Kubernetes on EDGE DAY

NORTH AMERICA

Edge DC Energy Efficiency:
A K8s Workload Allocation Optimizer with Generic Server Power Model

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NORTH AMERICA

Agenda

- Background
- Power Saving from the Server operation
  - Workload Allocation Optimizer (WAO on Kubernetes)
- Experimental result (performance of power saving)
  - test-bed data center with over 200 servers
- Conclusion

Who are we:

NEDO New Energy and Industrial Technology Development Organization

OPEN INNOVATION

Neutrix Cloud™ Japan

impress

NEC

大阪大学 OSAKA UNIVERSITY

Edge-Cloud Computing Orchestration Consortium

bitmedia

CISCO

OPTAGE

ISI 篠原電機株式会社

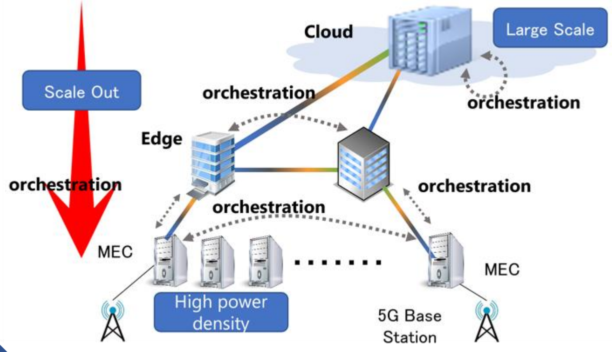
ADVANCED KNOWLEDGE LABORATORY

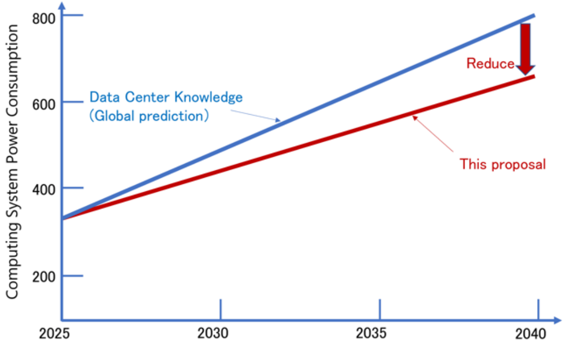
支援団体

JDCC 日本データセンター協会 Japan Data Center Council

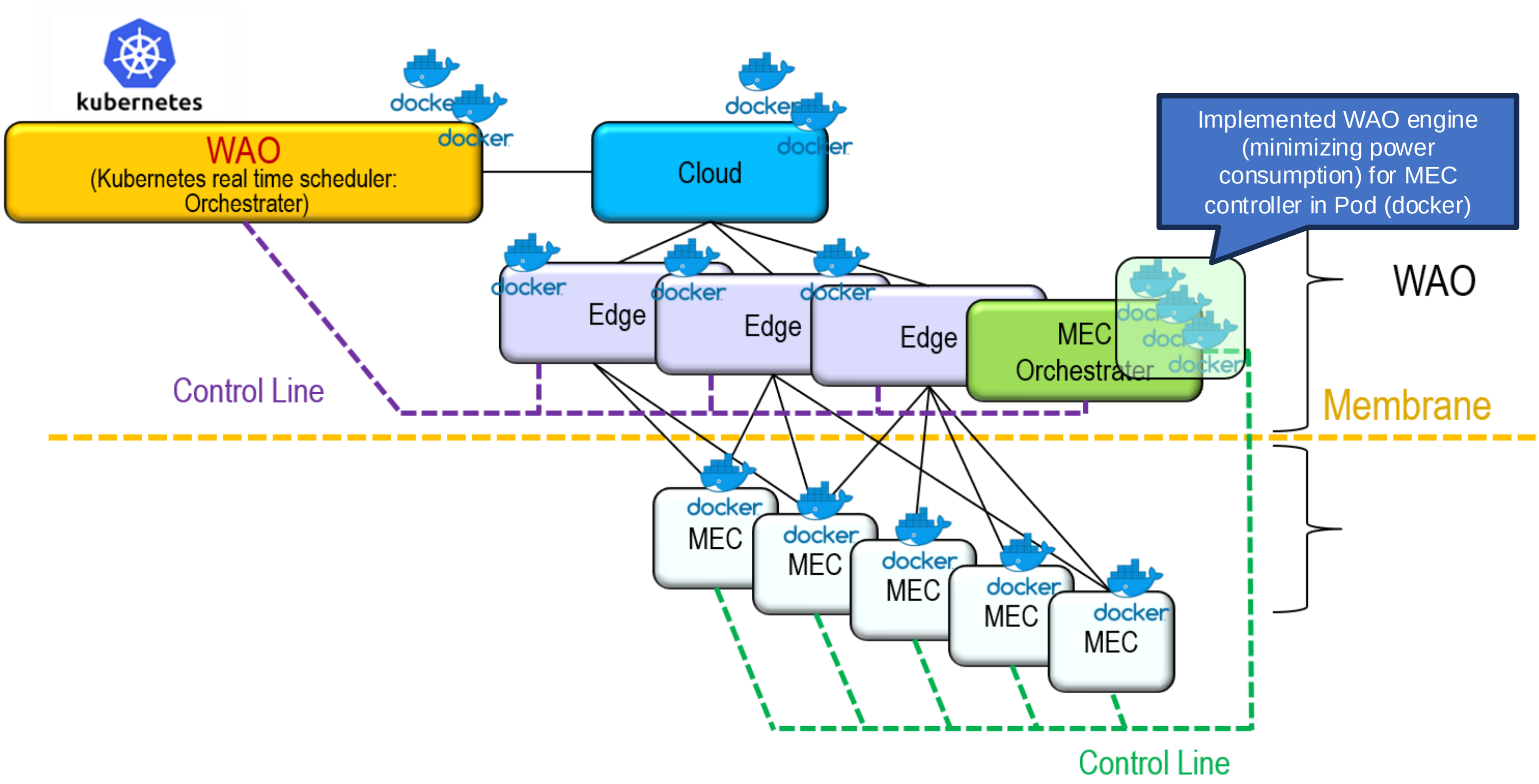
支援団体

JADOG Japan Datacenter Operators' Group



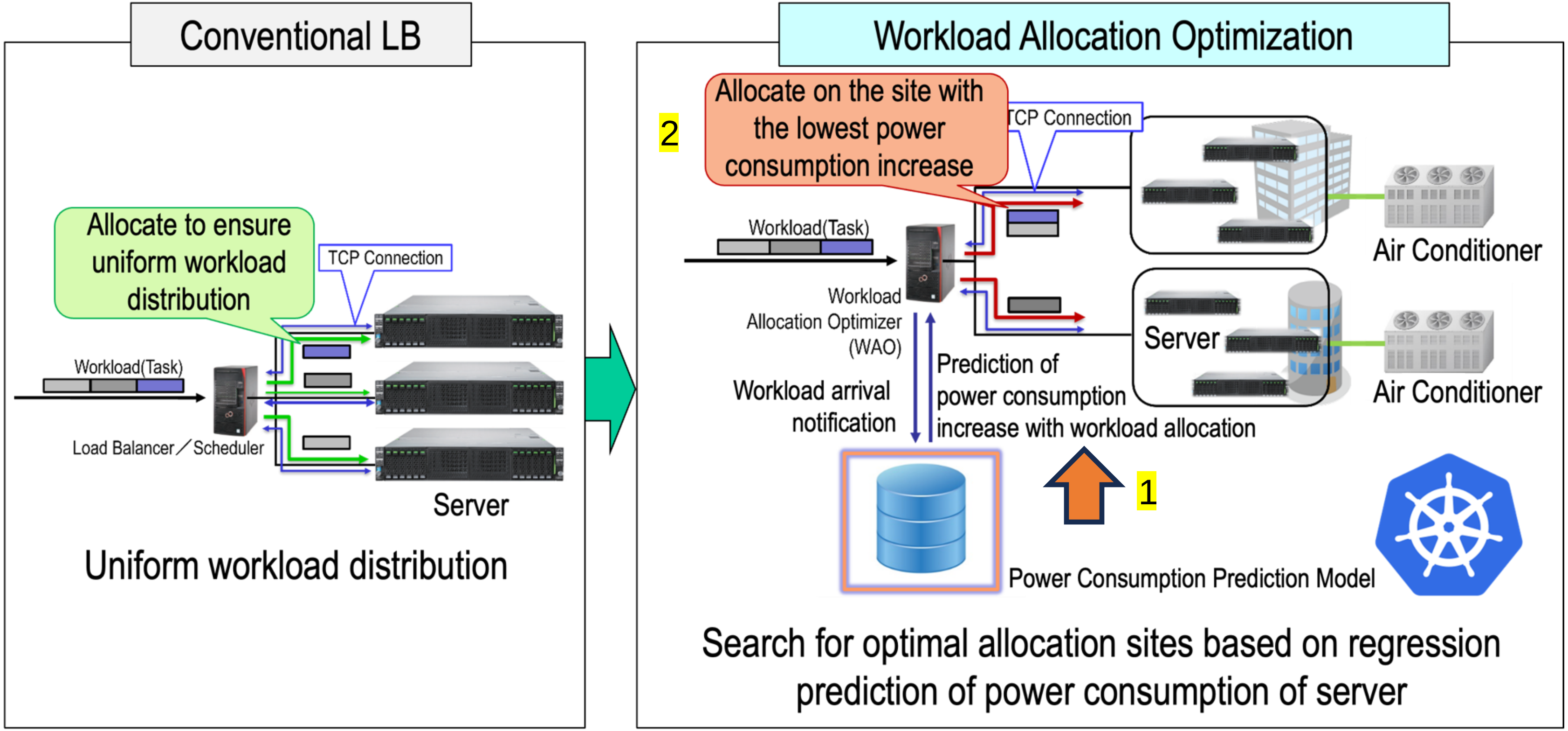


Architecture:
