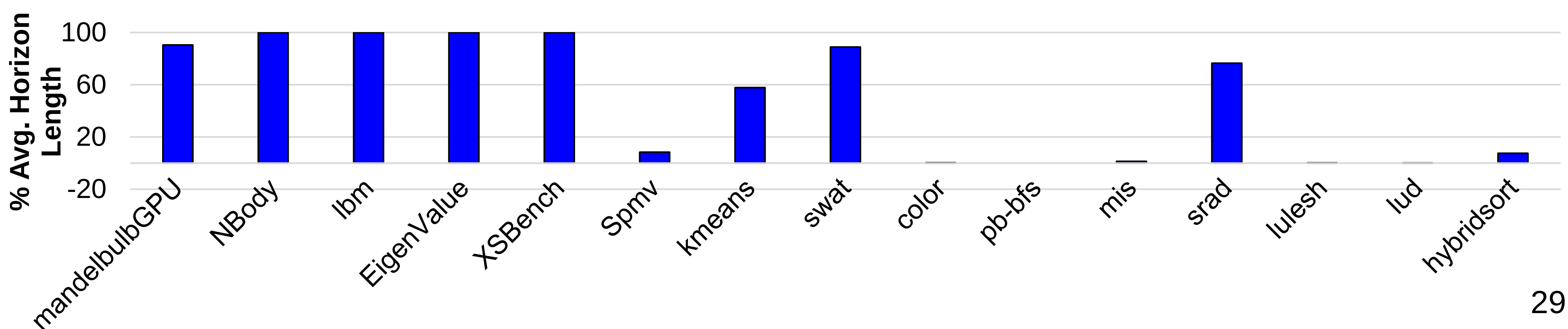




MPC Overhead







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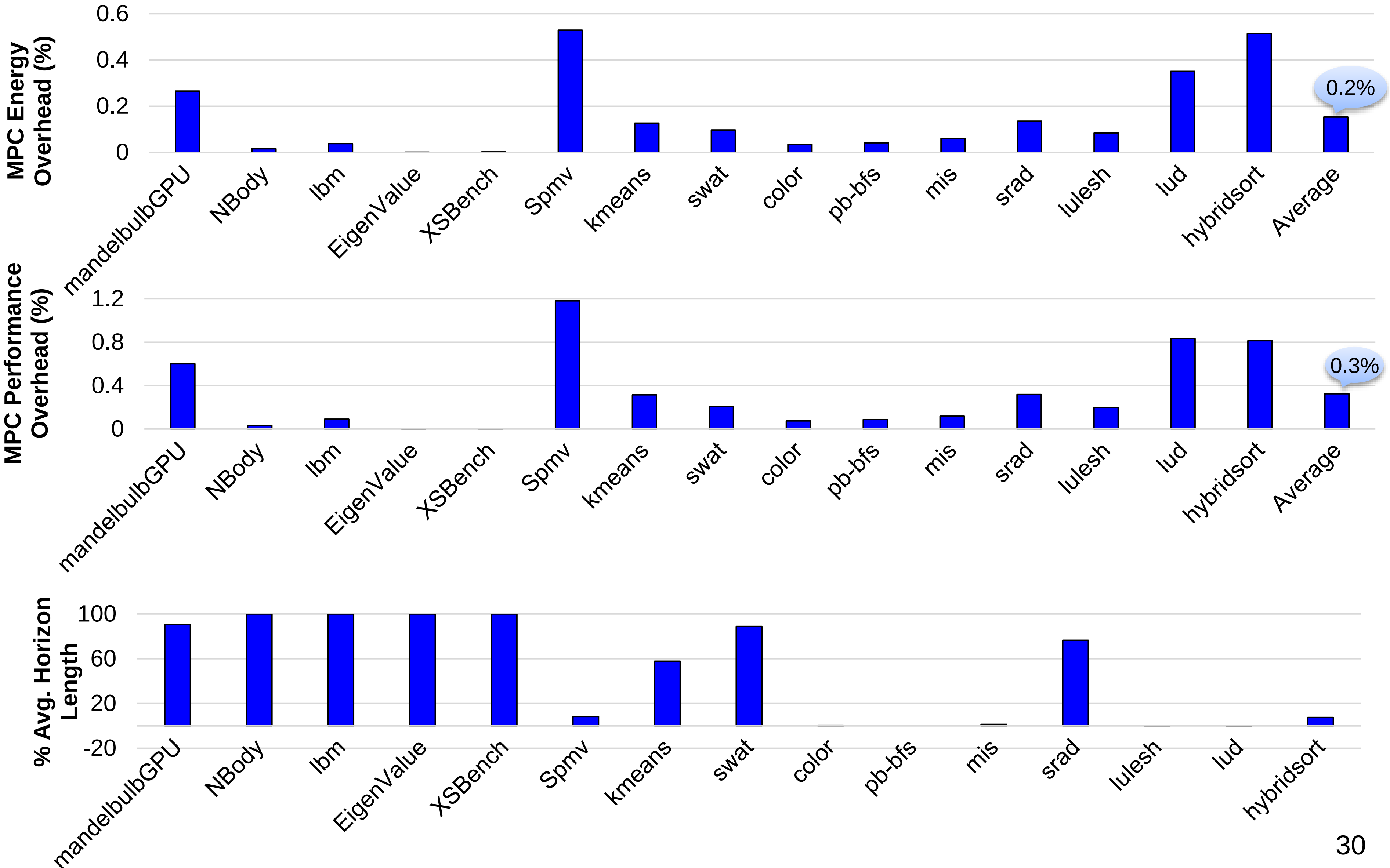
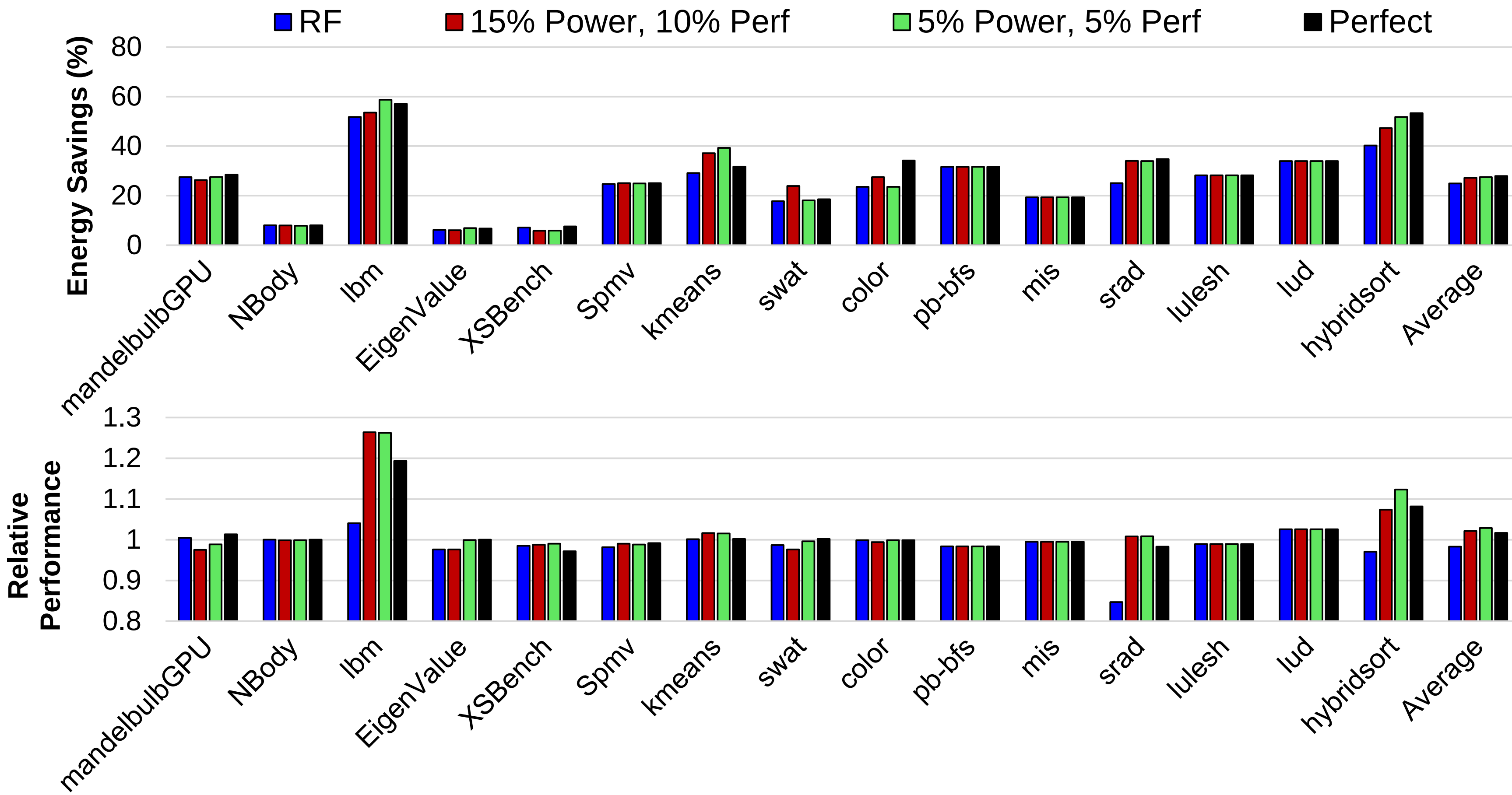


Ramification of Prediction Inaccuracy

- RF: 12% Power, 25% Perf
- 15% Power, 10% Perf: Wu et al. [HPCA 2015]
- 5% Power, 5% Perf: Paul et al. [ISCA 2015]



Conclusions

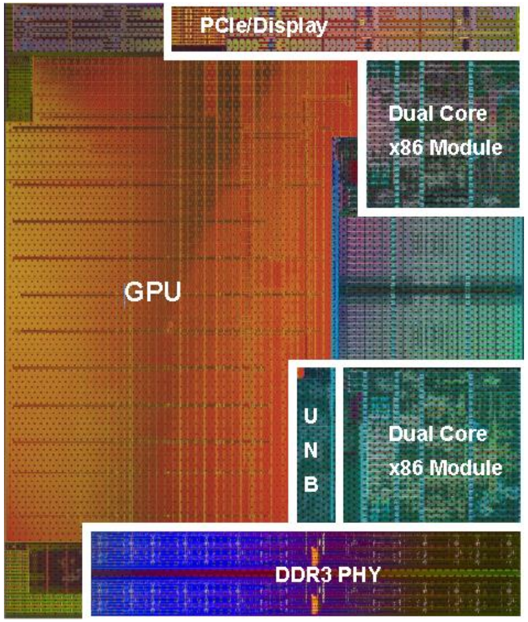
- MPC looks into the future to determine the best configuration for the current optimization time step
- Though effective in many domains, overheads far too high for short timescales of dynamic power management
- We devise an approximation of MPC that dramatically improves GPGPU energy-efficiency with orders of magnitude lower overhead
- Our approach reduces energy by 24.8% with only a 1.8% performance impact

Questions

Backup Slides

Performance-aware Power Management

- Optimum node-level power efficiency is a complex function of SOC configuration, workload characteristics, programming model, and node-level objective/constraints



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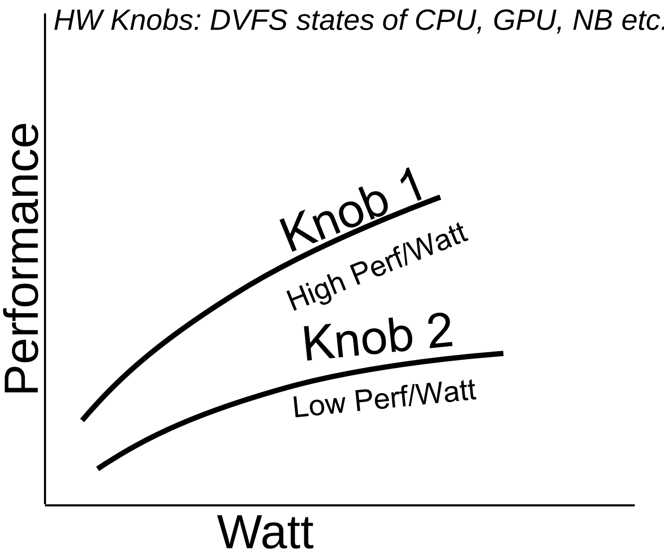

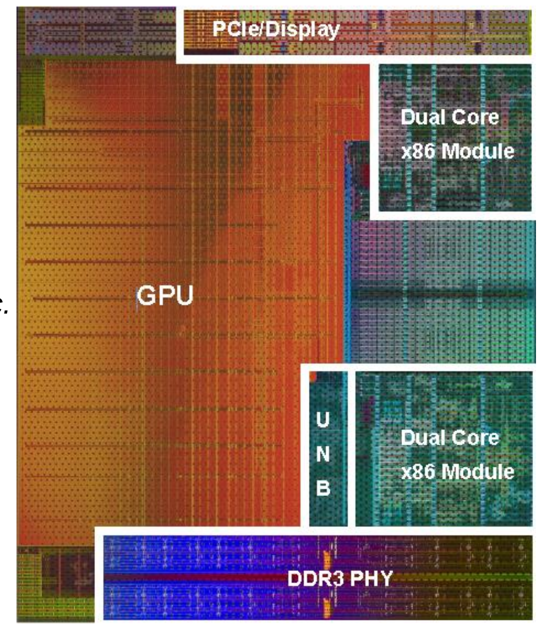

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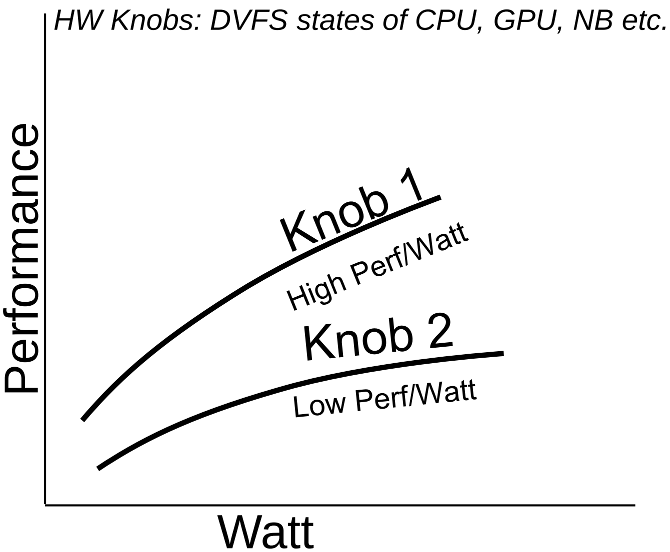
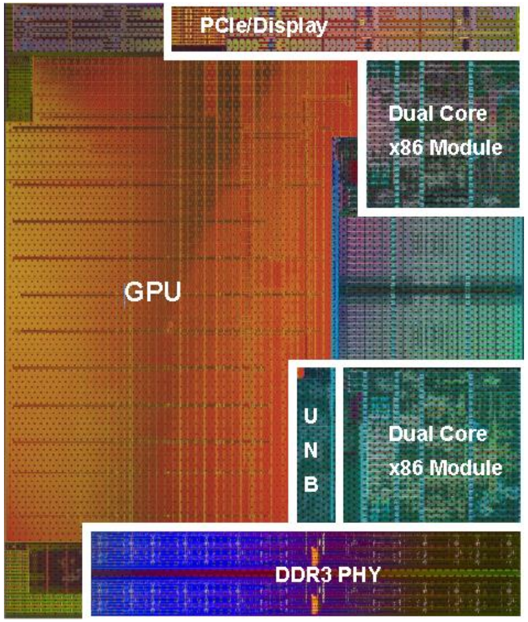
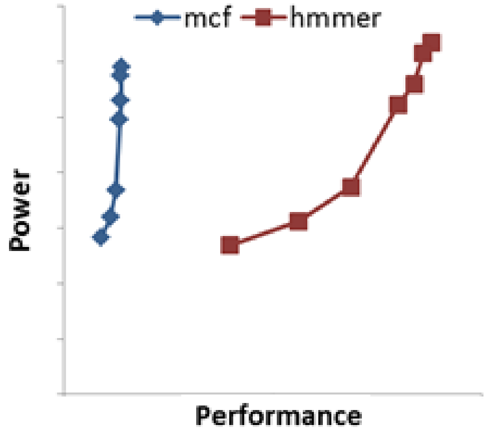
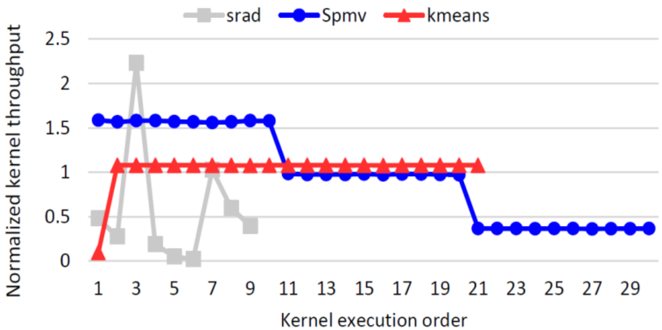






Non-linear power vs. performance curves



Time-varying Workload

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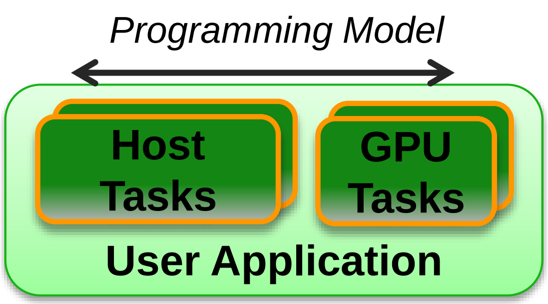

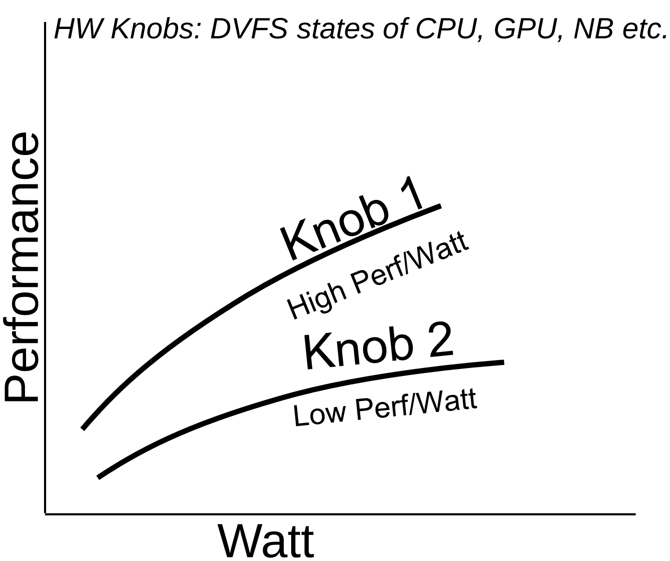

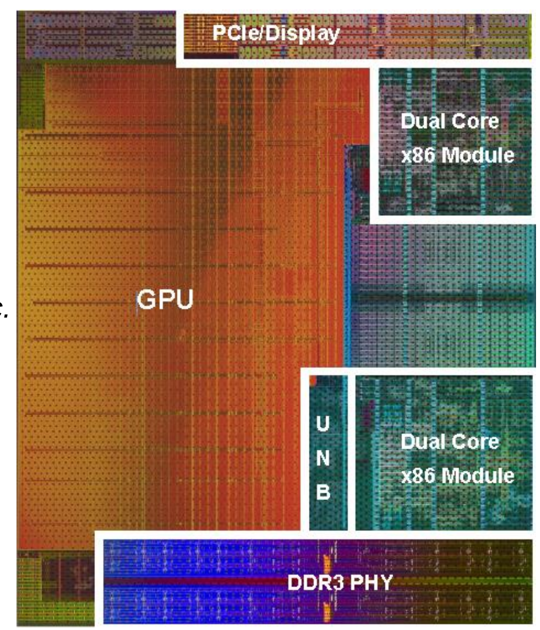

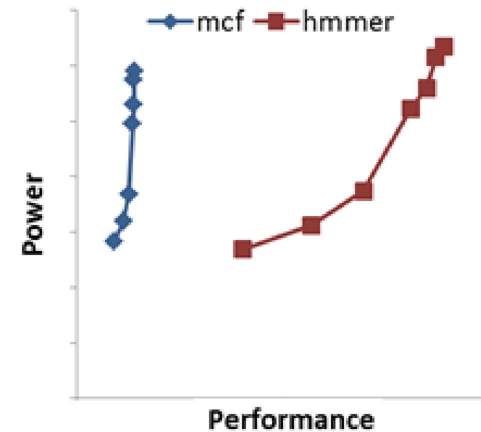

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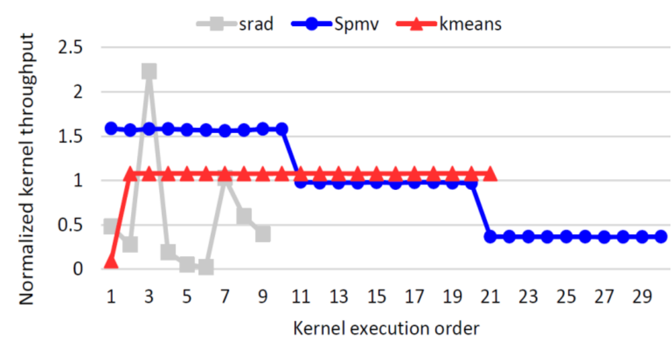

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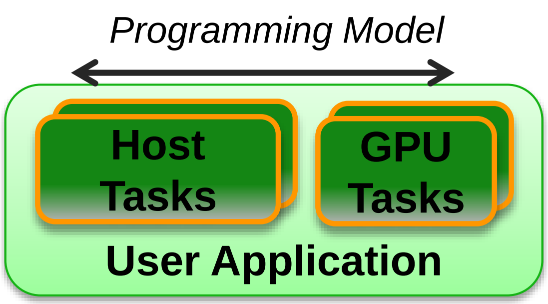