Data center power using Kubernetes orchestration

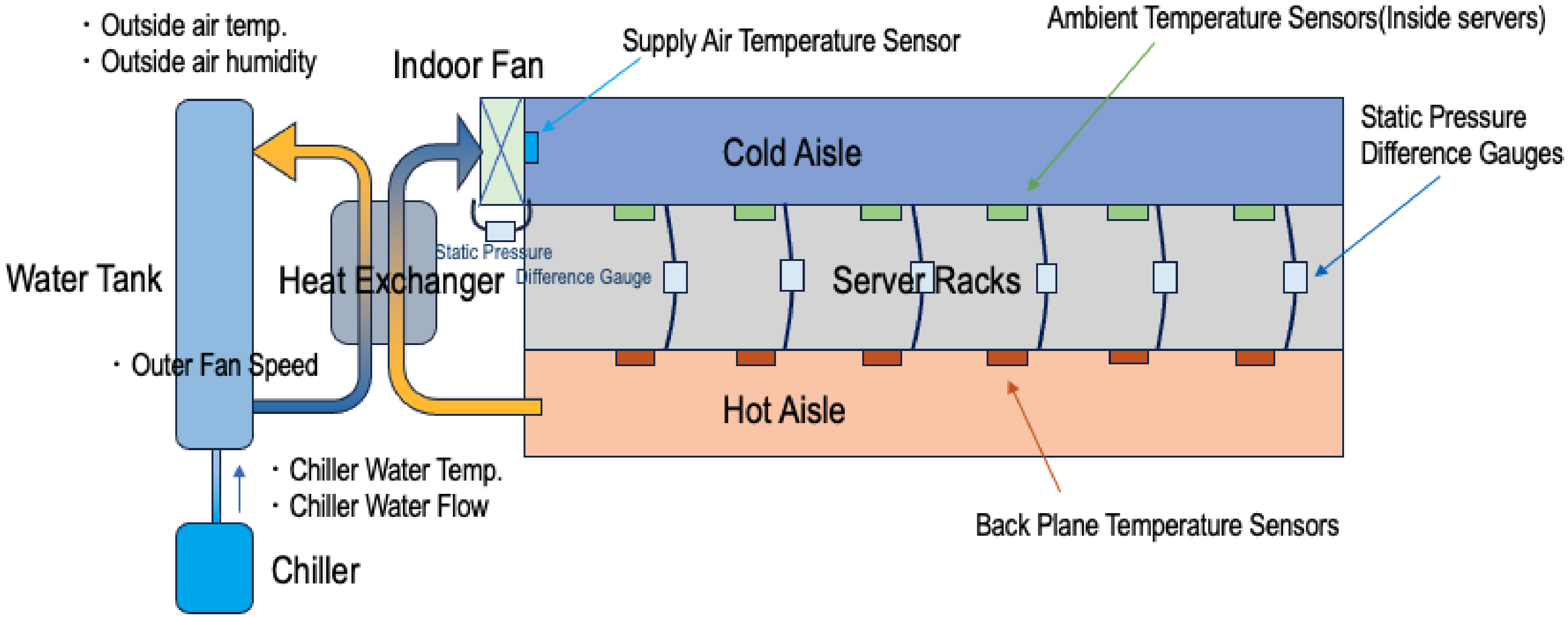


Approach 1: Power Saving from the Server operation

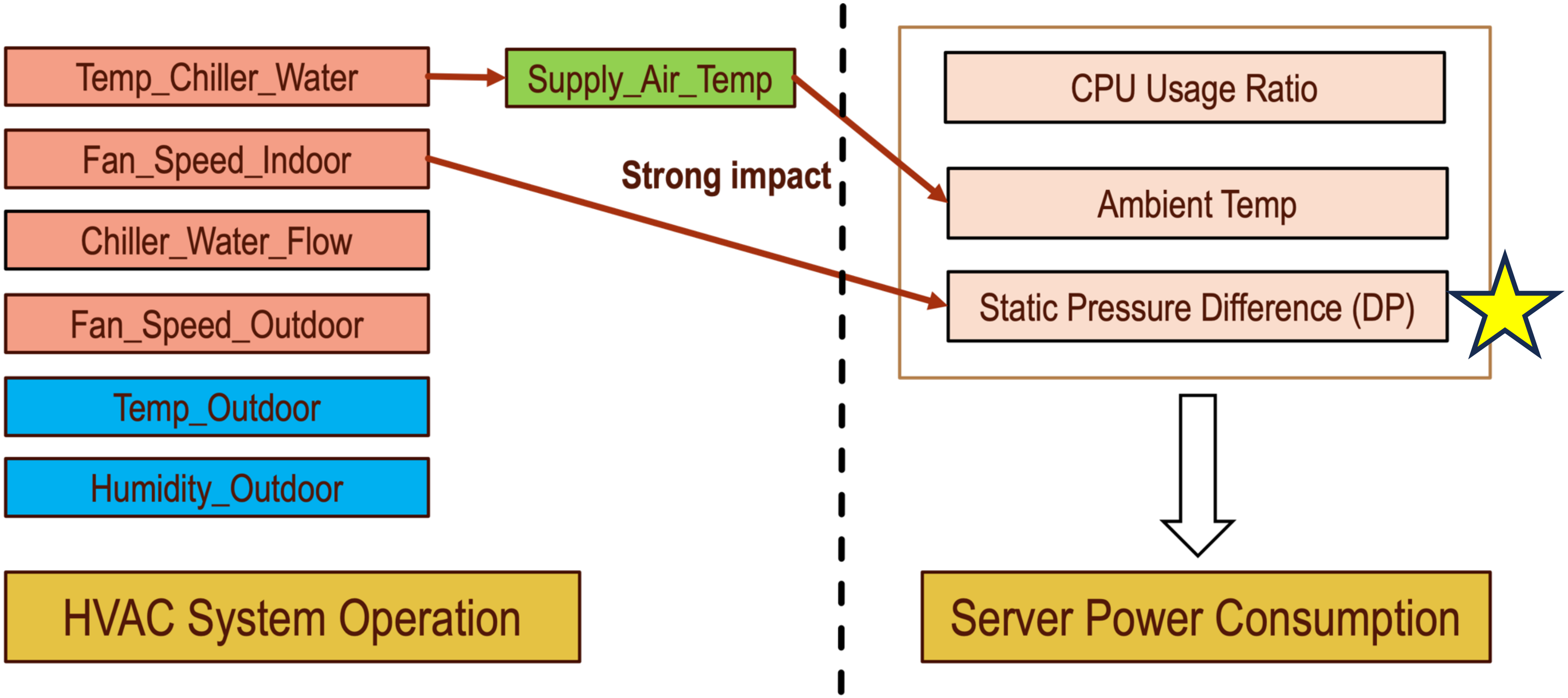
Workload Allocation Optimizer (WAO on Kubernetes)



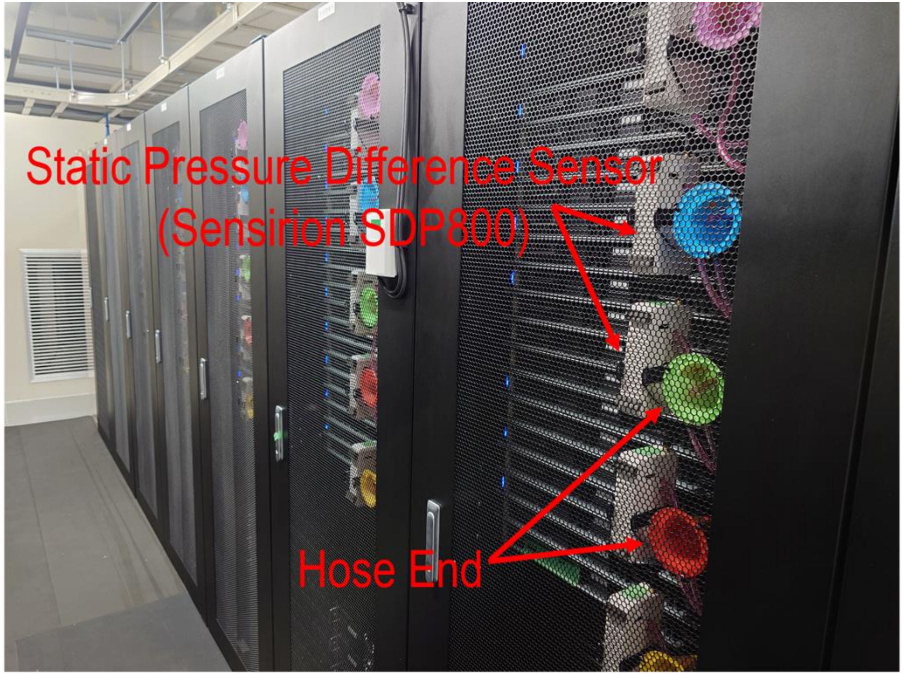
Approach 2: Power Saving from HVAC control (data center cooling operation)