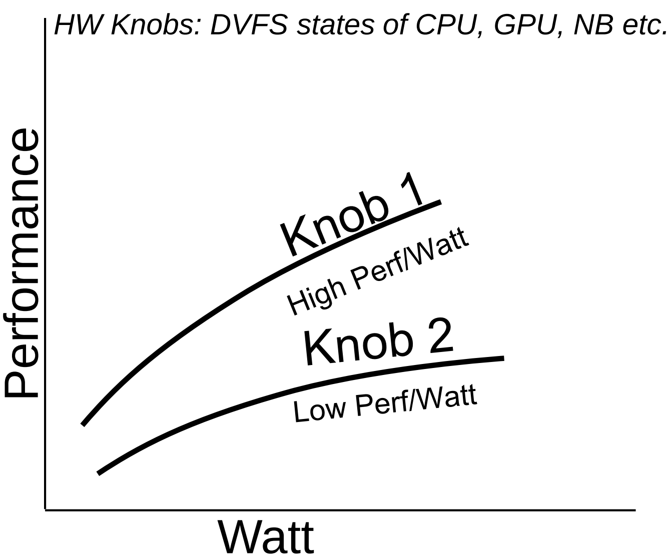

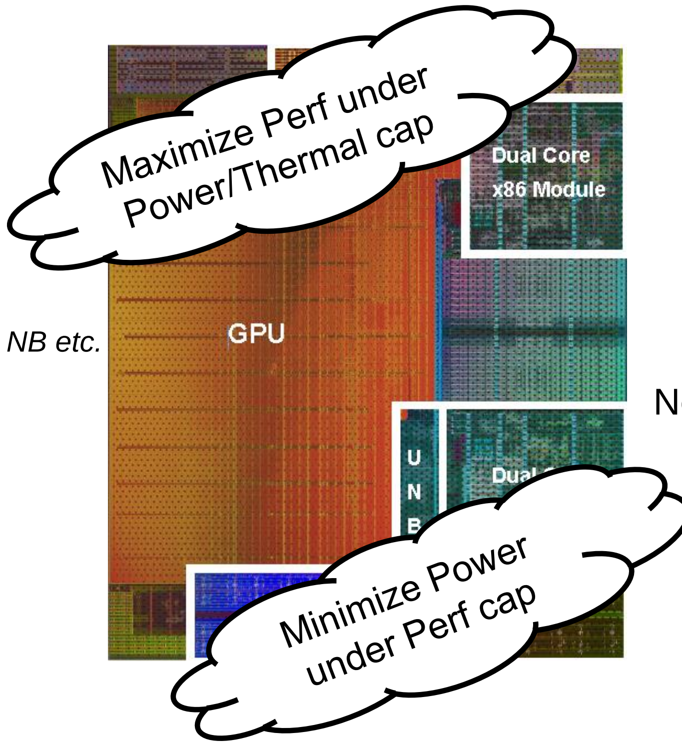

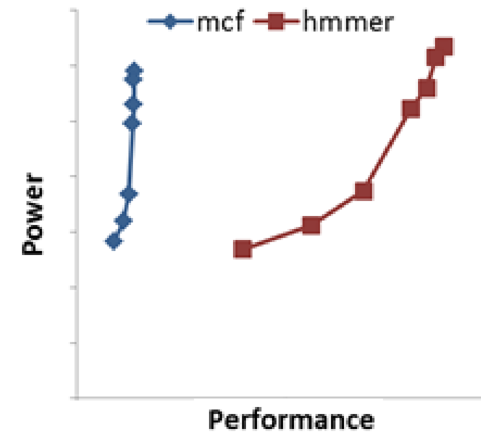

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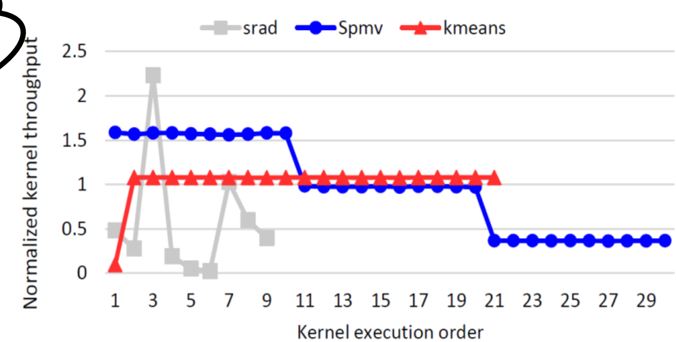

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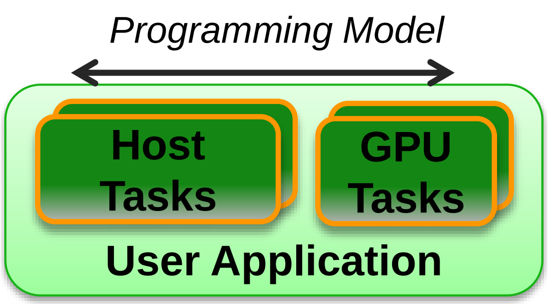
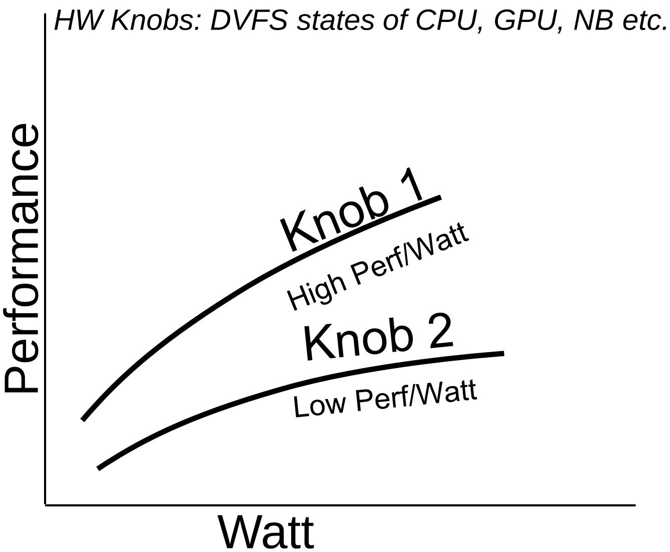
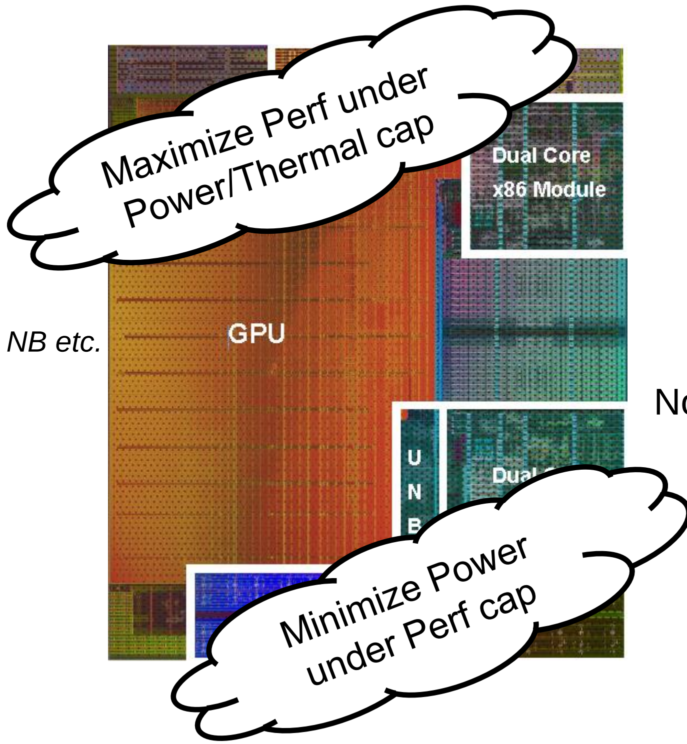
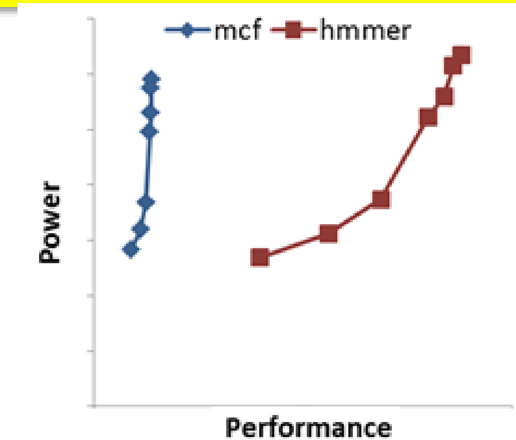
Reduce energy of the GPGPU kernel phase while performing better than a target









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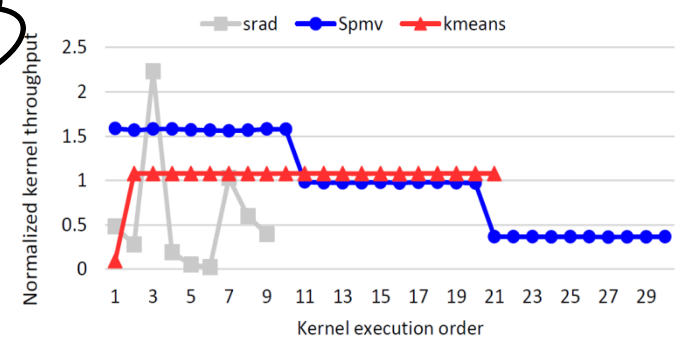

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Model Predictive Control (MPC)

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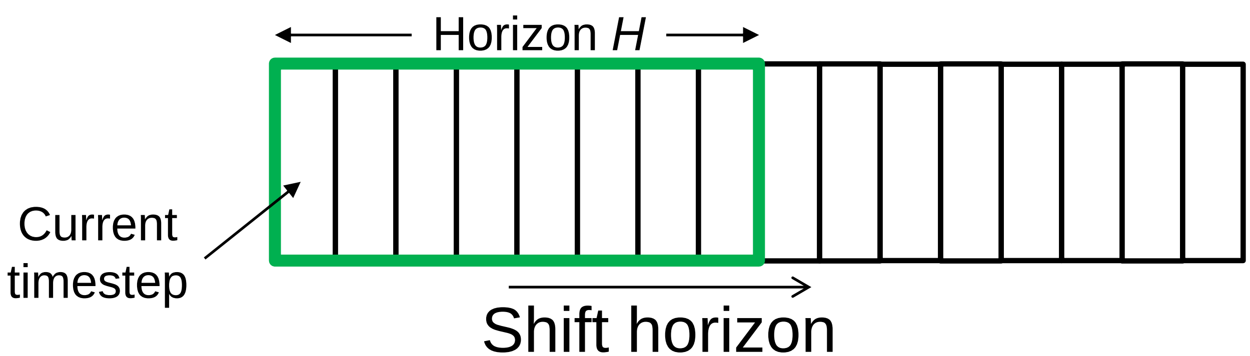

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- <u>Our approach</u>: An approximation of MPC that *dramatically improves* GPGPU energy-efficiency with *orders of magnitude lower* overhead

Dynamic GPGPU Power Management

- CPU and GPU consume significant power in servers
- Previous approaches to dynamic power management are locally predictive and ignore future kernel behavior
  - Performance loss or wasted energy

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Proactively looks ahead into the future

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Proactively looks ahead into the future

- Applying MPC is challenging for short timescales of dynamic power management
- **Goal:** Approximations to MPC that save GPGPU energy within the timescales of a typical server operation without degrading performance

Dynamic GPGPU Power Management

- **Goal:** Reduce GPGPU energy within the timescales of a typical server operation without degrading performance

- **Computationally Intensive**
  - NP-Hard
  - Challenging for short timescales of dynamic power management

- **Idea:** Improve energy efficiency by looking into future phases
  - Model Predictive Control (MPC)
  - Dynamically vary computation to limit performance overhead

Traditional Energy Management

- **Static**
  - Predefined set of decisions
- **Reactive**
  - Act after sensing a change in behavior
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Proactive Energy Management

Adapt from past and look-ahead into the future

Motivating Future Awareness

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- **Baseline**
  - AMD Turbo Core

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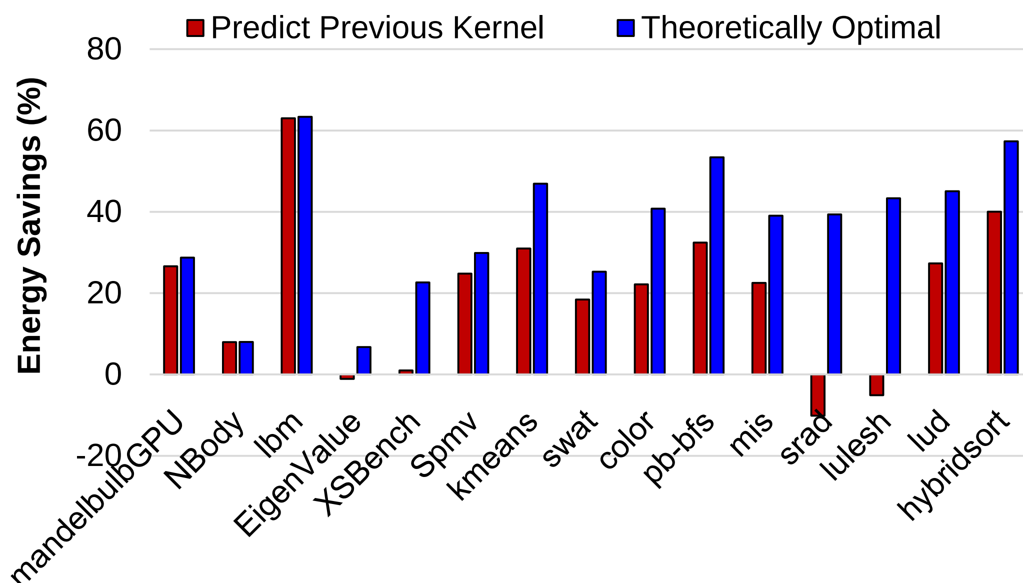

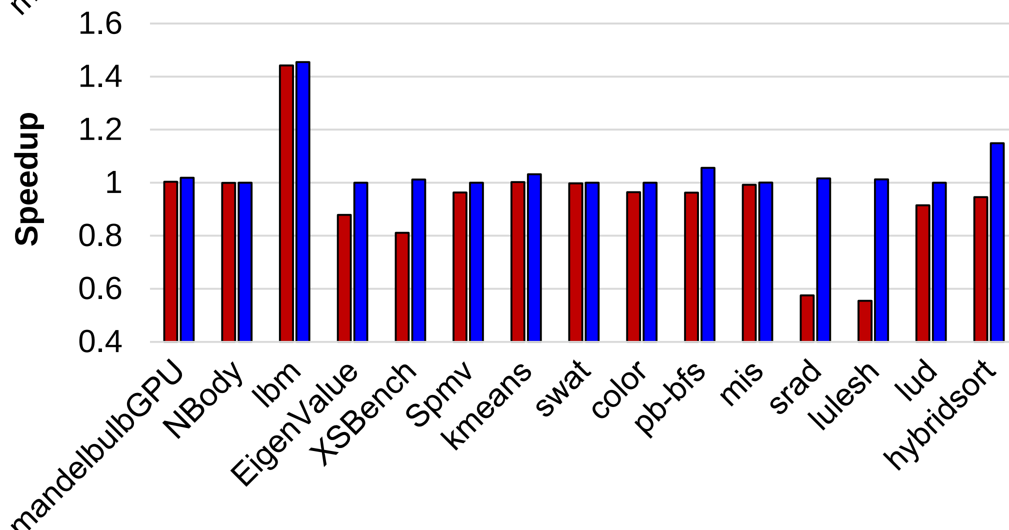

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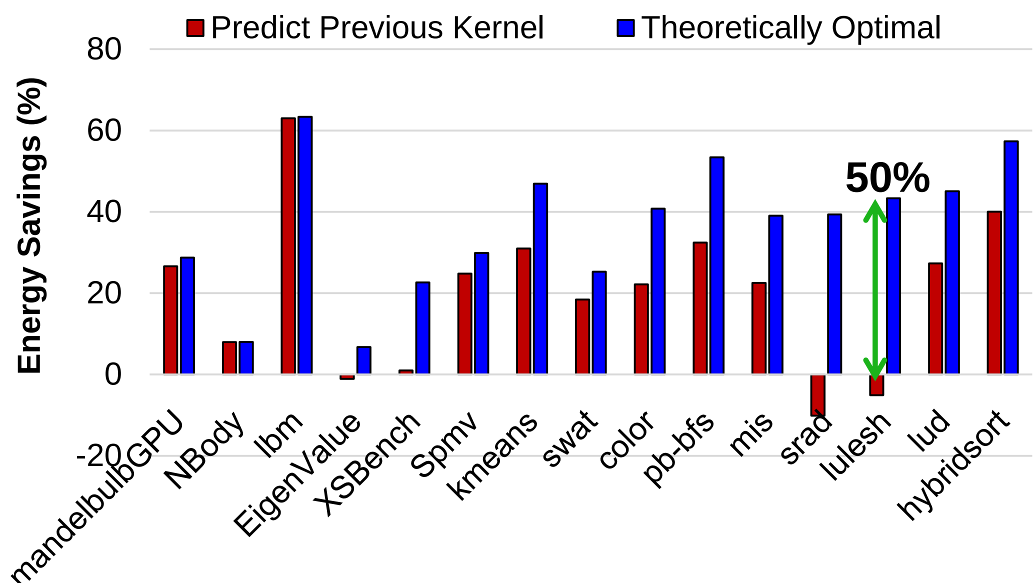
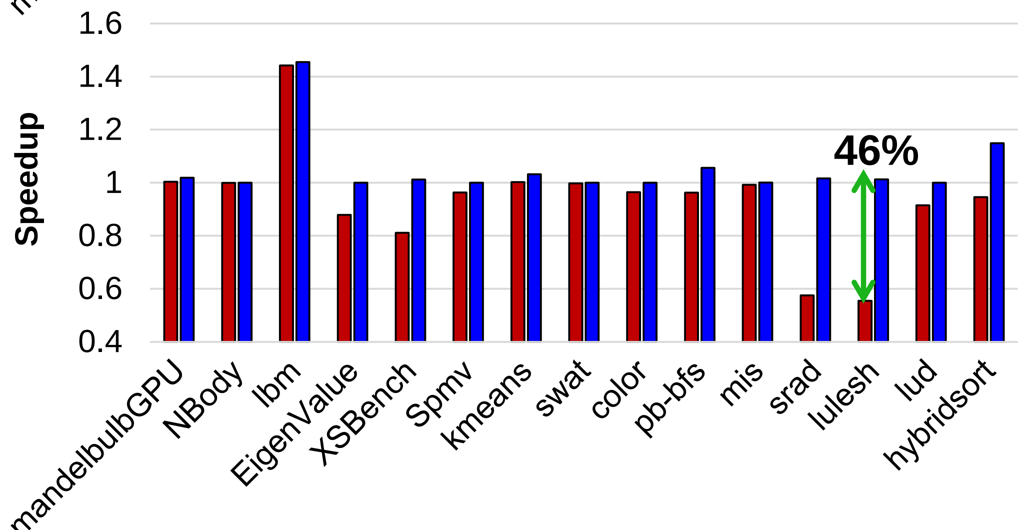
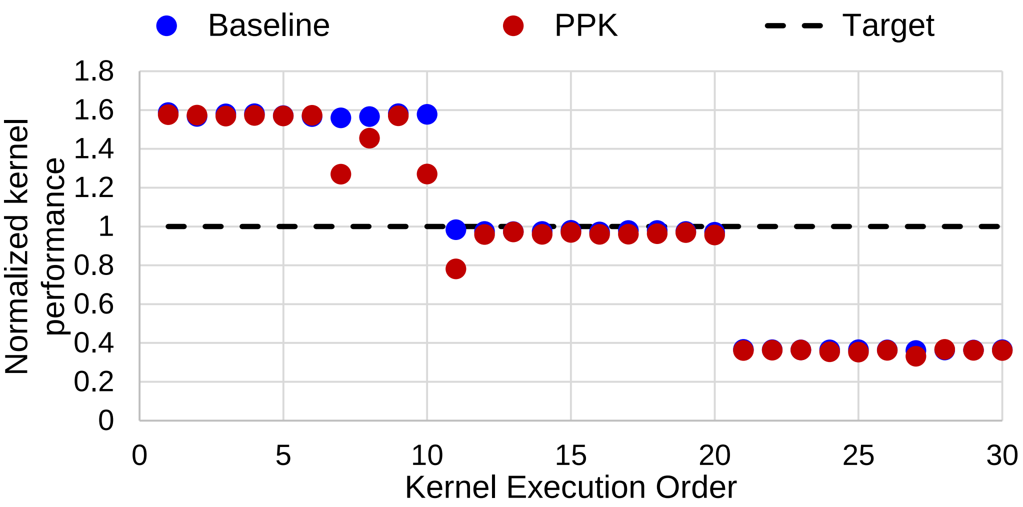
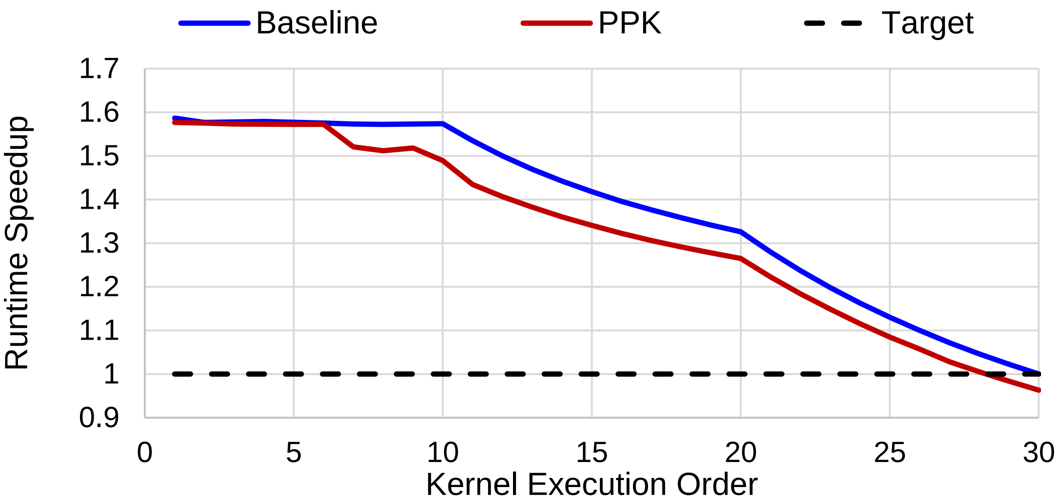




Ramifications of Ignoring Future

- Spmv





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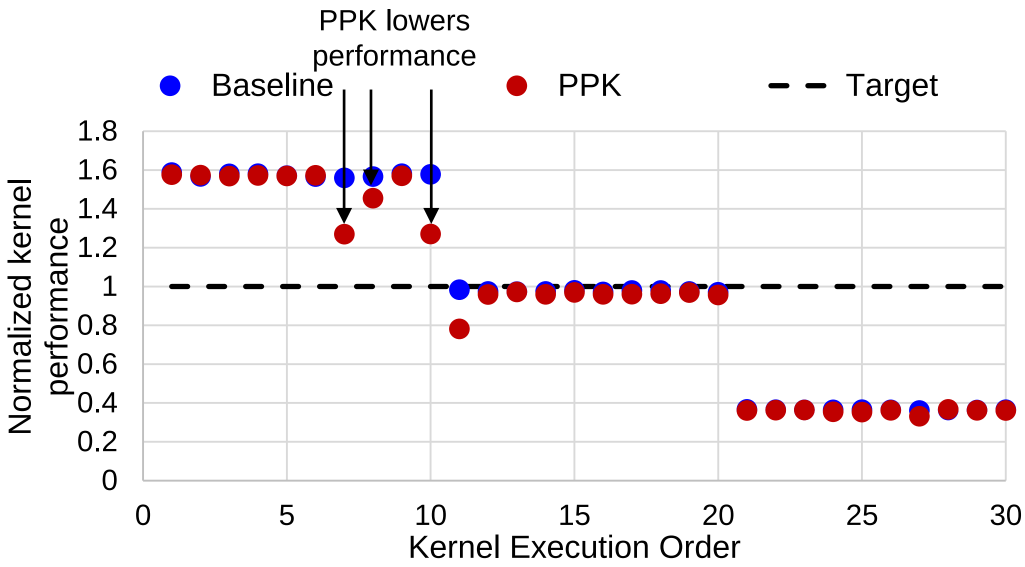

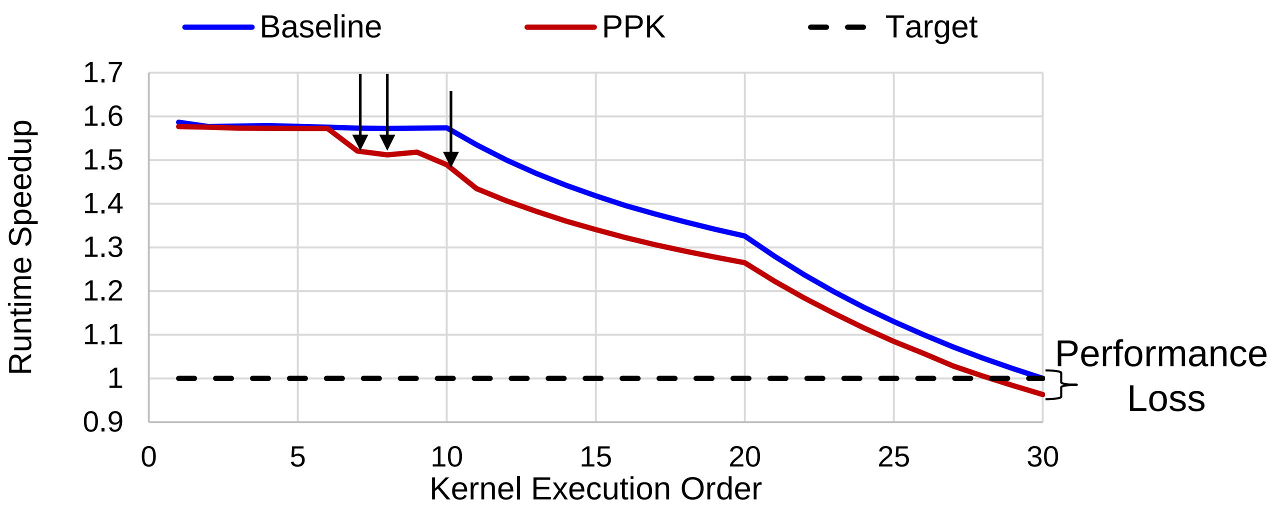

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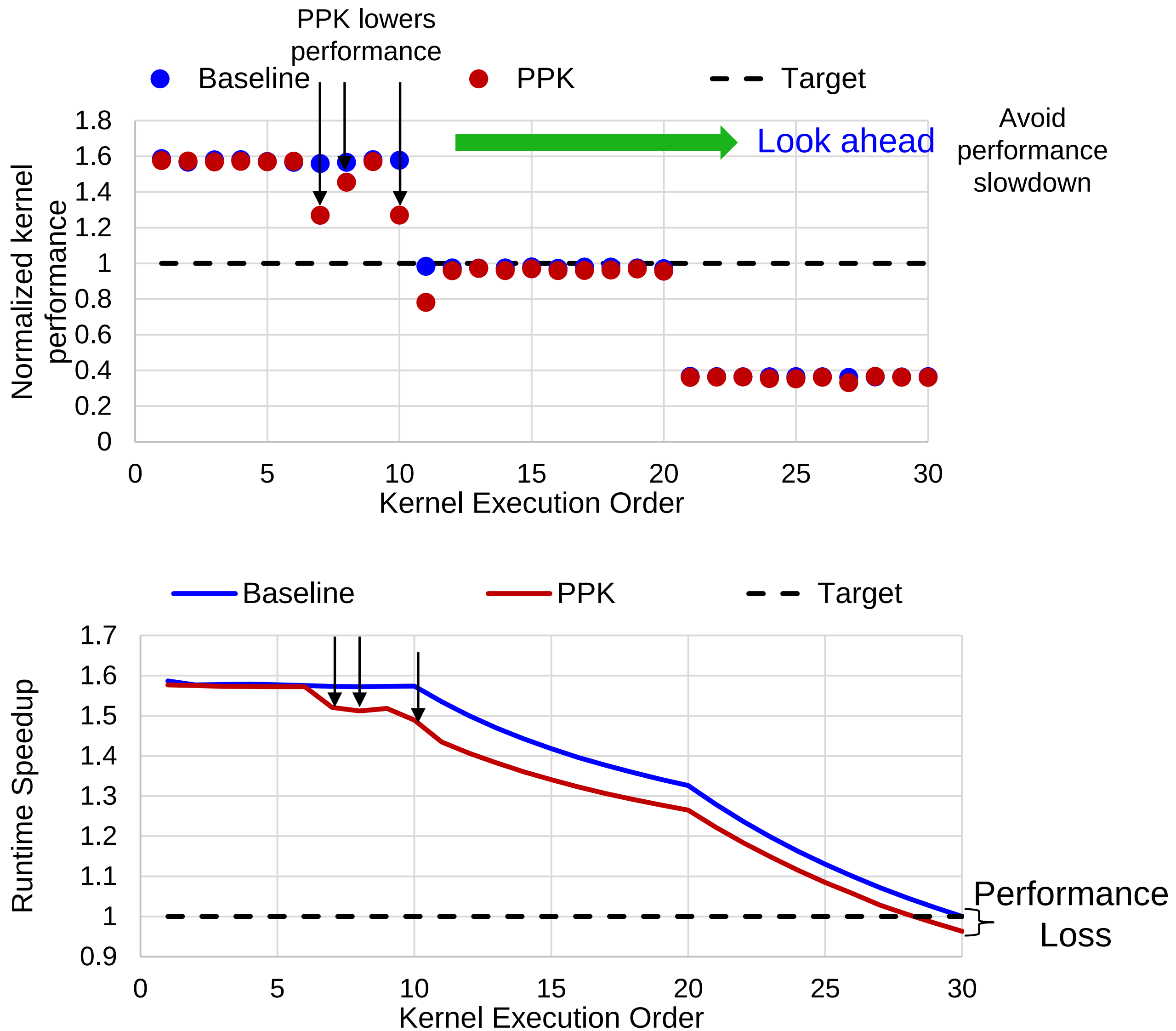

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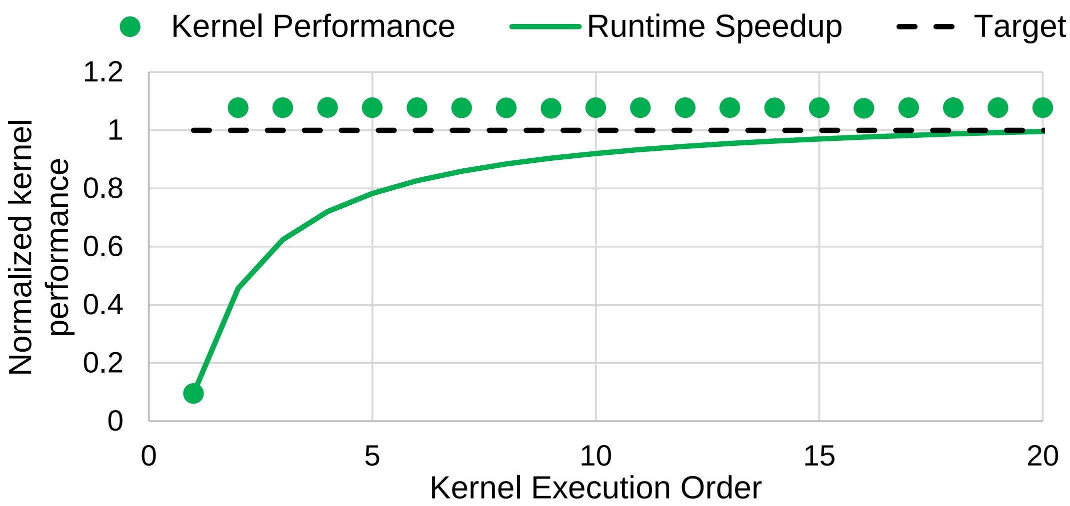

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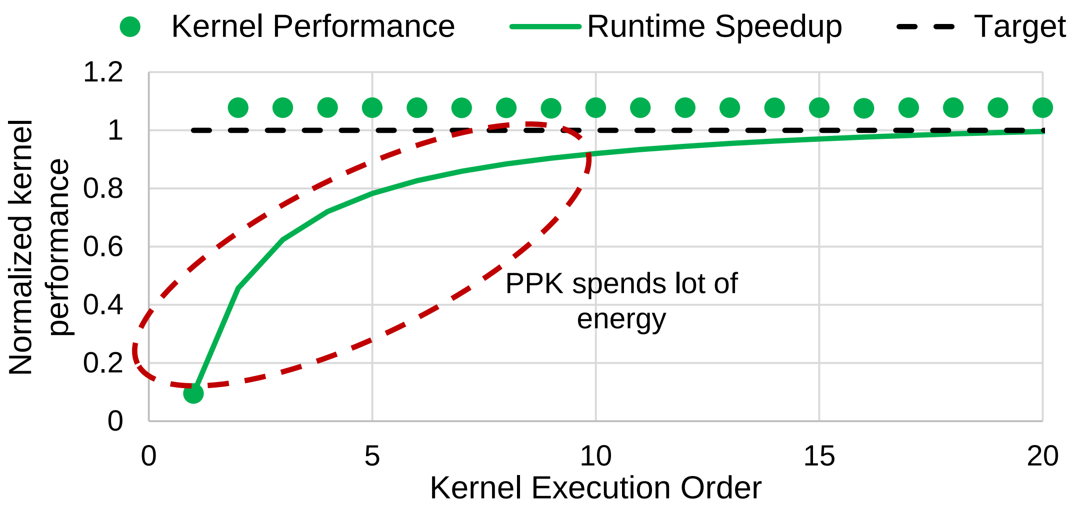

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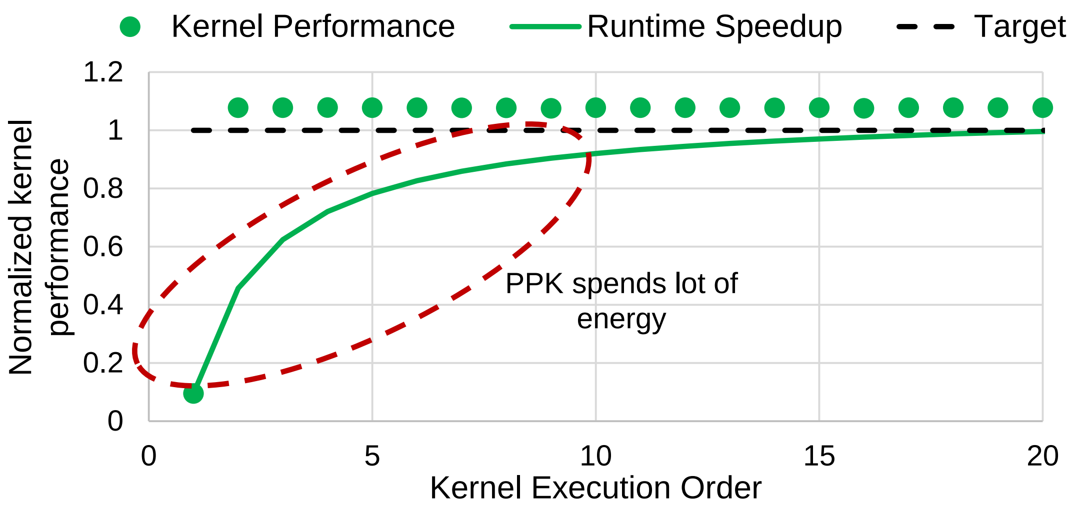

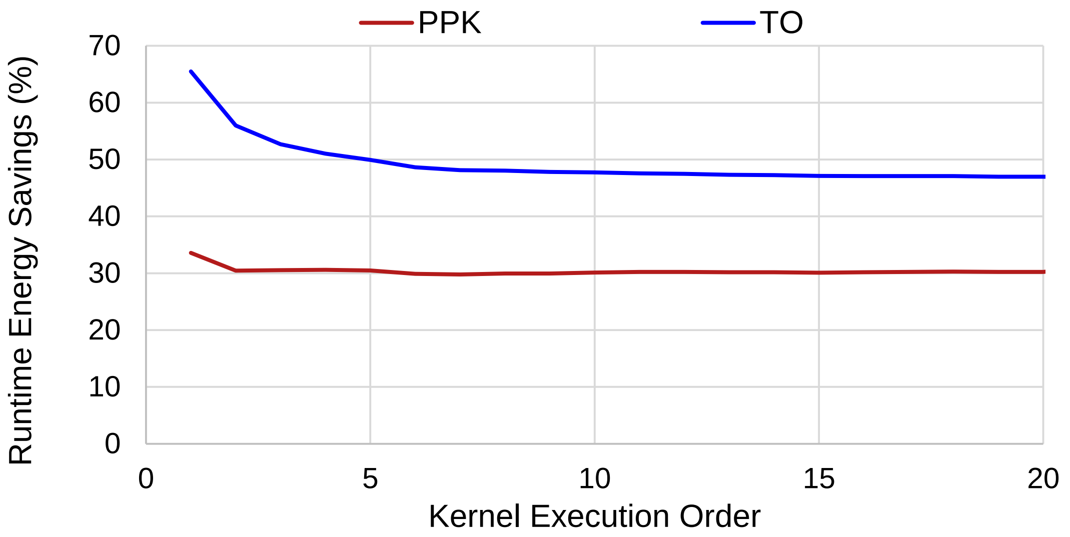

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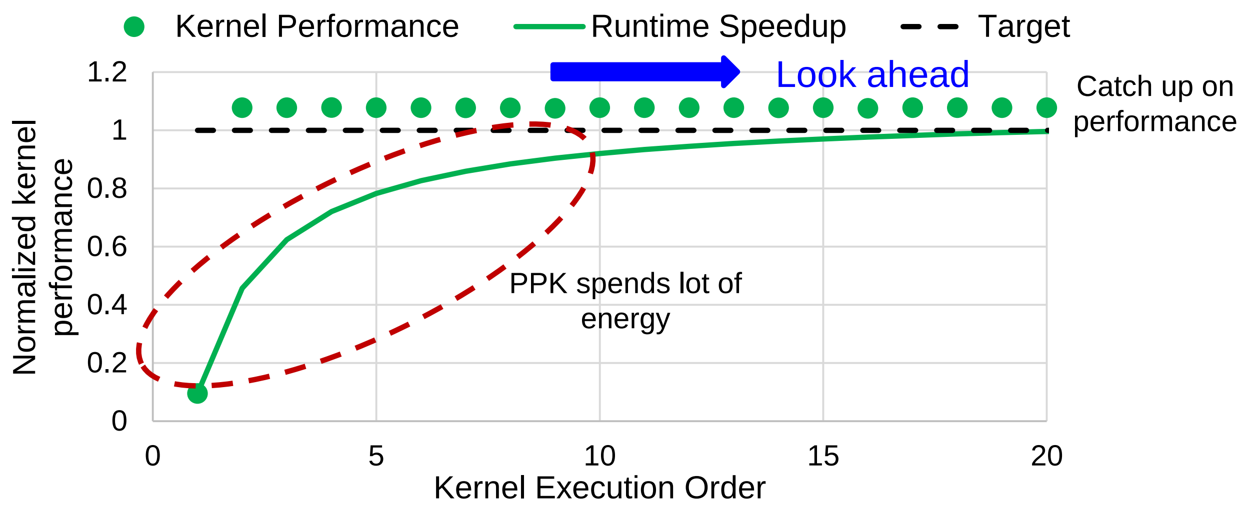
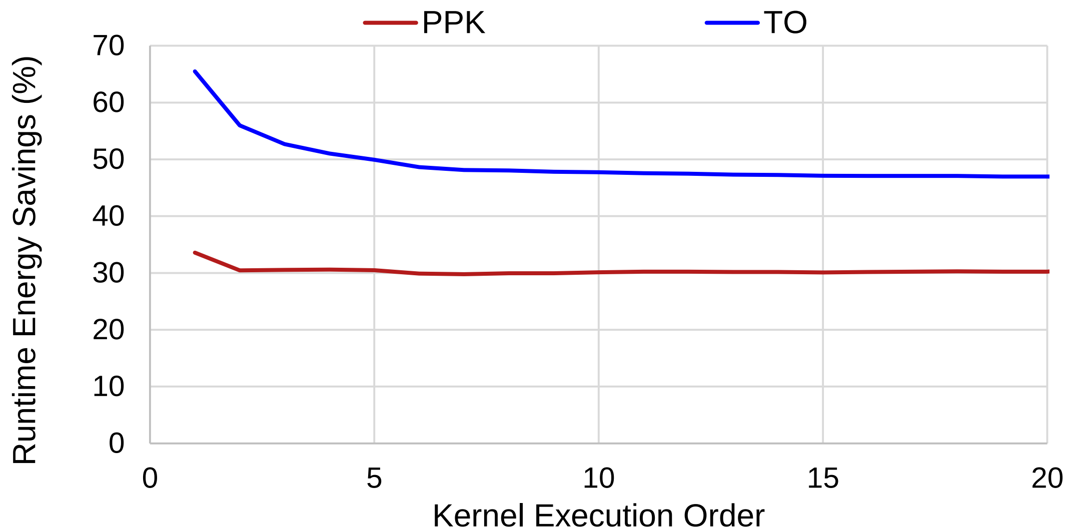
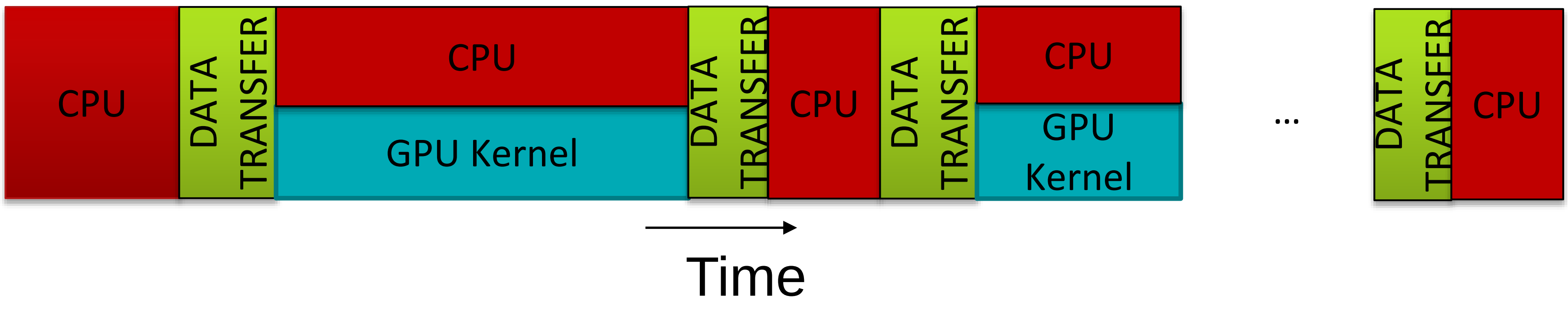