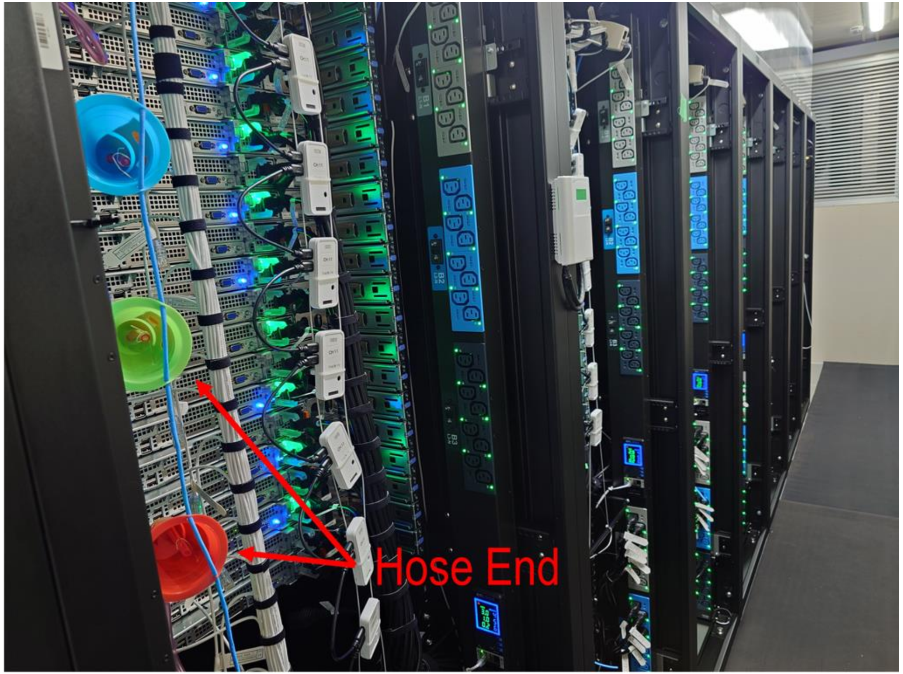
Parameters for HVAC control and generic server model