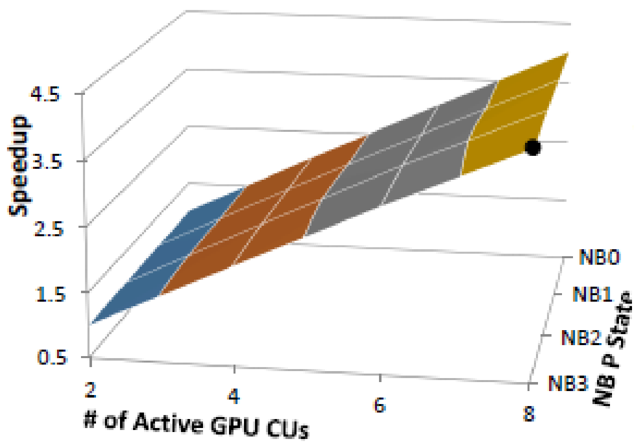
Background

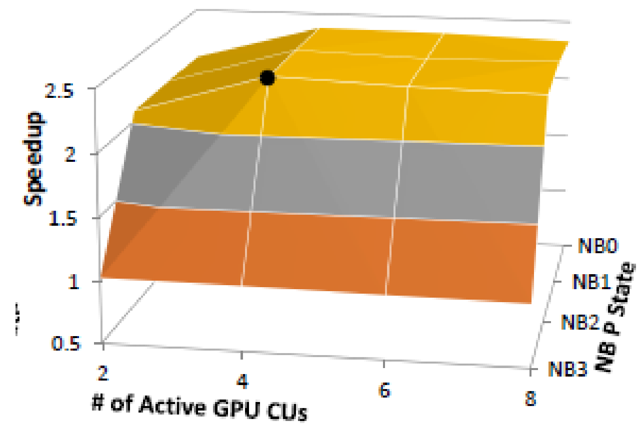
- Typical GPGPU application phase



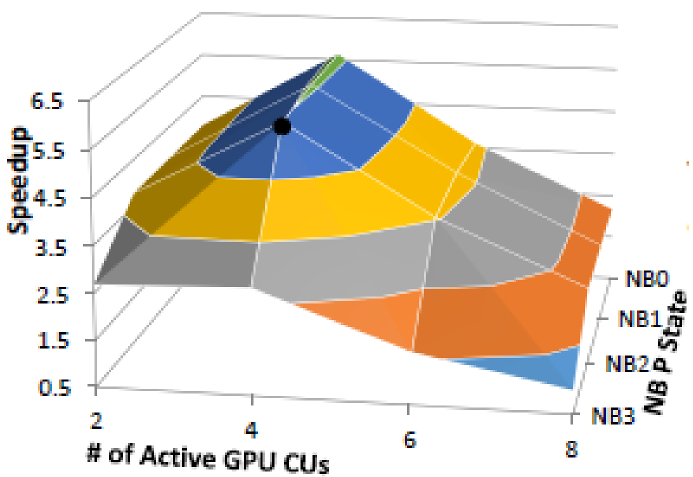
Kernel Performance Scaling

Energy-optimal configuration differ across kernels

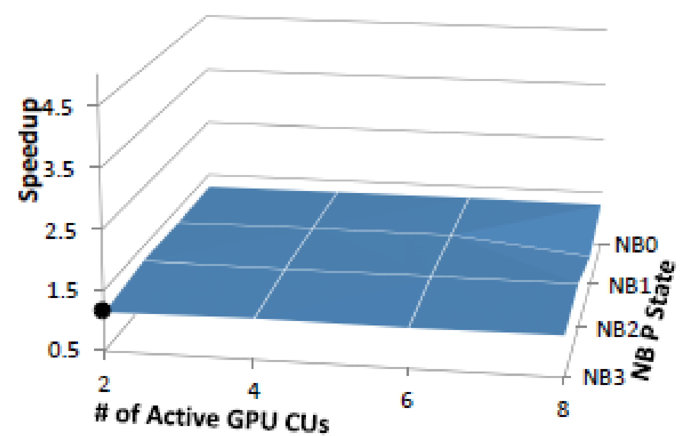




(b) Memory-bound: *readGlobalMemoryCoalsced*



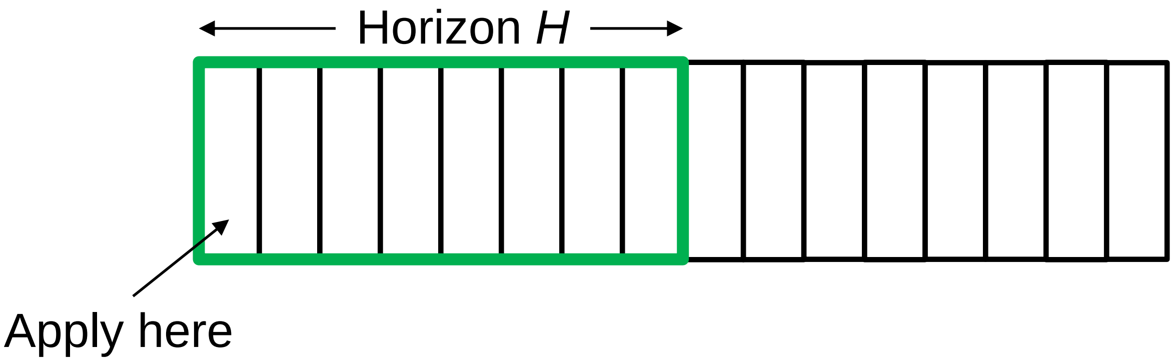
(c) Peak: *writeCandidates*



(d) Unscalable: *astar*

Model Predictive Control (MPC)

- General Idea



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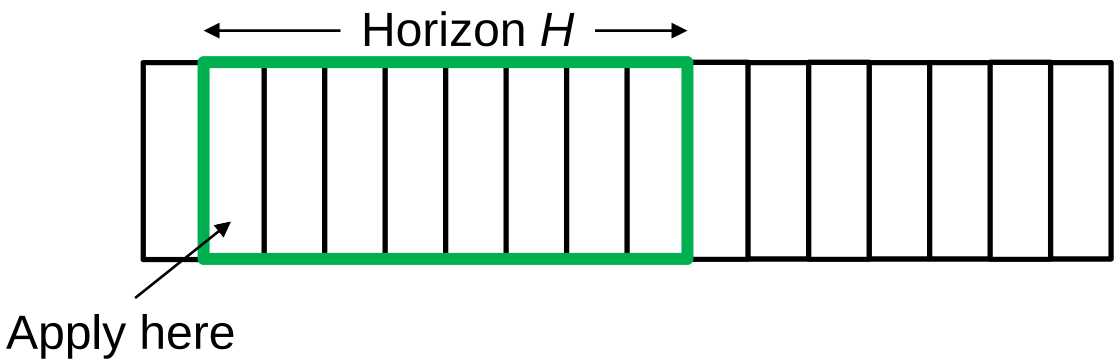

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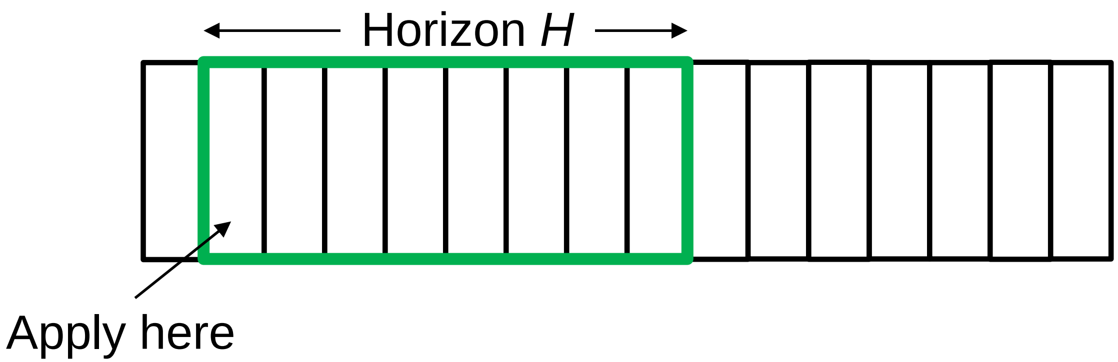

- MPC Components
  - Accurate system model
  - Future input forecast
  - Optimization

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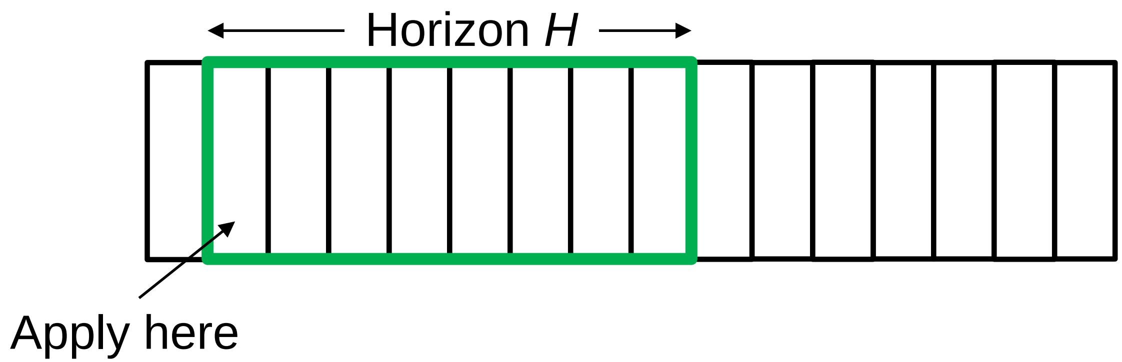
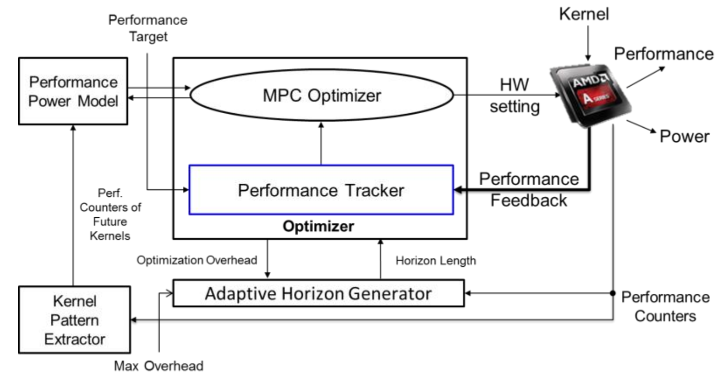


- MPC Components
  - Accurate system model → Power and performance prediction model
  - Future input forecast → Kernel pattern extractor
  - Optimization → Greedy and heuristic based optimizer

Feedback-based Performance Tracker

- Switch the optimization goal based on past performance and the target



Performance met previously?

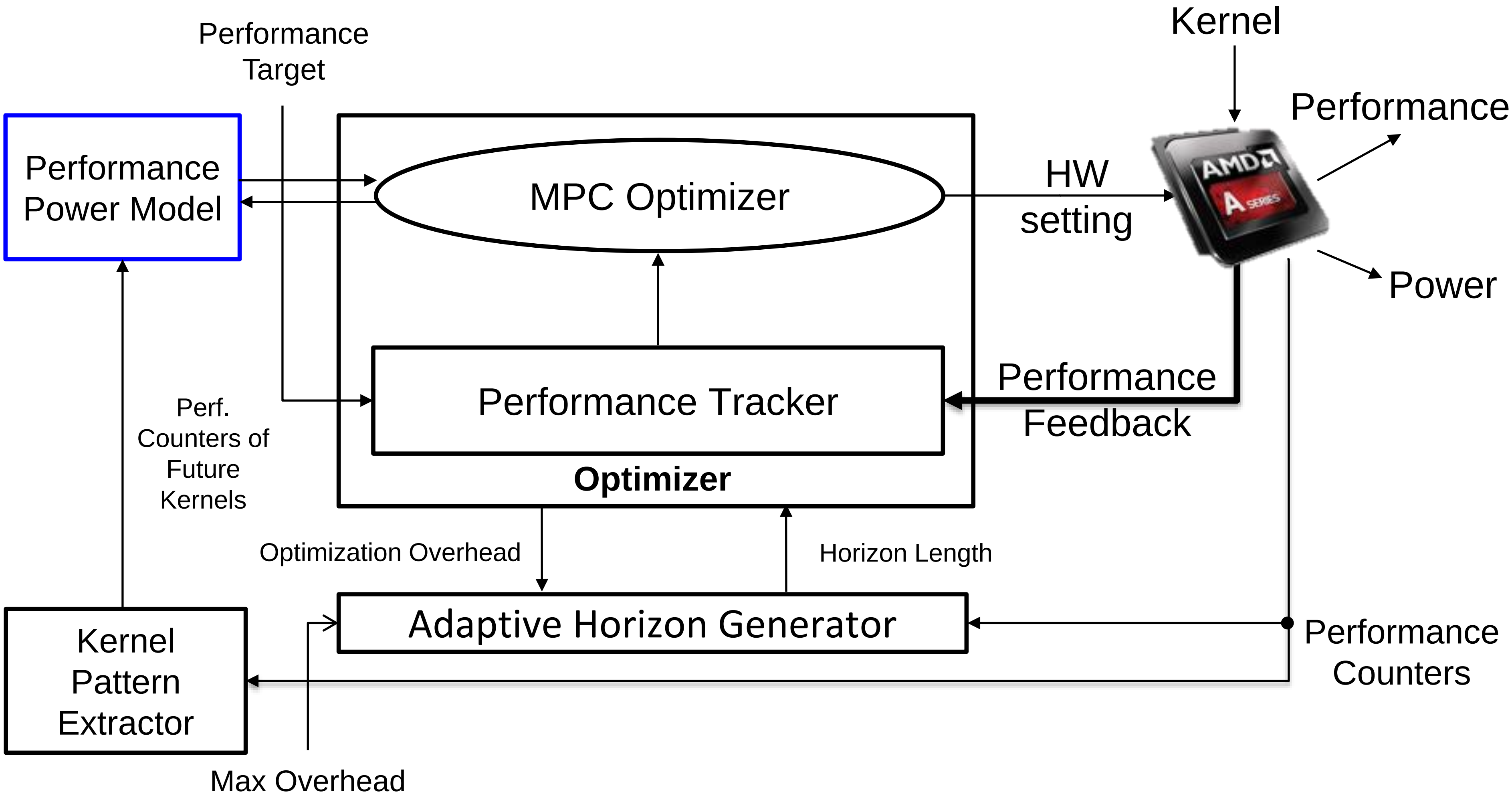
No

Relax optimization
Spend energy
↓
Reduce performance loss

Yes

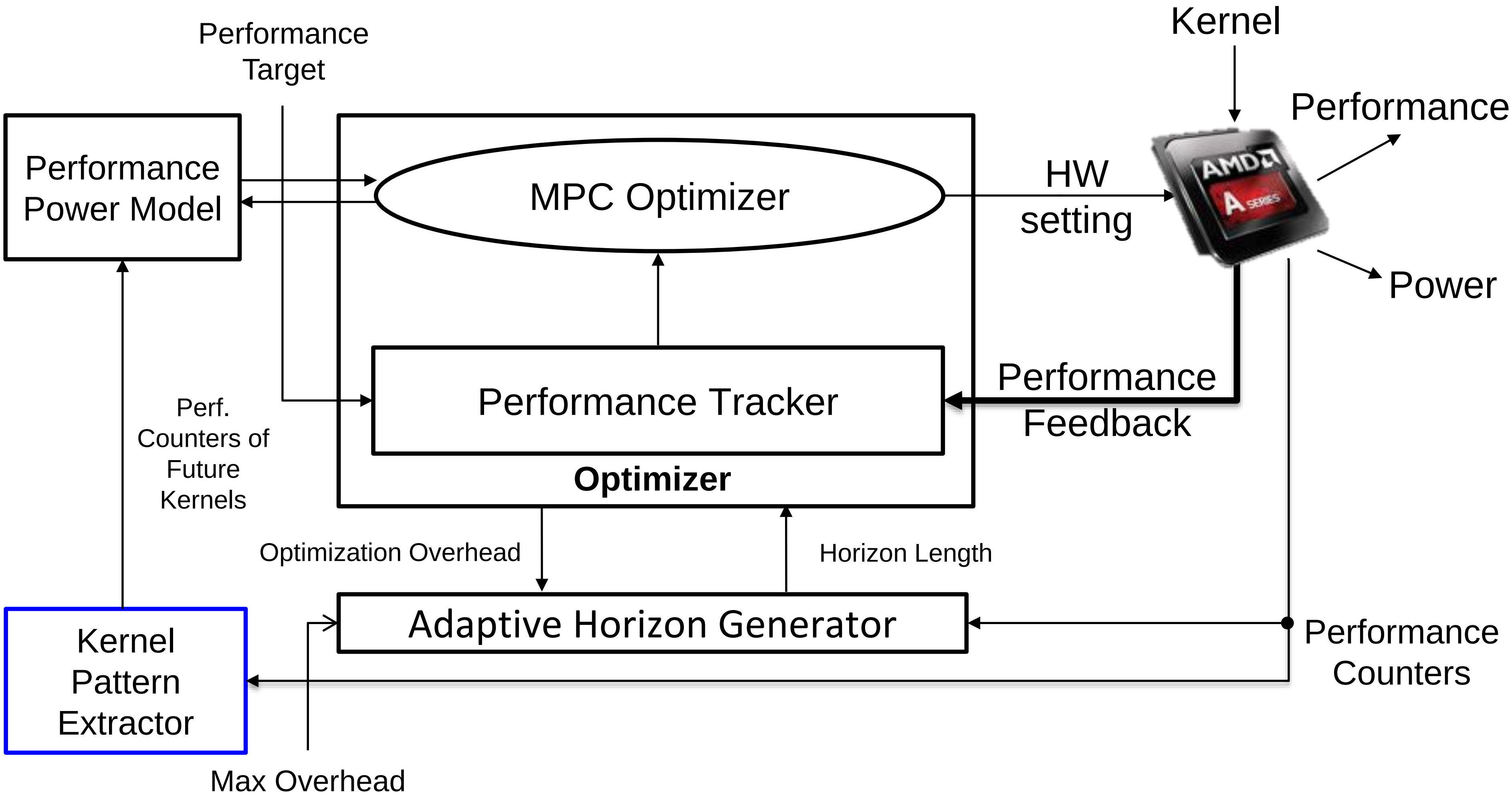
Optimize Aggressively
Reduce energy
↓
Avoid performance loss

Performance Power Model



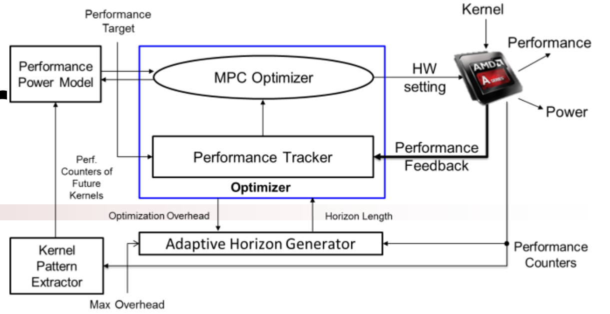
- Trained offline using Random Forest Learning Algorithm
- Estimates performance and power for any HW configuration

Kernel Pattern Extractor



- Extracts kernel execution pattern upon the first encounter
- Stores the performance counters of dissimilar kernels and retunes it

MPC Optimizer



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  - Using the predictor, select the HW knob with highest energy sensitivity
  - Search for low energy configuration using hill climbing

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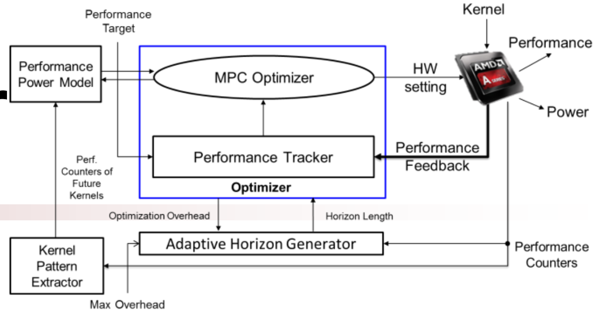

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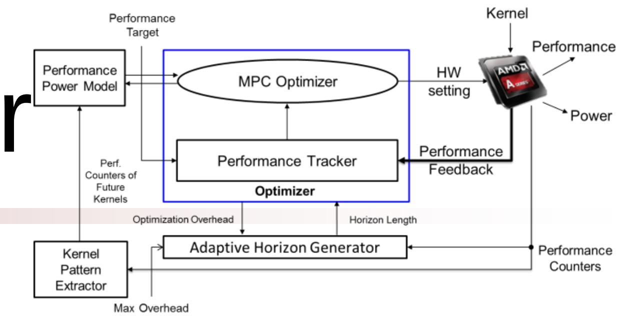

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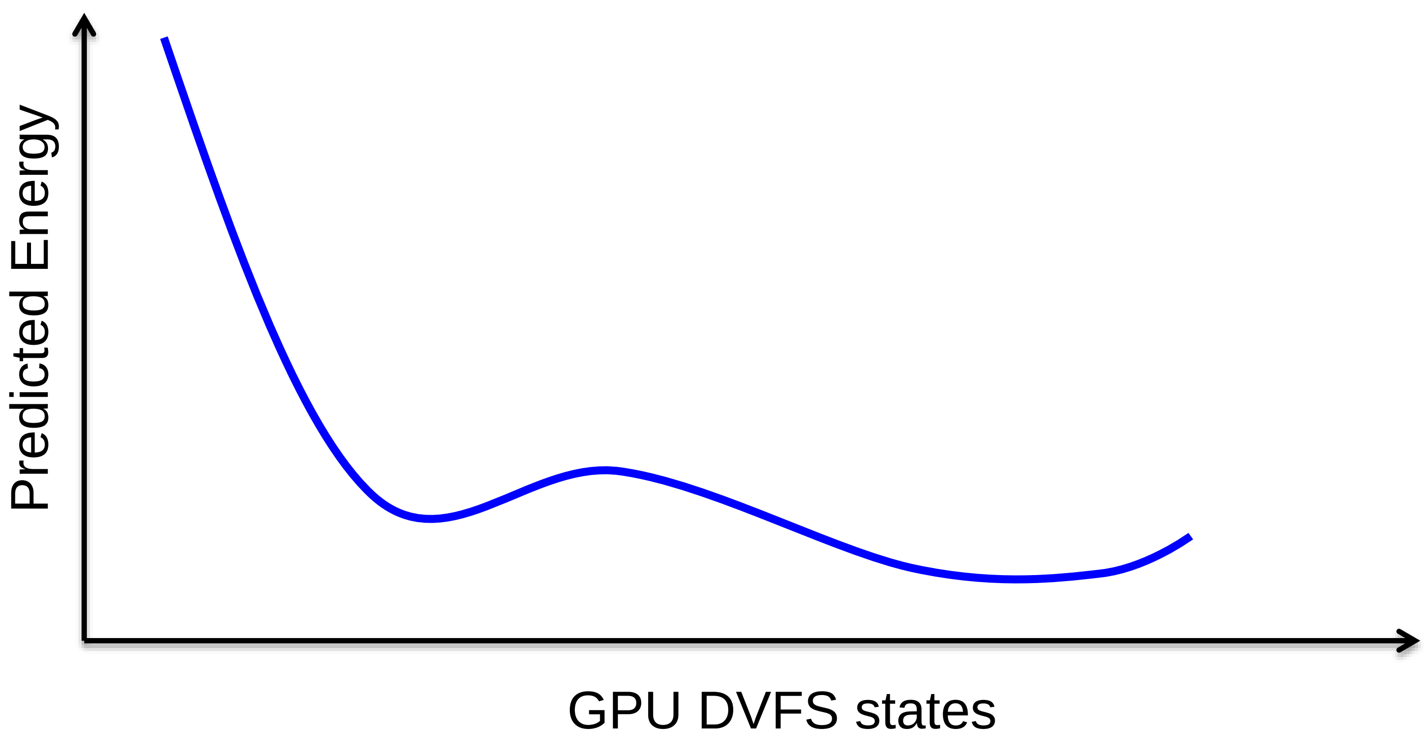

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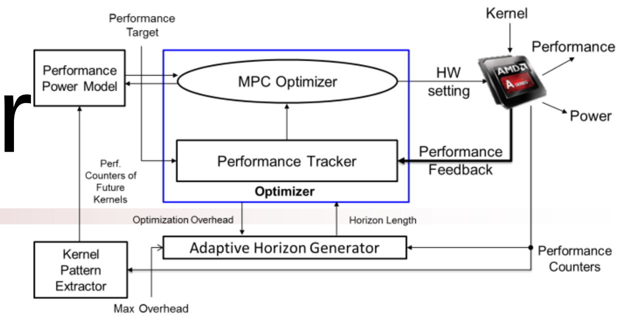

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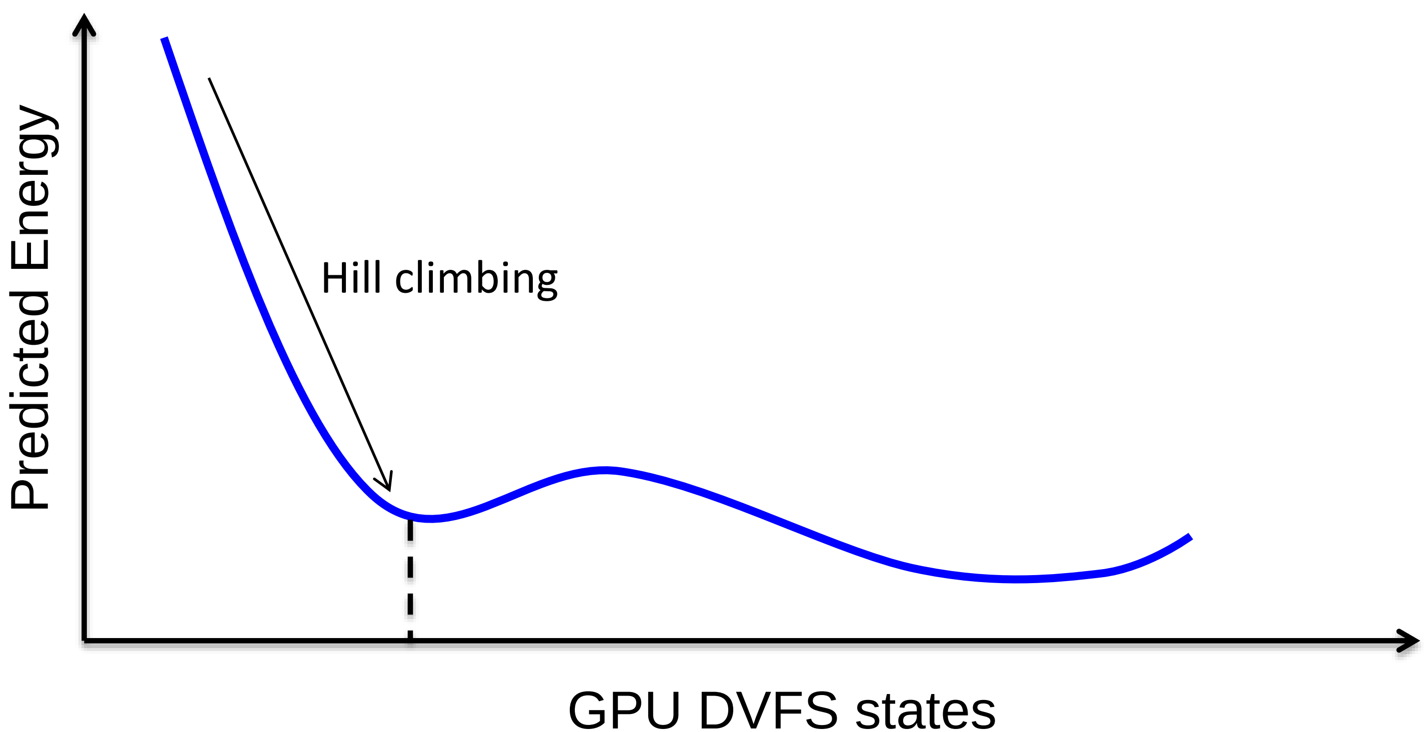

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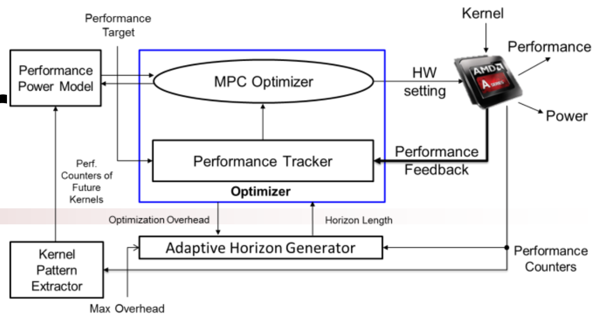

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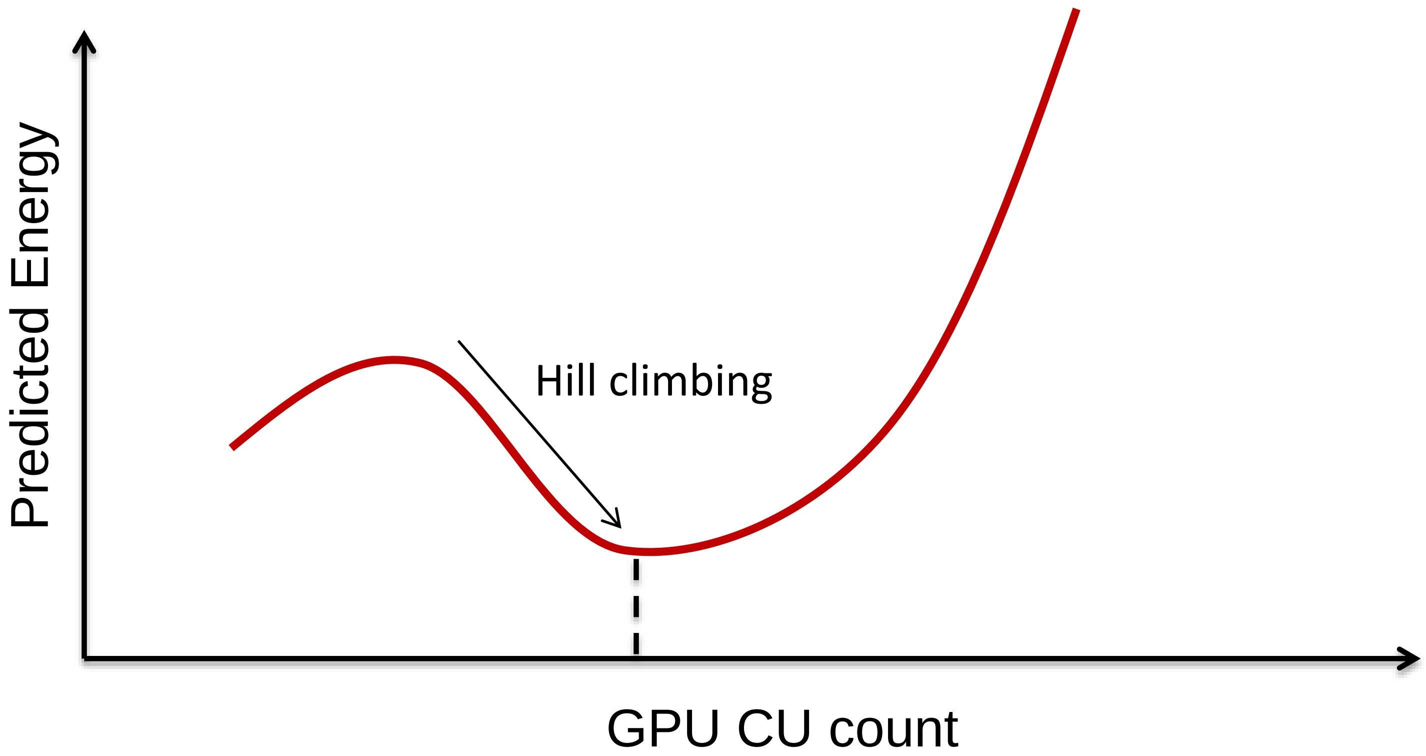

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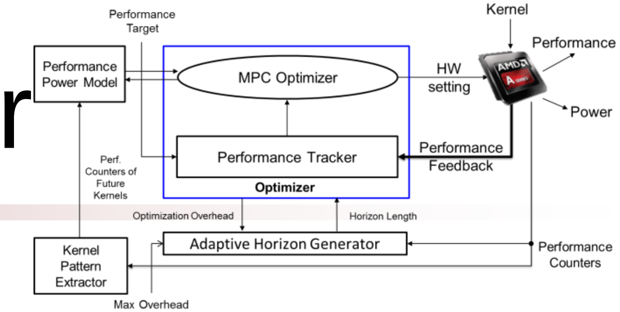

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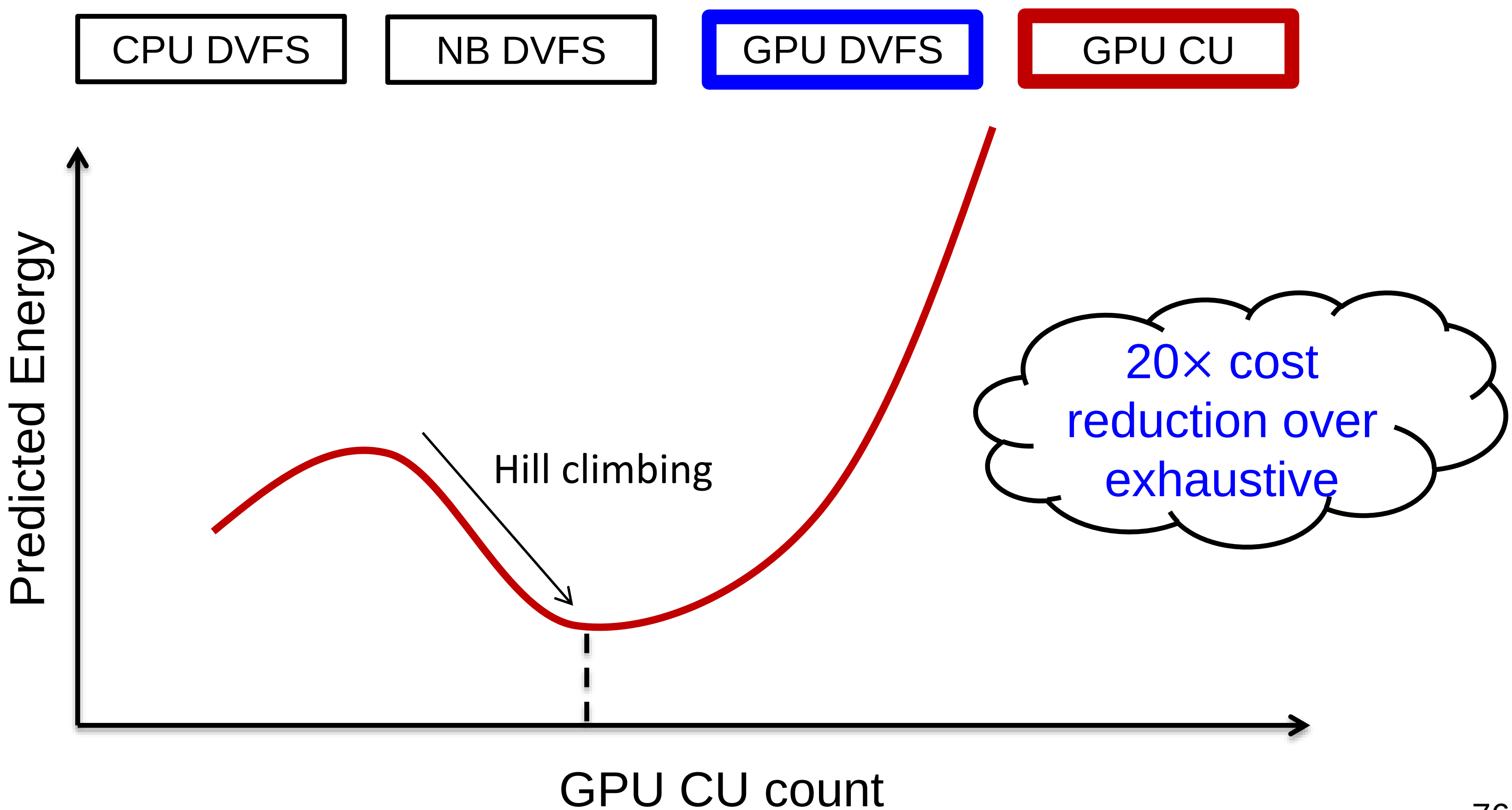

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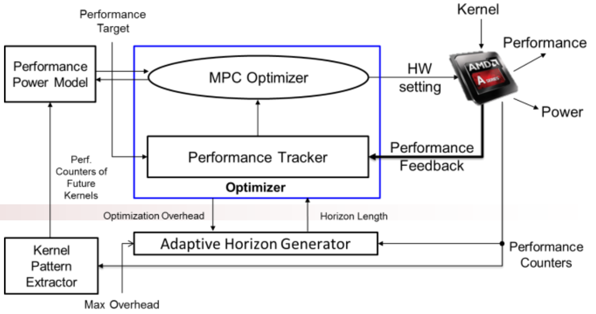

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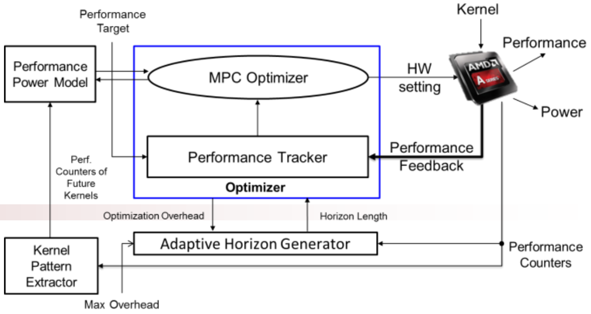

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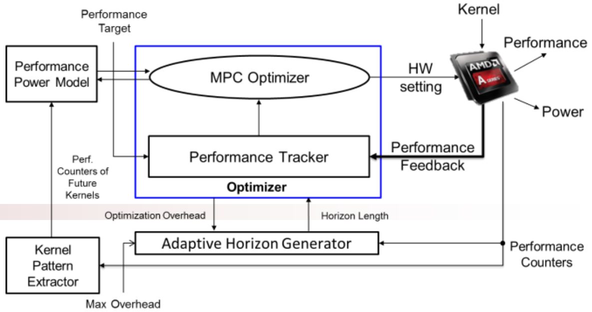

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  - General Idea
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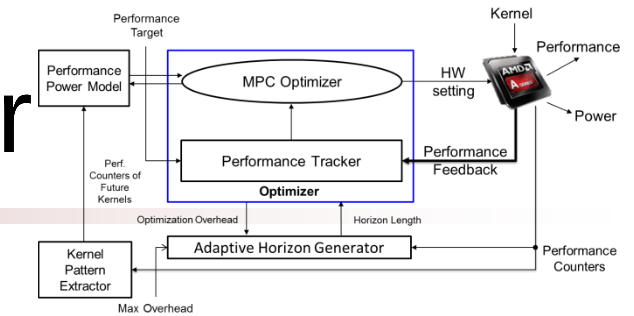
MPC Optimizer



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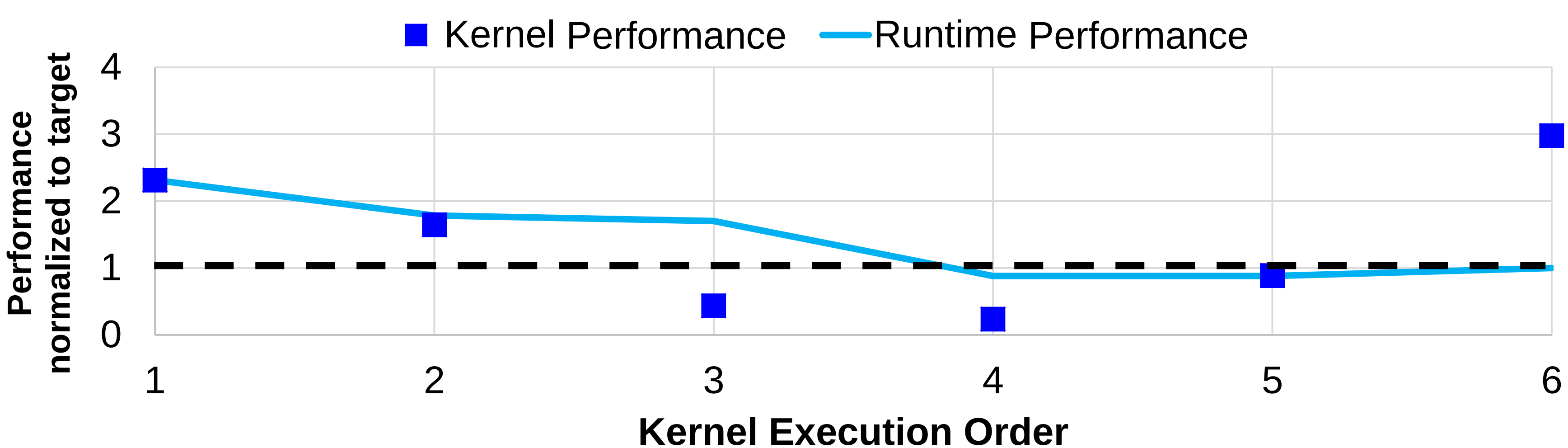

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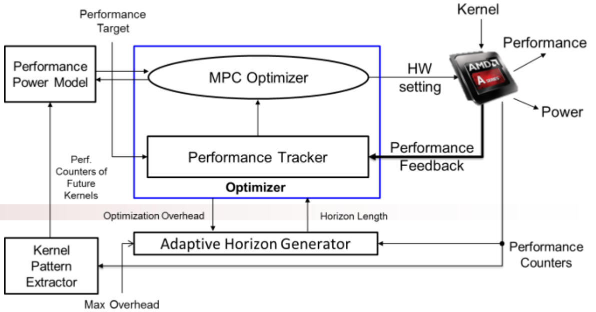

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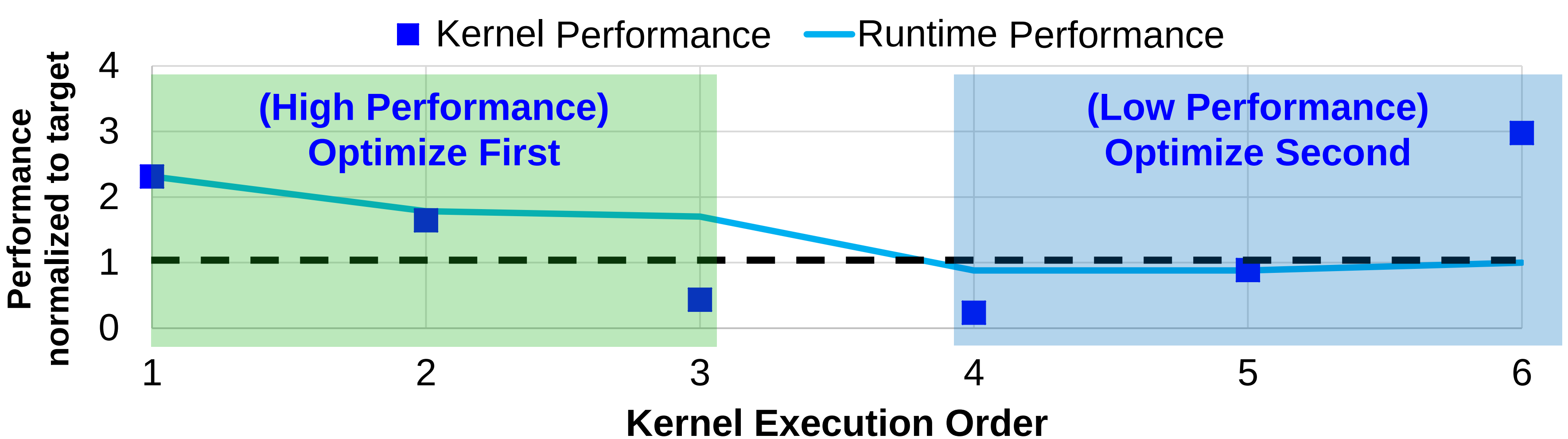

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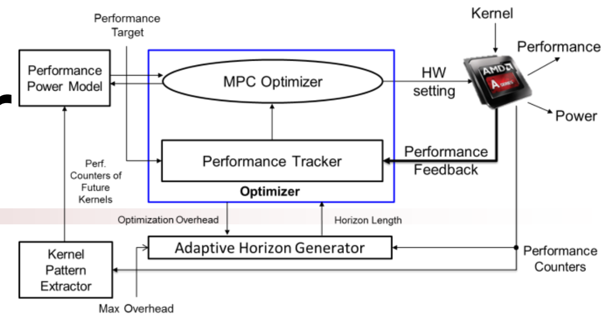

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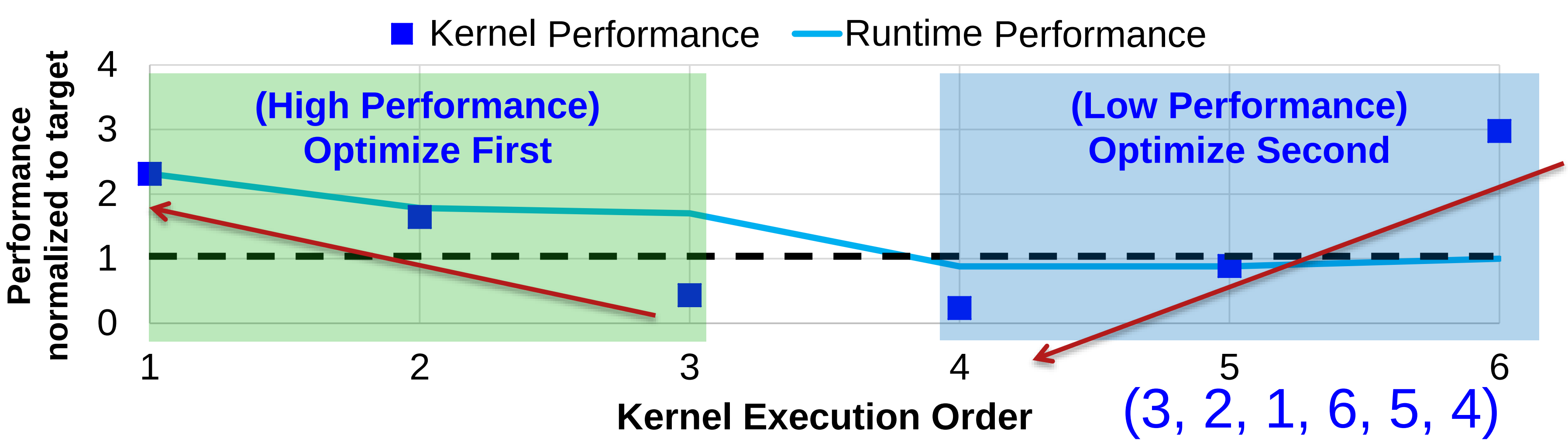