Mounted DP gauges to obtain the server to measure static pressure difference



Front Plane



Back Plane

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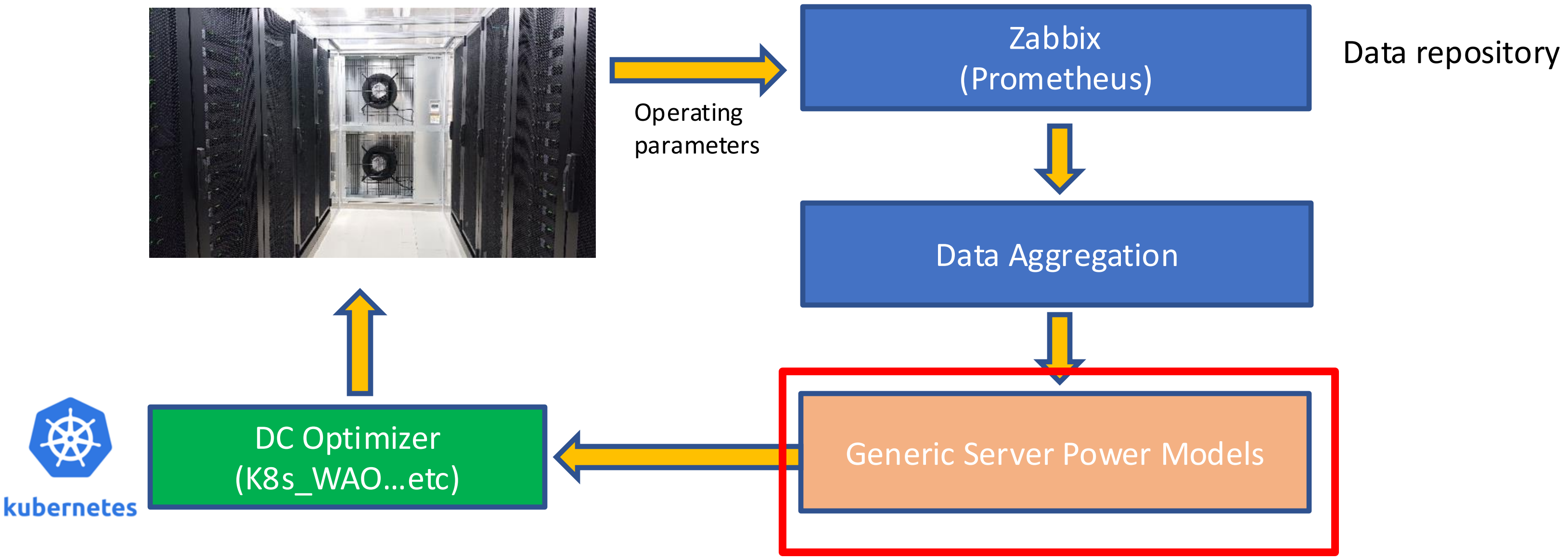
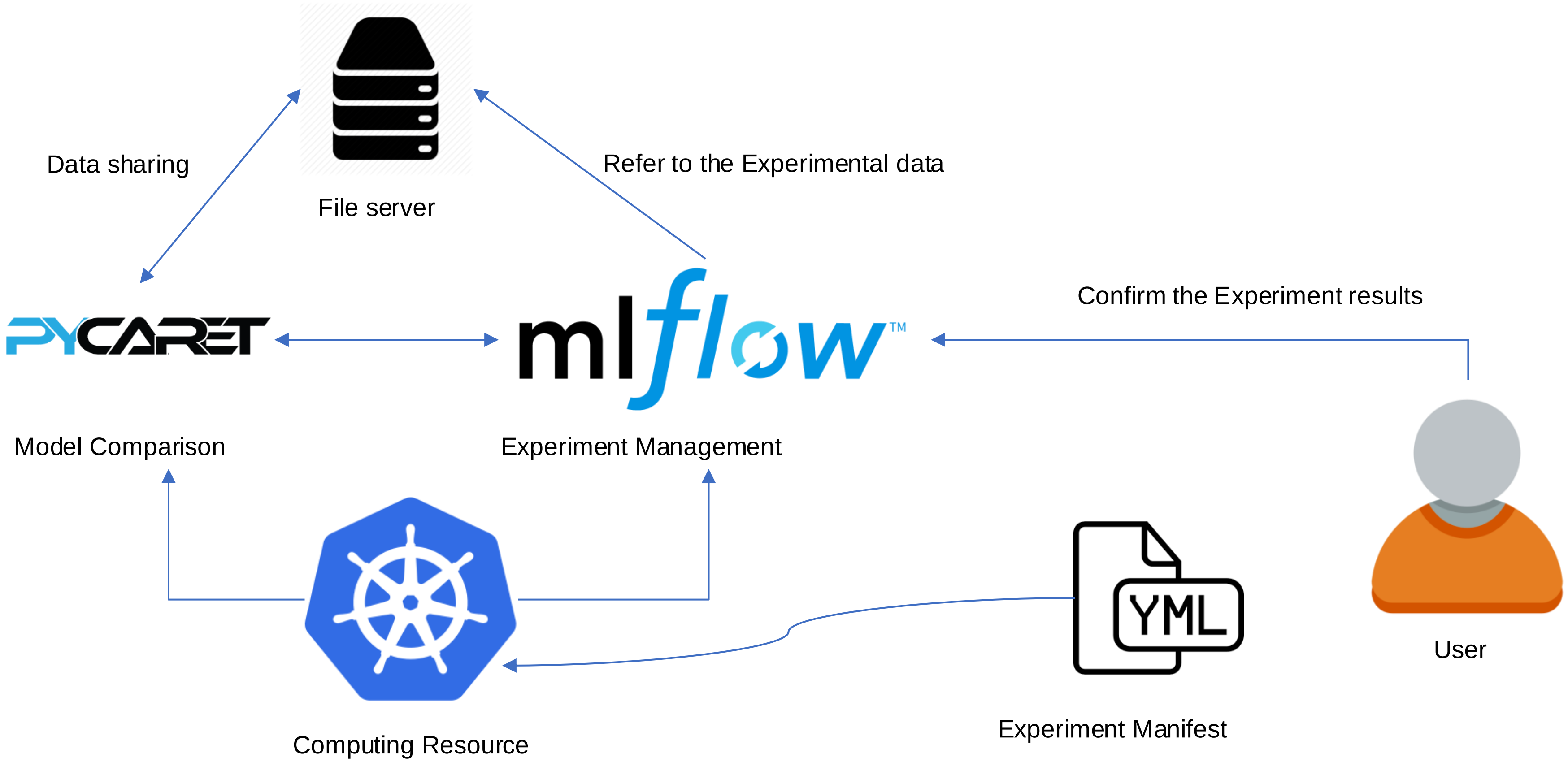
Methods