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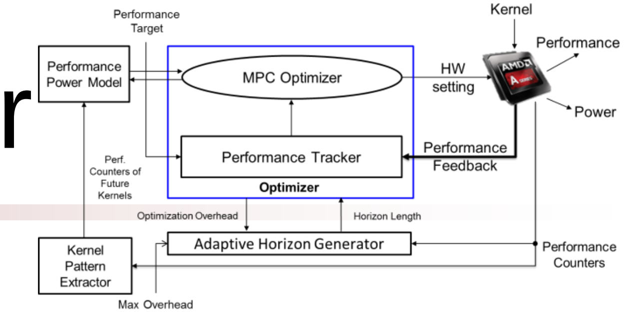

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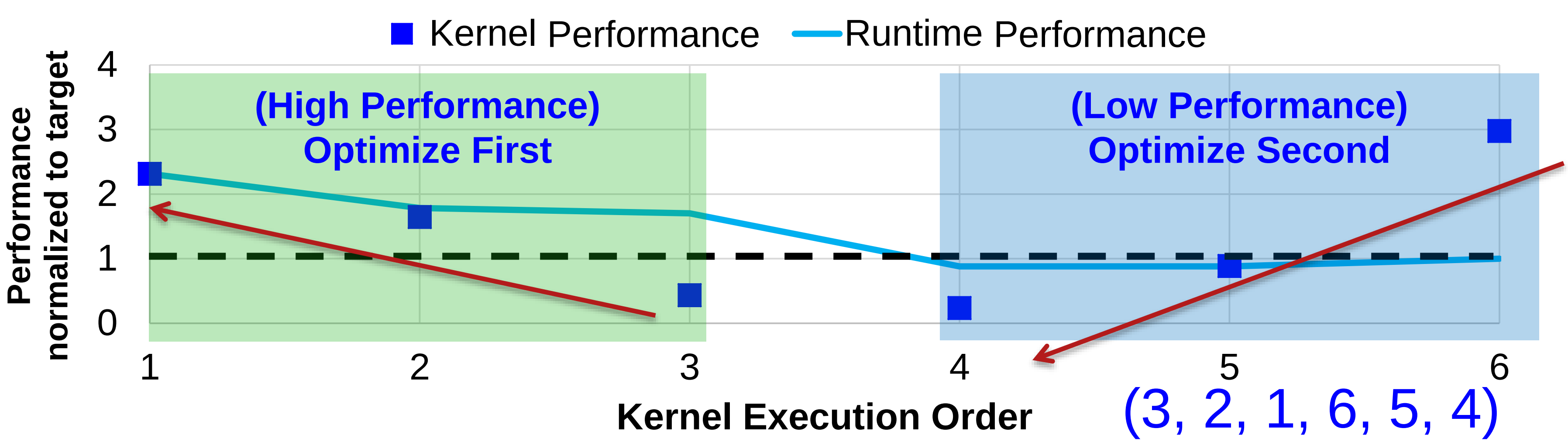
65× reduction in cost evaluation



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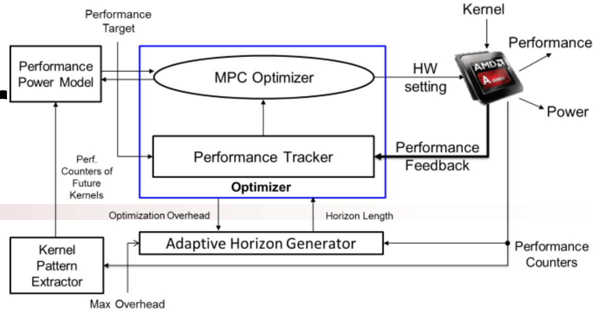

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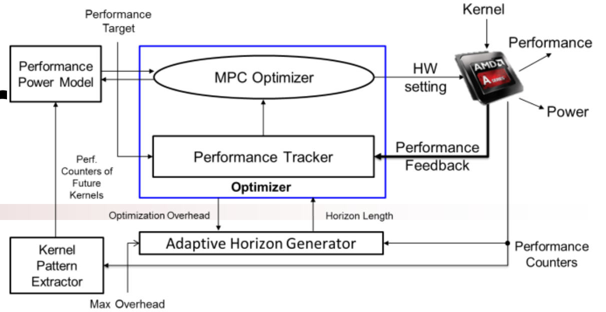

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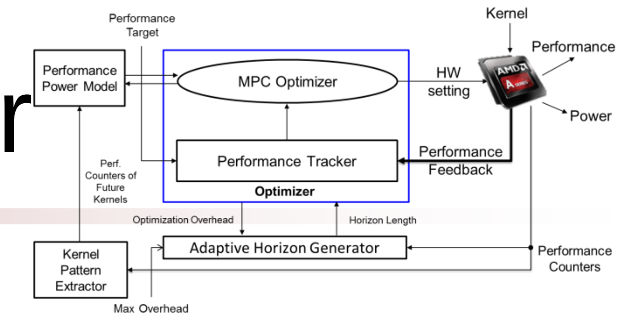

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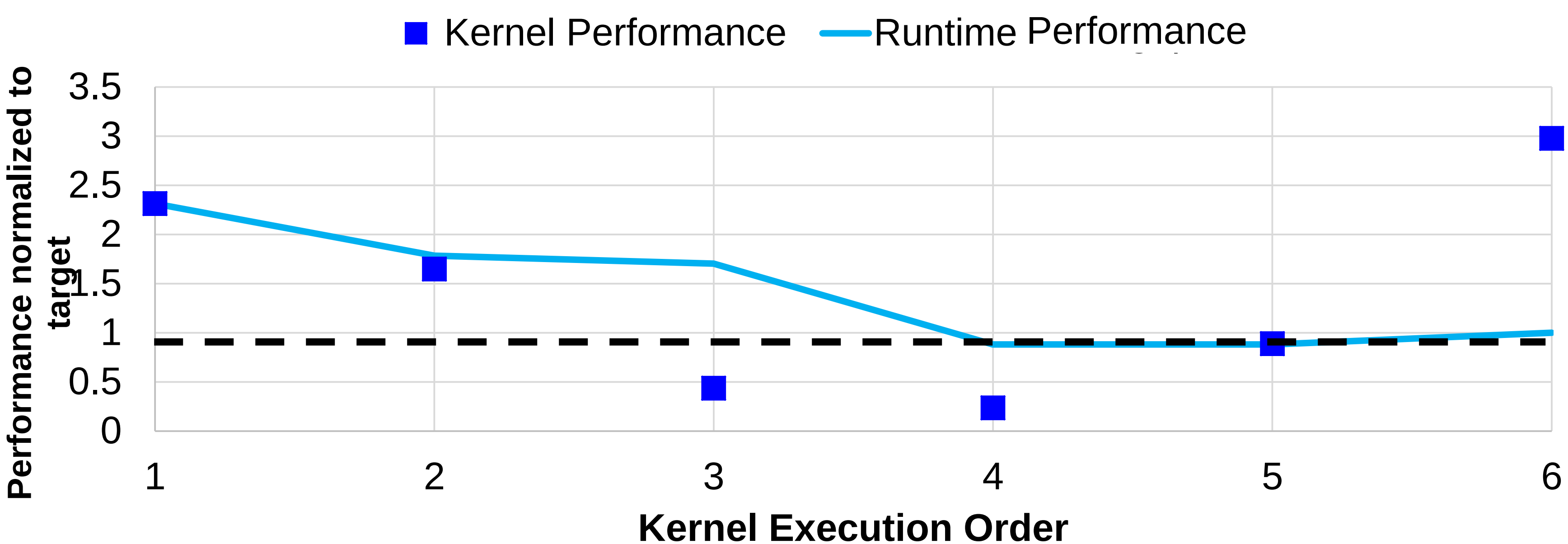

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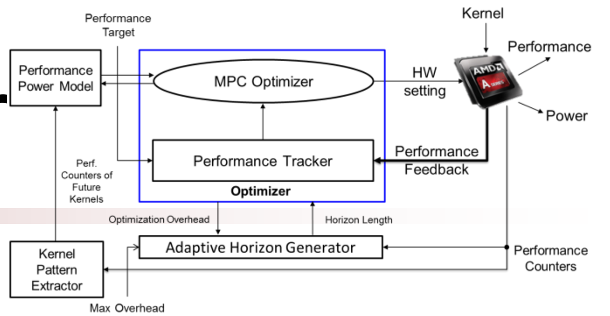

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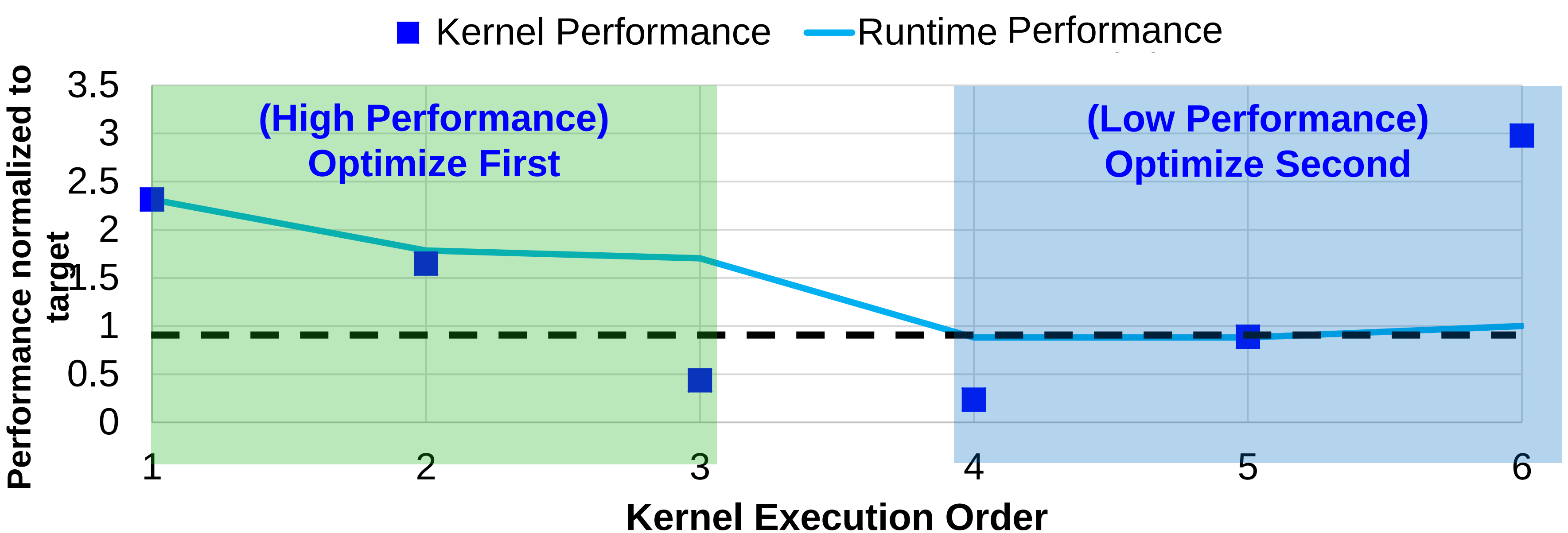
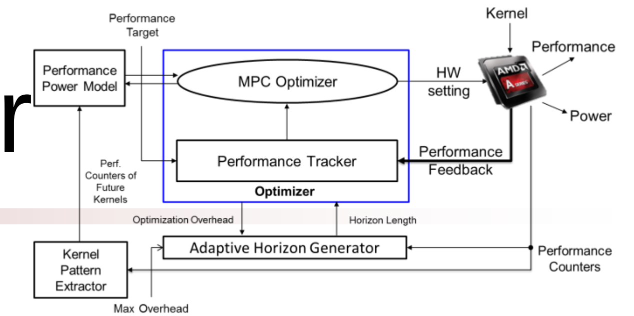


MPC Optimizer



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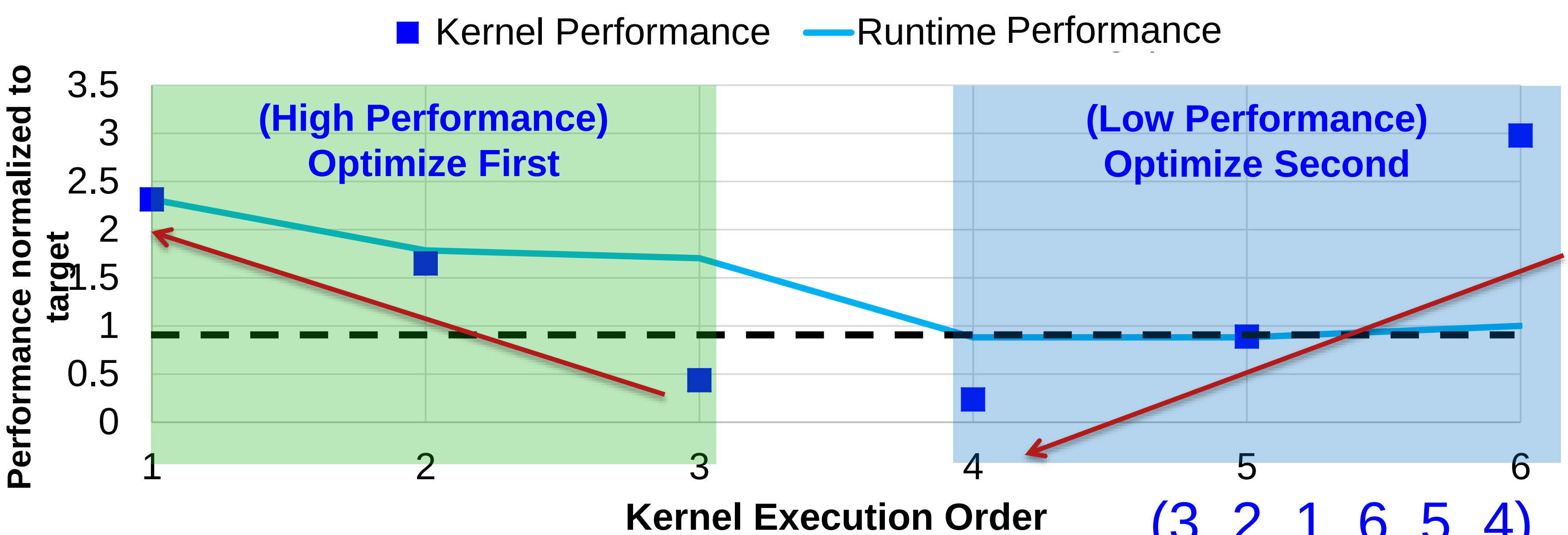
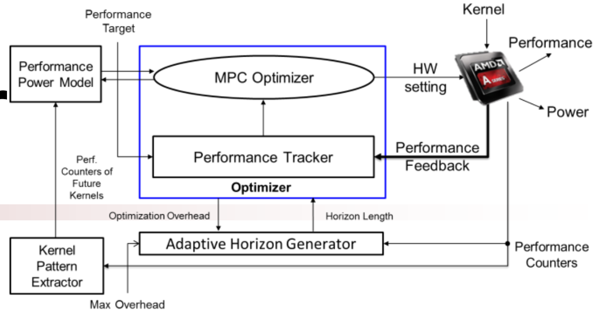


(3, 2, 1, 6, 5, 4)

MPC Optimizer



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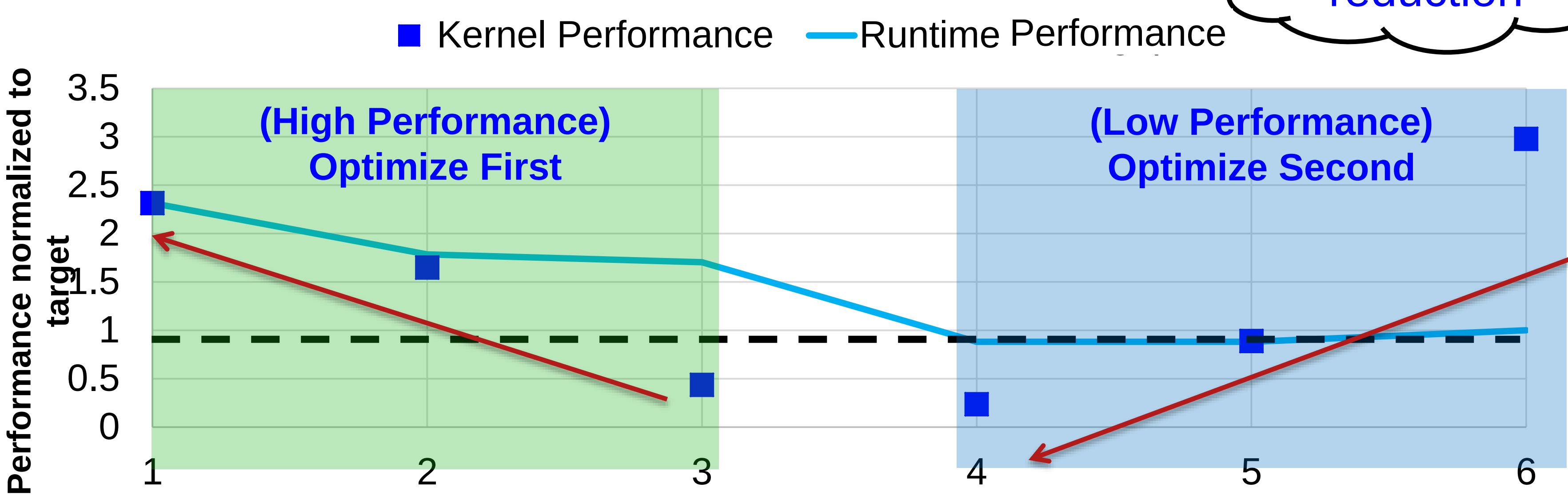
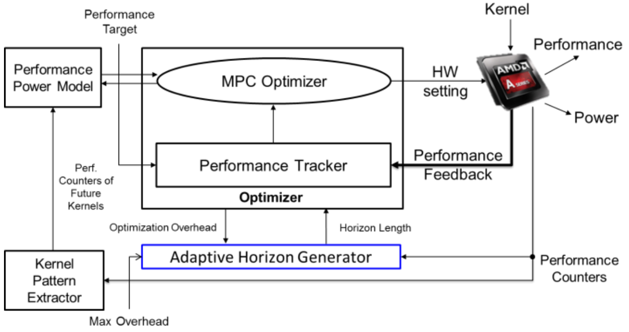
65× cost reduction



(3, 2, 1, 6, 5, 4)

Adaptive Horizon Generator

MPC runs between kernel invocations



Adaptive Horizon Generator

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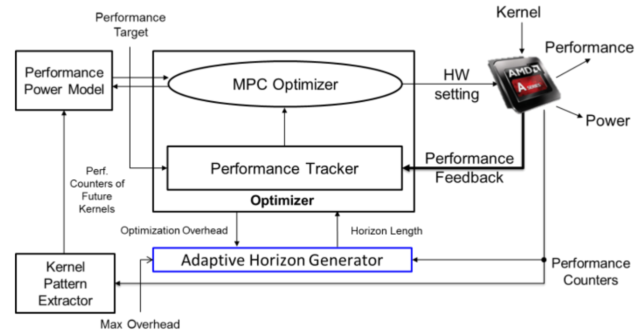
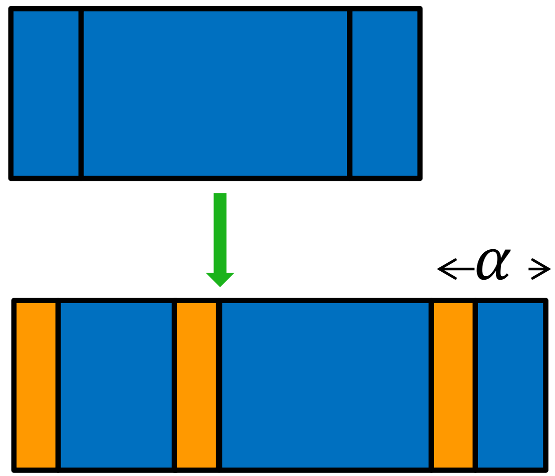


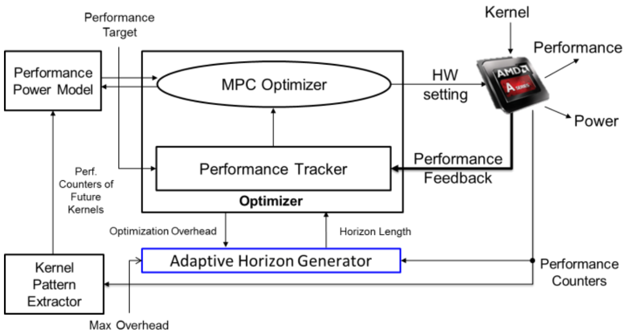


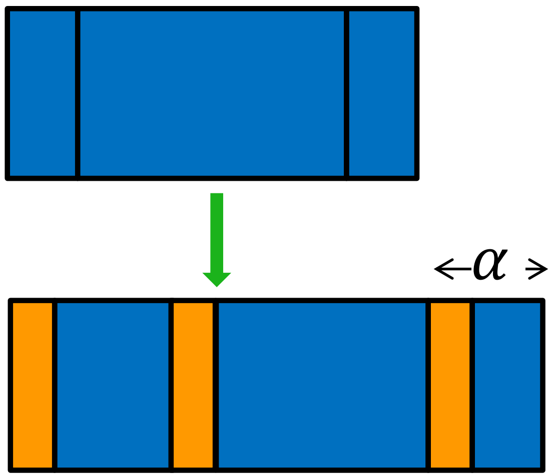
Kernels

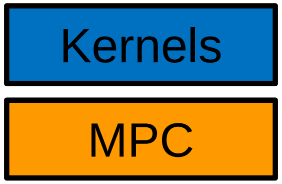
MPC

Adaptive Horizon Generator

MPC runs between kernel invocations

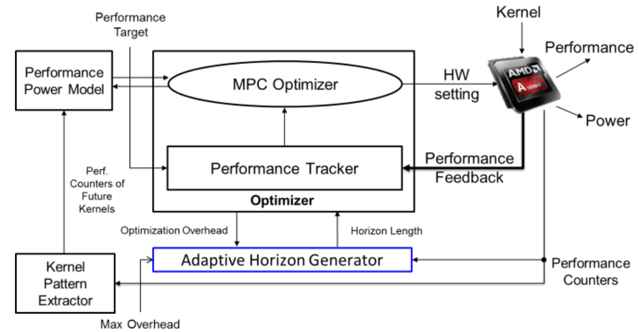




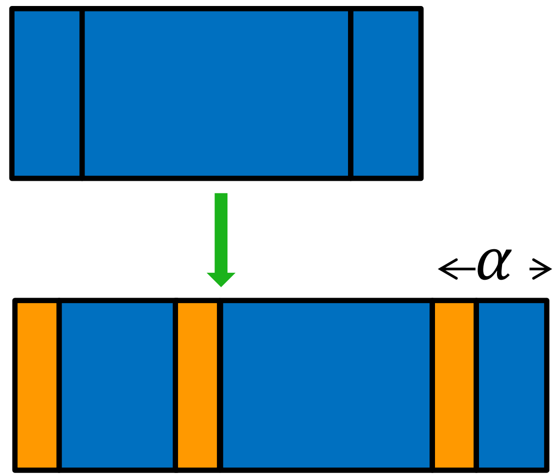


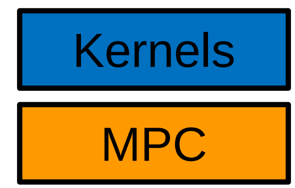
- Longer horizon increases MPC optimization time
- Limit the overhead α by dynamically varying the horizon length

Adaptive Horizon Generator



MPC runs between kernel invocations



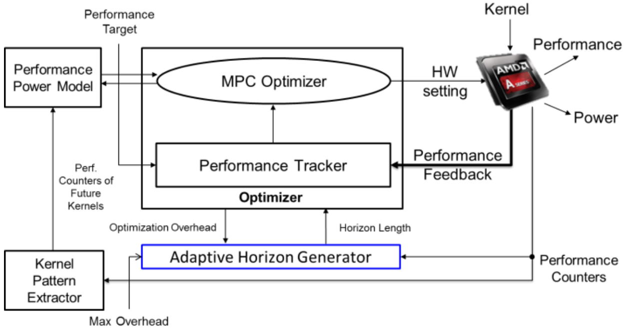


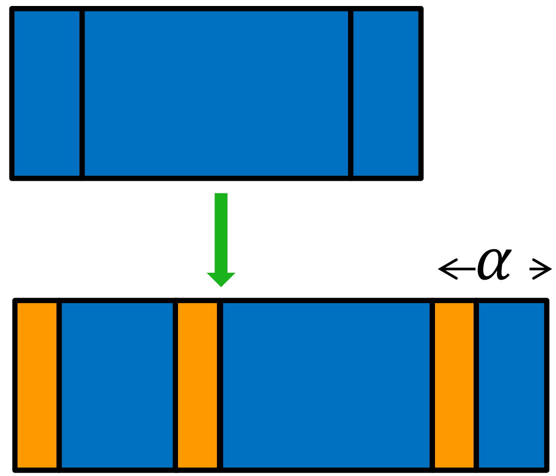
- Longer horizon increases MPC optimization time
- Limit the overhead α by dynamically varying the horizon length
- General Idea:

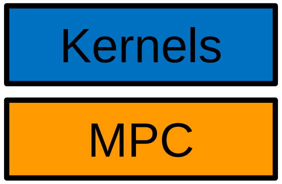
$$\frac{(Total\ Time\ of\ i-1\ kernels) + (Est.MPC\ Opt.\ Time) + (Est.Time\ of\ kernel\ i)}{Baseline\ Time\ of\ i\ kernels} \leq 1+\alpha$$

Adaptive Horizon Generator

MPC runs between kernel invocations







- Longer horizon increases MPC optimization time
- Limit the overhead α by dynamically varying the horizon length
- General Idea:

$$H_i \leq \frac{N}{N} \frac{\left(1+\alpha-\frac{1}{i}\right)\frac{i \times T_{total}}{N} - \sum_{j=1}^{i-1}\left(T_j + T_{MPC,j}\right)}{T_{PPK}}$$

Dynamic GPGPU Power Mgmt. Formulation

- Minimize energy over N GPU kernels such that the performance target is met

$$\min_{\vec{s}} \sum_{i=1}^{N} E_i(s_i)$$

such that

$$\frac{\sum_{i=1}^{N} I_i}{\sum_{i=1}^{N} T_i(s_i)} \geq \frac{I_{total}}{T_{total}}$$

$$s_i \in S \qquad \forall 1 \leq i \leq N$$

$$S = \overrightarrow{cpu} \times \overrightarrow{nb} \times \overrightarrow{gpu} \times \overrightarrow{cu}$$

Theoretically Optimal

- GLPK to solve the Integer Linear Programming (ILP) formulation

$$\min \sum_{i=1}^{N} \sum_{j \in S} E_i(j) X_{ij}$$

such that

$$\sum_{i=1}^{N} I_i - \frac{I_{total}}{T_{total}} \sum_{i=1}^{N} \sum_{j \in S} T_i(j) X_{ij} \geq 0$$

$$\sum_{j \in S} X_{ij} = 1 \qquad \forall\ 1 \leq i \leq N$$

$$X_{ij} \in \{0, 1\} \qquad 1 \leq i \leq N \text{ and } \forall j \in S$$

Predict Previous Kernel (PPK)

- Minimize energy of kernel i such that the runtime performance so far exceeds the target

$$\min_{s_i \in S} E_i(s_i)$$

such that

$$\frac{\sum_{j=1}^{i} I_j}{\sum_{j=1}^{i} T_j(s_j)} \geq \frac{I_{total}}{T_{total}} \qquad \forall 1 \leq i \leq N \text{ and } \forall s_j \in S$$

MPC-based GPGPU Power Manager

- Optimize energy for next H kernels such that the runtime performance at the end of H kernels exceeds the target

$$\min_{\vec{s}} \sum_{j=i}^{i+H-1} E_j(s_j)$$

such that

$$\frac{\sum_{j=1}^{i+H-1} I_j}{\sum_{j=1}^{i+H-1} T_j(s_j)} \geq \frac{I_{total}}{T_{total}} \qquad \forall 1 \leq i \leq N \text{ and } \forall s_j \in S$$

Runtime Performance Tracker

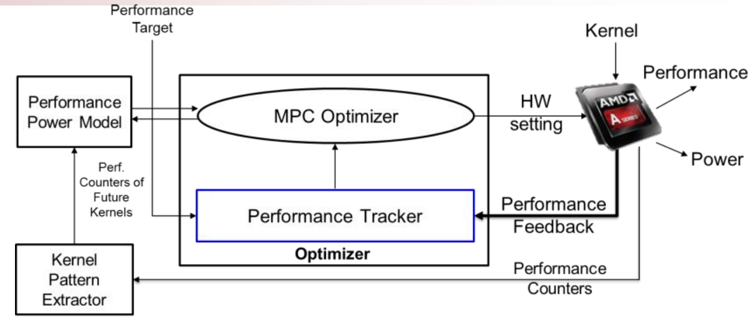
- Performance requirement of kernel, k, is enforced as follows:

$$\frac{\sum_{j=1}^{k-1} I_j + \mathbb{E}[I_k]}{\sum_{j=1}^{k-1} T_j(s_j) + \mathbb{E}[T_k(s_k)]} \geq \frac{I_{total}}{T_{total}}$$

- Kernel time headroom is updated according to:

$$\mathbb{E}[T_k(s_k)] \leq \left(\sum_{j=1}^{k-1} I_j + \mathbb{E}[I_k]\right) \Bigg/ \left(\frac{I_{total}}{T_{total}}\right) - \sum_{j=1}^{k-1} T_j(s_j)$$

Feedback-based Performance Tracker



Performance met previously?

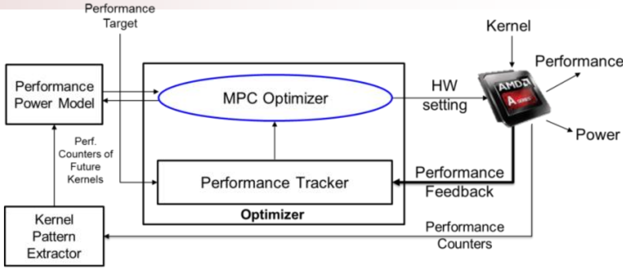
No

Relax optimization
Spend energy
↓
Reduce performance loss

Yes

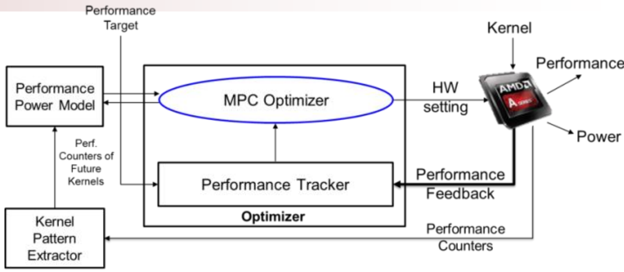
Optimize Aggressively
Reduce energy
↓
Avoid performance loss

MPC Optimizer

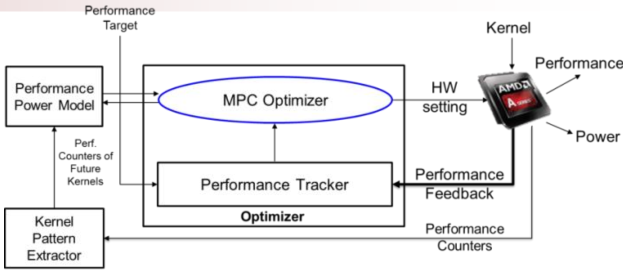


MPC Optimizer

- **Greedy Hill Climbing optimization**
  - Select the HW knob with highest energy sensitivity and search for low energy configuration using hill climbing



MPC Optimizer



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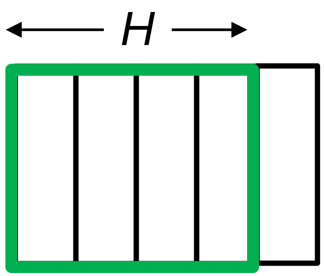
  - Determine a static order requiring no backtracking
  - General Idea
    - High to low performance (e.g. Spmv): Optimize low performing kernels first
    - Low to high performance (e.g. Kmeans): Optimize high performing kernels first
  - Search cost becomes polynomial

- 65X average reduction in total cost evaluations

An Example

- Search order = (2, 1, 4, 5, 3)



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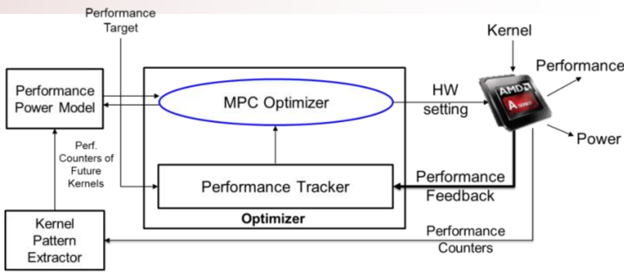

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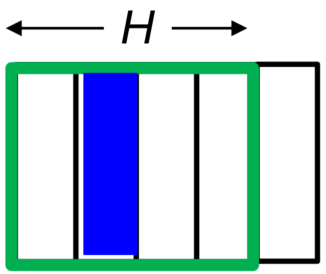

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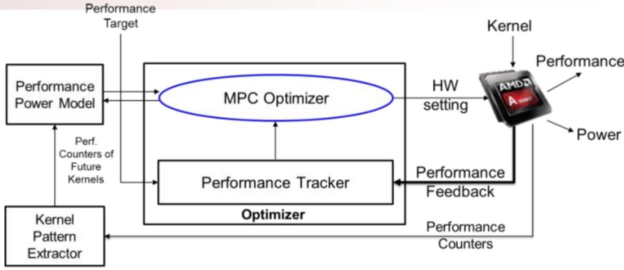

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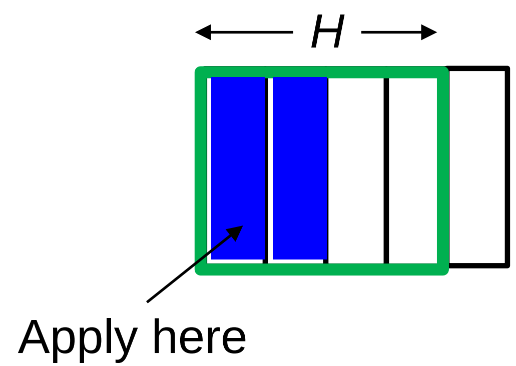
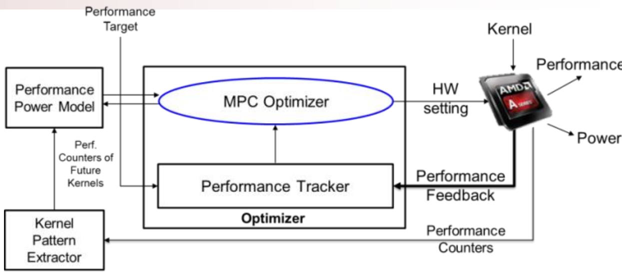


MPC Optimizer

- Greedy hill climbing optimization
  - **Greedy**: Select the HW knob with highest energy sensitivity
  - **Hill Climbing**: Continue finding low energy configuration (within perf target), and stop
  - Reduces search cost by 20X



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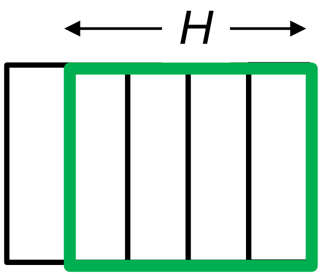

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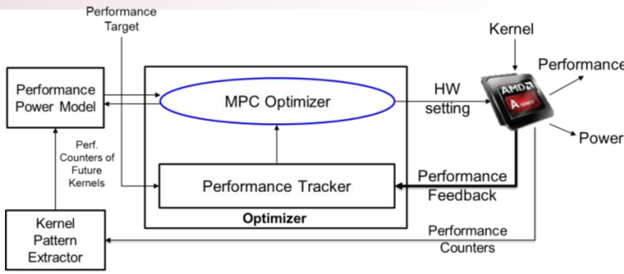

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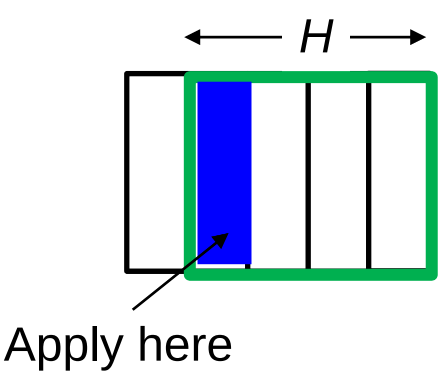

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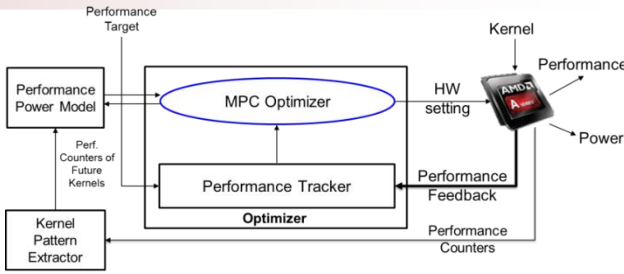

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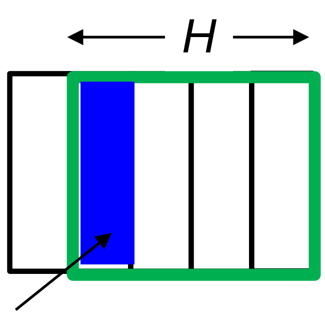
  - Search becomes polynomial
- Average reduction in total cost evaluations: 65X



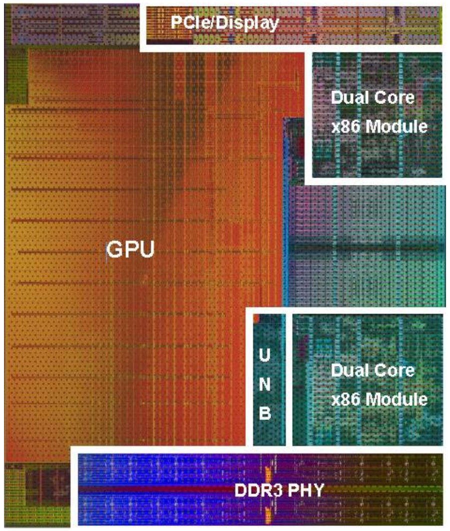
Apply here

GPGPU Benchmarks

Category	Benchmarks	Benchmark Suite	Regular Expression
Regular	mandelbulbGPU	Phoronix	A^{20}
	Nbody	AMD APP SDK	A^{10}
	juliaGPU	Phoronix	A^{10}
Irregular with repetitive pattern	EigenValue	AMD APP SDK	$(AB)^{5}$
	XSBench	Exascale	$(ABC)^{2}$
Irregular with non-repetitive pattern	Spmv	SHOC	$A^{10}B^{10}C^{10}$
	Kmeans	Rodinia	AB^{20}
Irregular with kernels varying with input	swat	OpenDwarfs	Complex pattern
	color	Pannotia	
	pb-bfs	Parboil	
	mis	Pannotia	
	srad	Rodinia	
	lulesh	Exascale	
	lud	Rodinia	
	hybridsort	Rodinia	

Experimental Testbed (Detailed)

- AMD A10-7850K APU
  - 2 out-of-order dual core CPUs
  - GPU contains 512 processing elements (8 CUs) at 720 MHz
    - Each CU has 4 SIMD Vector Units
    - 16 PEs per SIMD vector unit



- DVFS states

CPU P States	Voltage (V)	Freq (GHz)
P1	1.325	3.9
P2	1.3125	3.8
P3	1.2625	3.7
P4	1.225	3.5
P5	1.0625	3
P6	0.975	2.4
P7	0.8875	1.7

NB and GPU share the same voltage rail

NB P States	Freq (GHz)	Memory Freq (MHz)
NB0	1.8	800
NB1	1.6	800
NB2	1.4	800
NB3	1.1	333

GPU P States	Voltage (V)	Freq (GHz)
DPM0	0.95	351
DPM1	1.05	450
DPM2	1.125	553
DPM3	1.1875	654
DPM4	1.225	720

- GPU CUs and DVFS states changed in multiples of 2
- Total HW configuration: 336

Experimental Setup

- **15 GPGPU Benchmarks**
  - Sampled from 73 benchmarks
  - 75% irregular
  - 44% vary with input

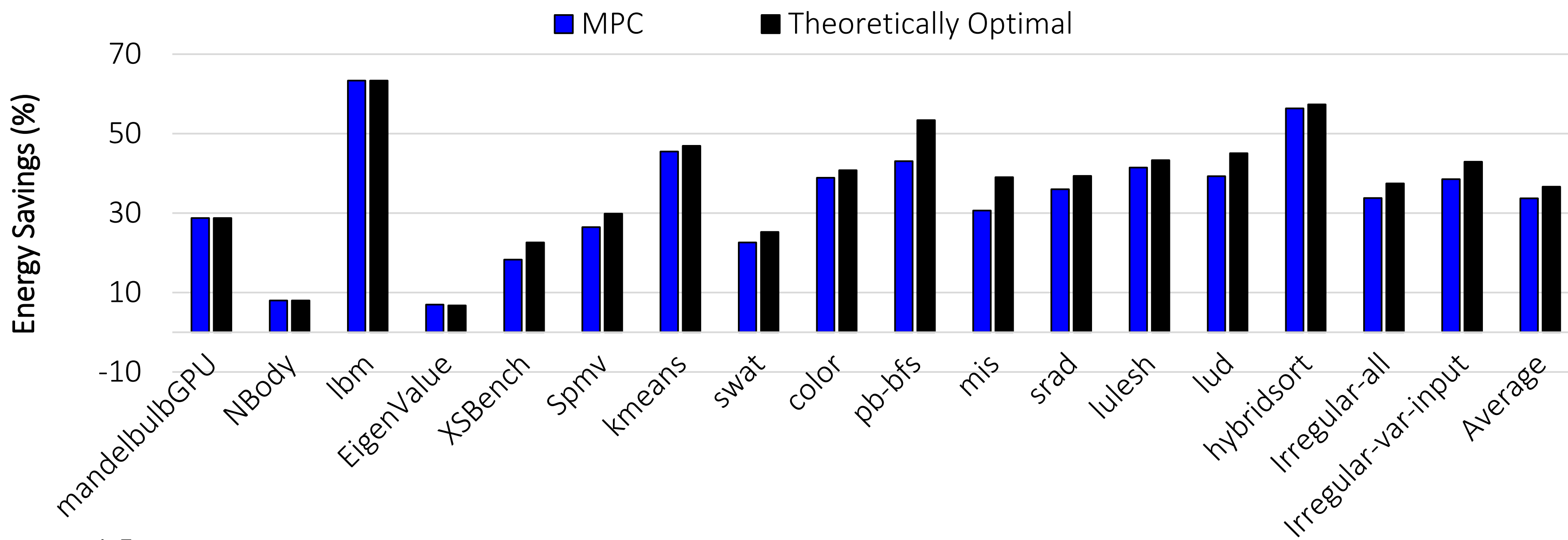
Category	Benchmarks	Benchmark Suite	Regular Expression
Regular	mandelbulbGPU	Phoronix	A^{20}
	Nbody	AMD APP SDK	A^{10}
	juliaGPU	Phoronix	A^{10}
Irregular with repetitive pattern	EigenValue	AMD APP SDK	$(AB)^{5}$
	XSBench	Exascale	$(ABC)^{2}$
Irregular with non-repetitive pattern	Spmv	SHOC	$A^{10}B^{10}C^{10}$
	Kmeans	Rodinia	AB^{20}
Irregular with kernels varying with input	swat	OpenDwarfs	Complex pattern
	color	Pannotia	
	pb-bfs	Parboil	
	mis	Pannotia	
	srad	Rodinia	
	lulesh	Exascale	
	lud	Rodinia	
	hybridsort	Rodinia	