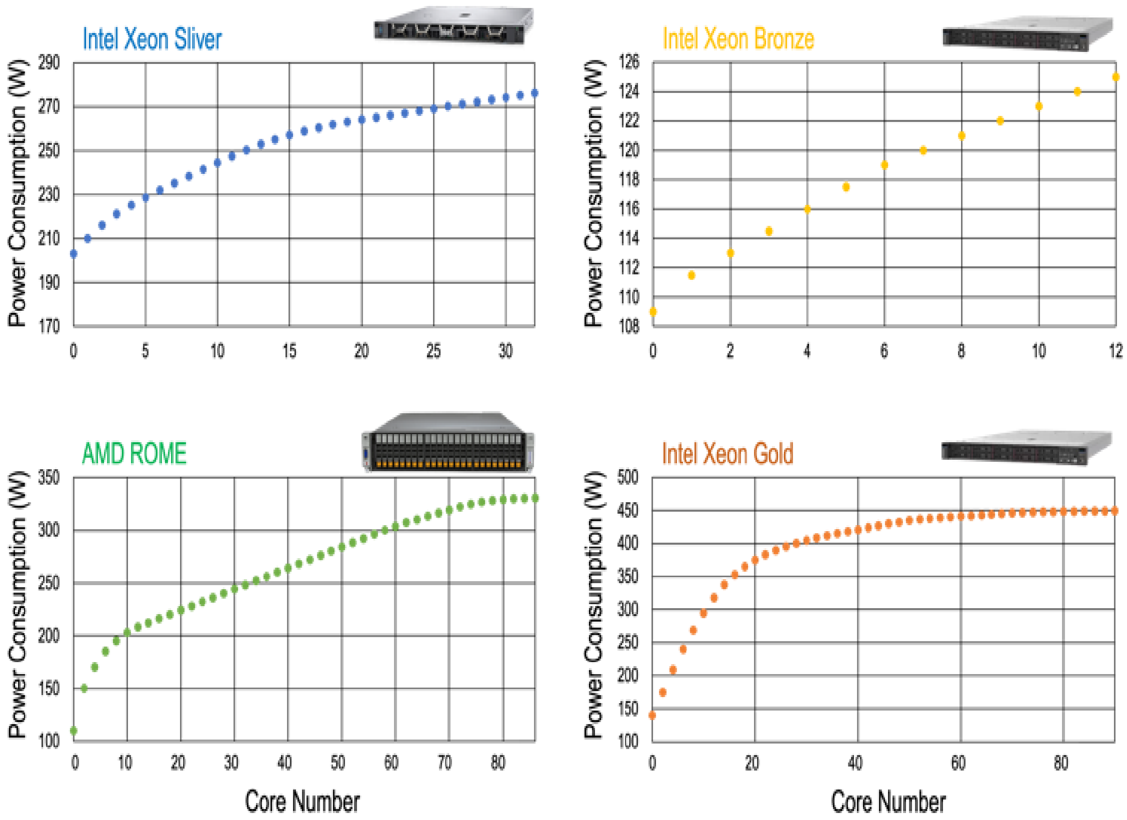
Goal: **<u>Data Center Energy Reduction</u>**