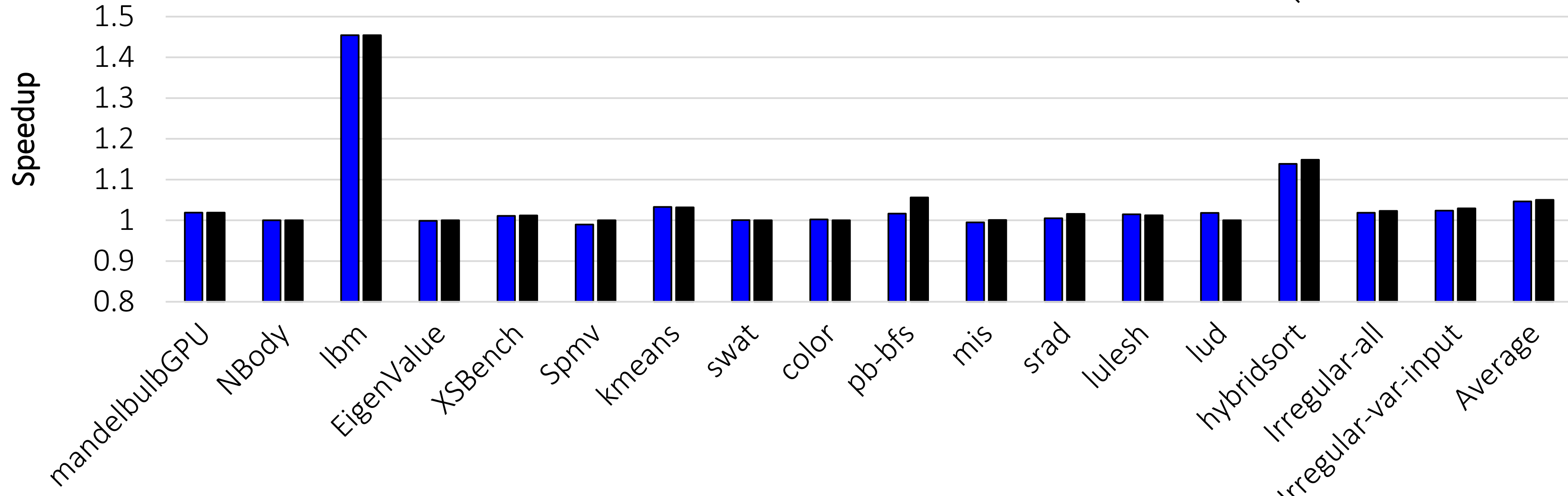
- **Baseline scheme**
  - AMD Turbo Core

- **Algorithms**
  - PPK
  - MPC
  - TO

- **Results based on real hardware traces**

Polynomial MPC w/ Theoretical Optimal





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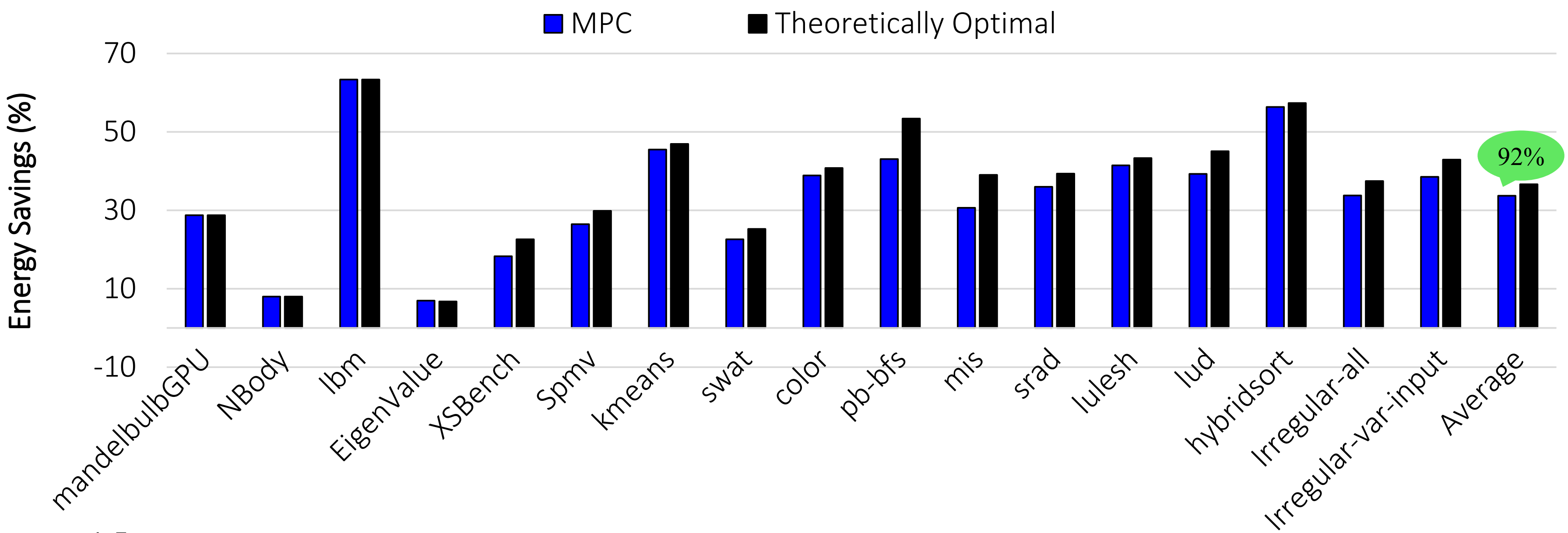
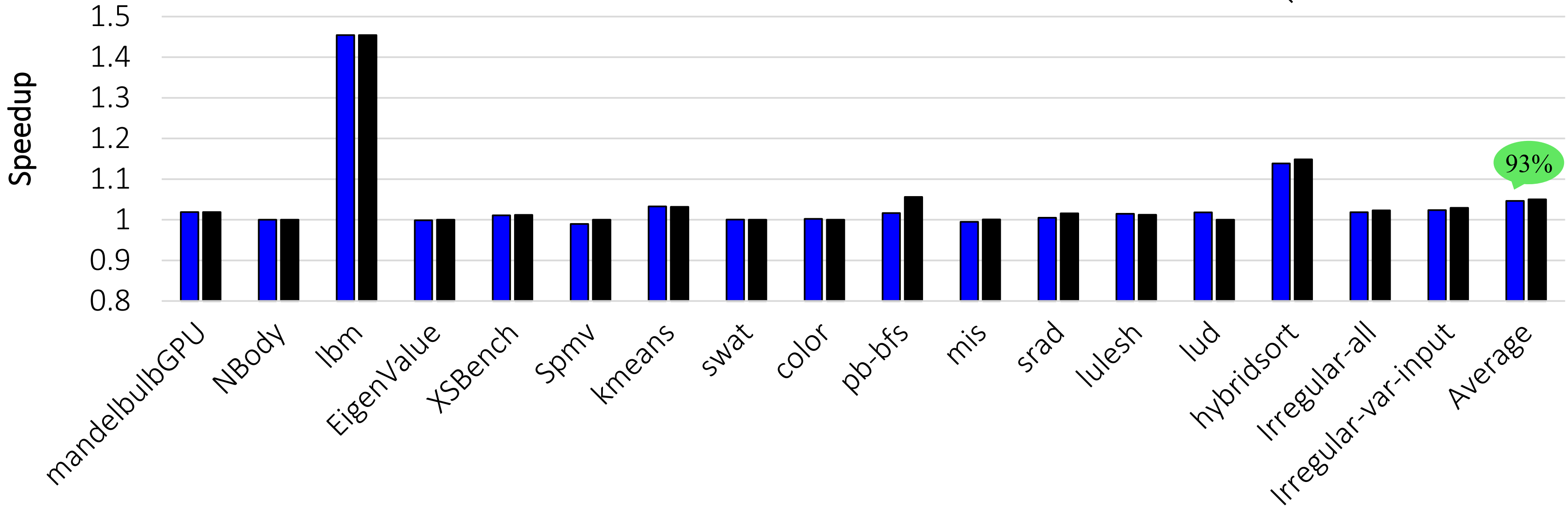
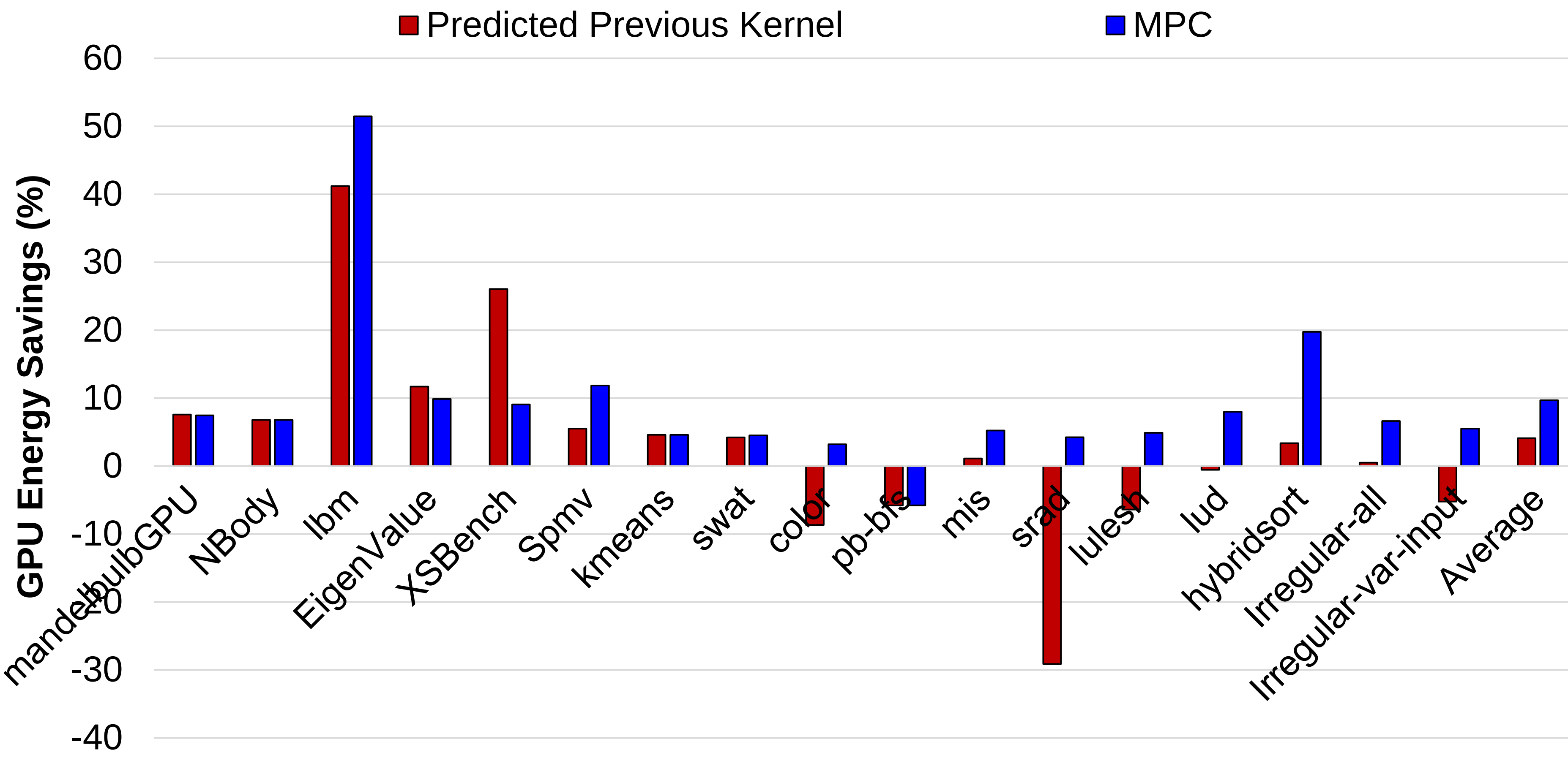
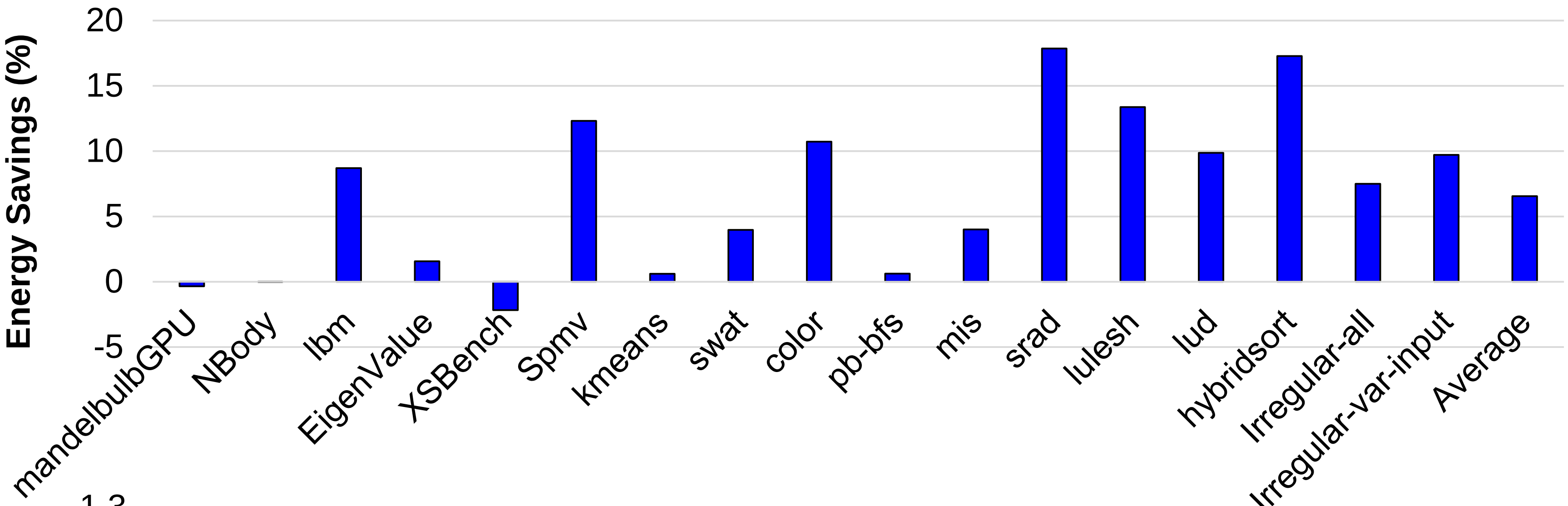


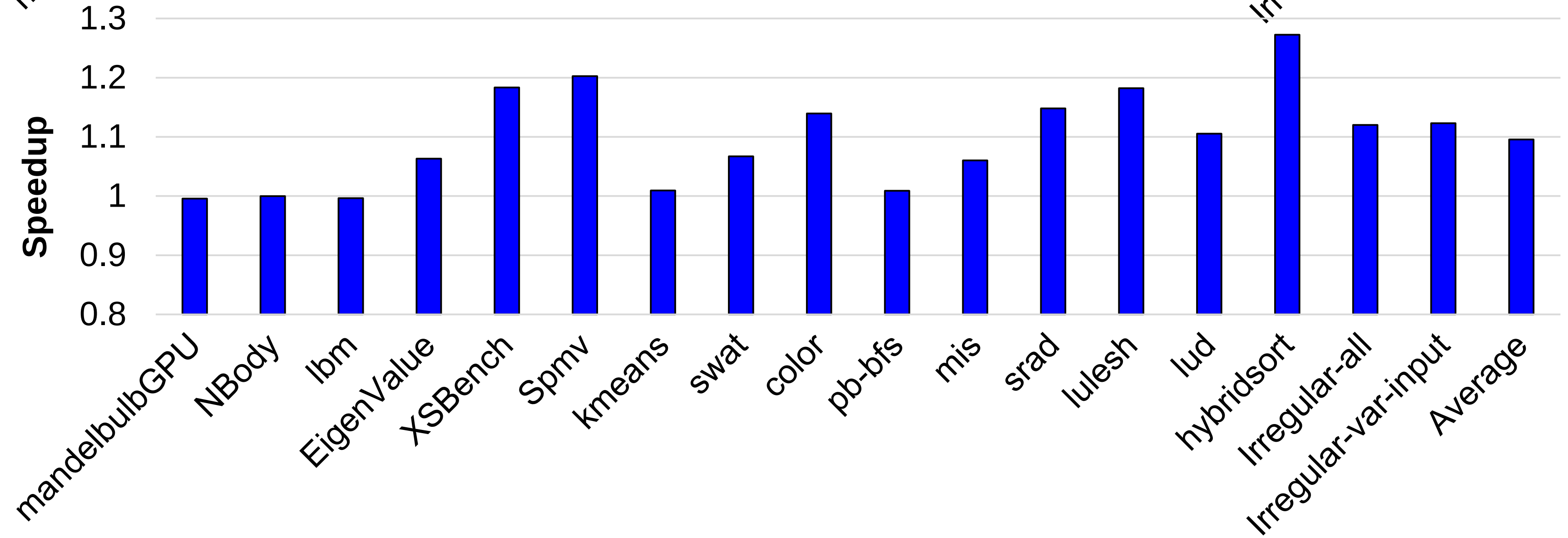


GPU Energy Savings

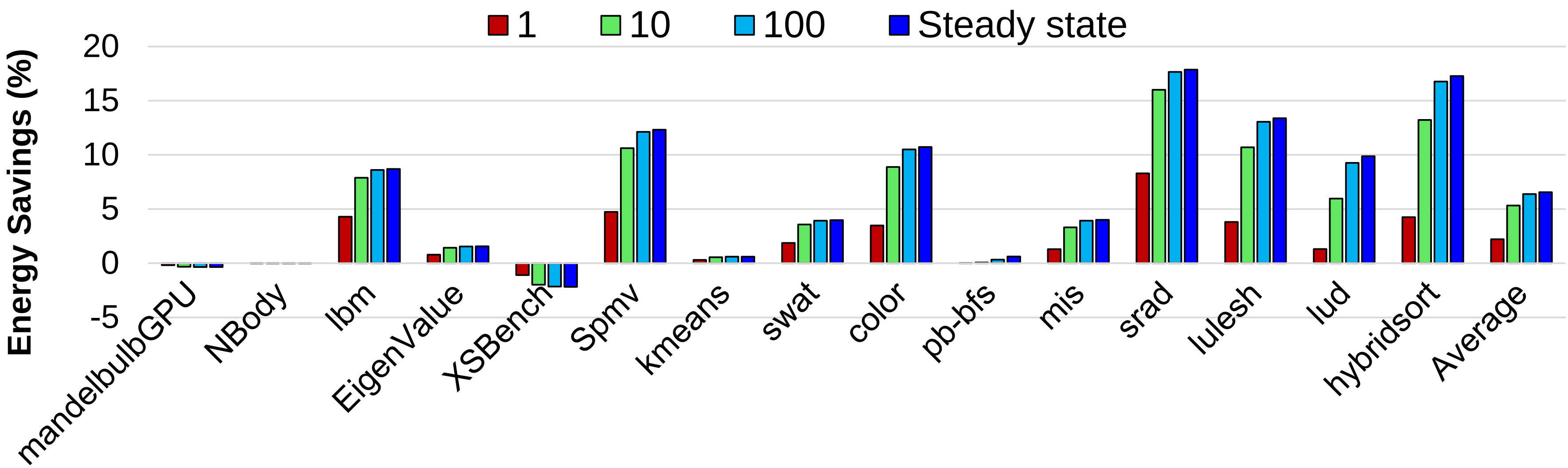


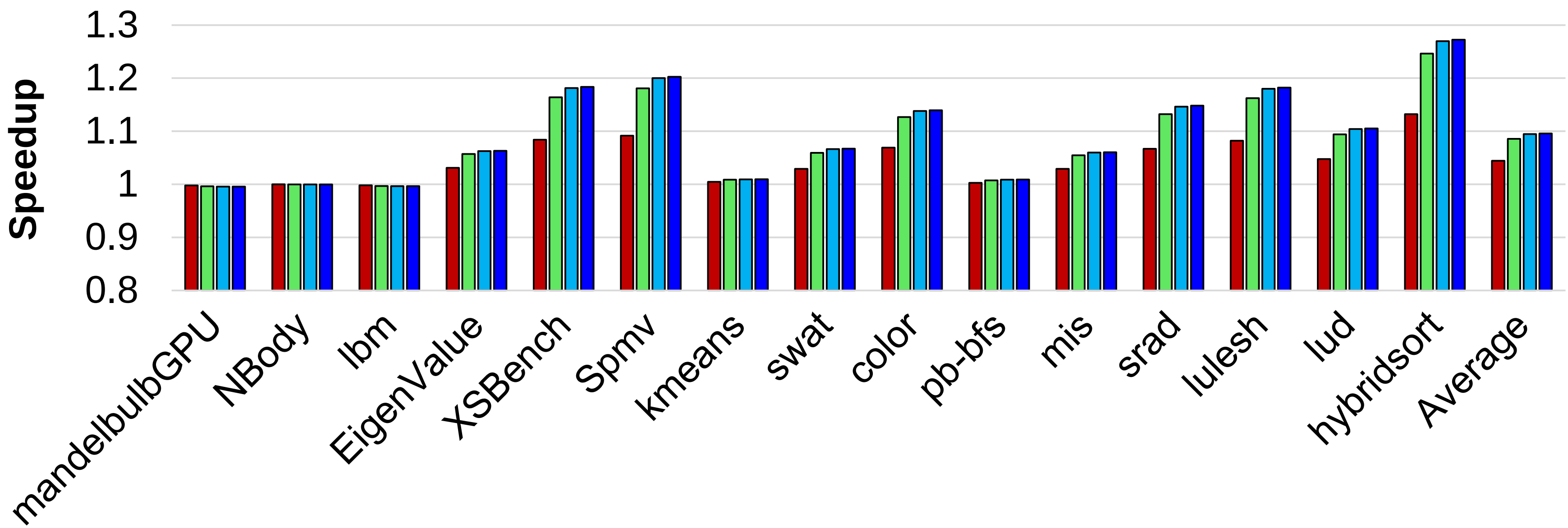
MPC Energy-Performance w.r.t PPK





Amortization of Initial Loses





Final Takeaway

- MPC is a versatile scheme
  - Does not hurt gains of regular benchmarks
  - Improves energy savings
  - Reduces performance loss
- Online MPC reduces performance loss compared to traditional approaches
- Online MPC is resilient to prediction inaccuracy due to
  - Performance feedback
  - MPC's greedy and heuristic approximations depend minimally on prediction models