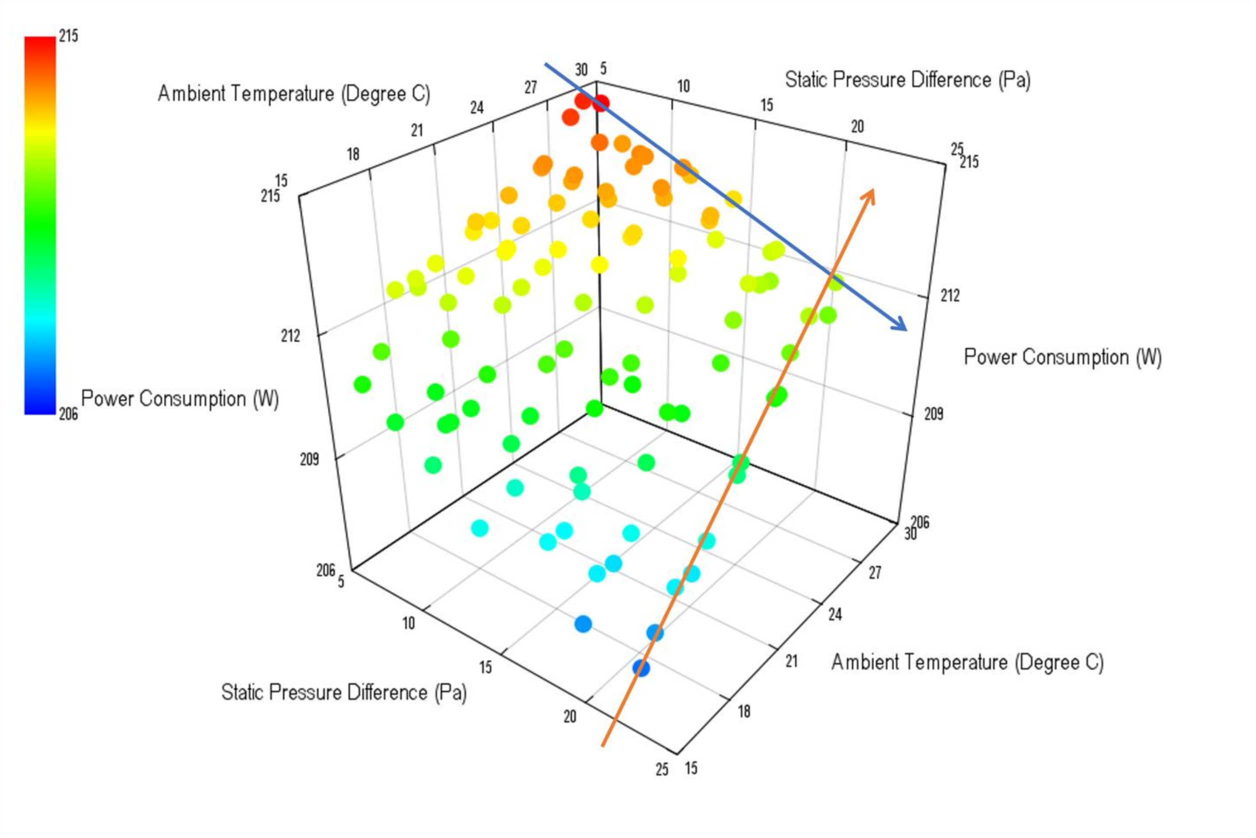
Generic Server Power Models



Server power consumption with CPU ratio



Server power consumption with ambient temperature and DP(static pressure difference)



Performance of server power prediction

Intel Xeon Gold CPU

Hyper Parameter Tuning was processed for the Top 5 algorithms for prediction accuracy (Initial)⇒XGBoost achieves the best power prediction accuracy

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
rf	Random Forest Regressor	4.9462	61.7643	7.8544	0.9969	0.0218	0.0161	0.166
xgboost	Extreme Gradient Boosting	5.063	62.9306	7.928	0.9968	0.0218	0.0162	0.052
et	Extra Trees Regressor	5.1058	68.0104	8.2399	0.9966	0.0228	0.0166	0.078
gbr	Gradient Boosting Regressor	5.3888	68.0627	8.2444	0.9966	0.0227	0.0173	0.081
catboost	CatBoost Regressor	5.2939	68.1497	8.2494	0.9966	0.0233	0.017	0.352
lightgbm	Light Gradient Boosting Machine	5.3151	69.1649	8.3082	0.9965	0.0237	0.0171	0.133
knn	K Neighbors Regressor	5.7692	88.865	9.4121	0.9955	0.0298	0.019	0.008
dt	Decision Tree Regressor	6.1028	102.1304	10.0931	0.9948	0.0283	0.0202	0.009
ada	AdaBoost Regressor	7.5115	116.0387	10.7669	0.9941	0.0308	0.0242	0.036
lar	Least Angle Regression	52.5933	3758.009	61.2979	0.8099	0.2228	0.2033	0.005
lr	Linear Regression	52.5933	3758.009	61.2979	0.8099	0.2228	0.2033	0.141
ridge	Ridge Regression	52.5933	3758.009	61.2979	0.8099	0.2228	0.2033	0.005
br	Bayesian Ridge	52.5994	3758.01	61.298	0.8099	0.2228	0.2033	0.005
lasso	Lasso Regression	52.6467	3758.161	61.2993	0.8099	0.2227	0.2035	0.207
llar	Lasso Least Angle Regression	52.6467	3758.161	61.2993	0.8099	0.2227	0.2035	0.006
en	Elastic Net	52.7764	3759.182	61.3077	0.8099	0.2225	0.2041	0.181
huber	Huber Regressor	51.0287	3807.55	61.6986	0.8074	0.2128	0.1852	0.009
omp	Orthogonal Matching Pursuit	57.5343	4231.873	65.049	0.786	0.2323	0.2232	0.005
par	Passive Aggressive Regressor	63.4403	8532.67	88.4586	0.5662	0.2458	0.198	0.006
dummy	Dummy Regressor	134.3858	19811.96	140.7471	-0.0012	0.5282	0.5928	0.005

Decision tree algorithm-based opportunity learning algorithm along with CatBoost and LightGBM High-speed and accurate machine learning framework that does not require preprocessing of data to convert categorical string variables to numeric, One-Hot encoding, etc.

Power consumption prediction error for each server for XGBoost with hyper parameter tuning

Server (CPU)	RMSE(W/%)**
A (Intel Xeon Bronze)	1.5W/1.2%
B (Intel Xeon Silver)	3.7W/1.3%
C (Intel Xeon Gold)	7.7W/1.7%
D (AMD ROME)	6.5W/2.0%

** : maximum power consumption ratio

RMSE: Root Mean Squared Error

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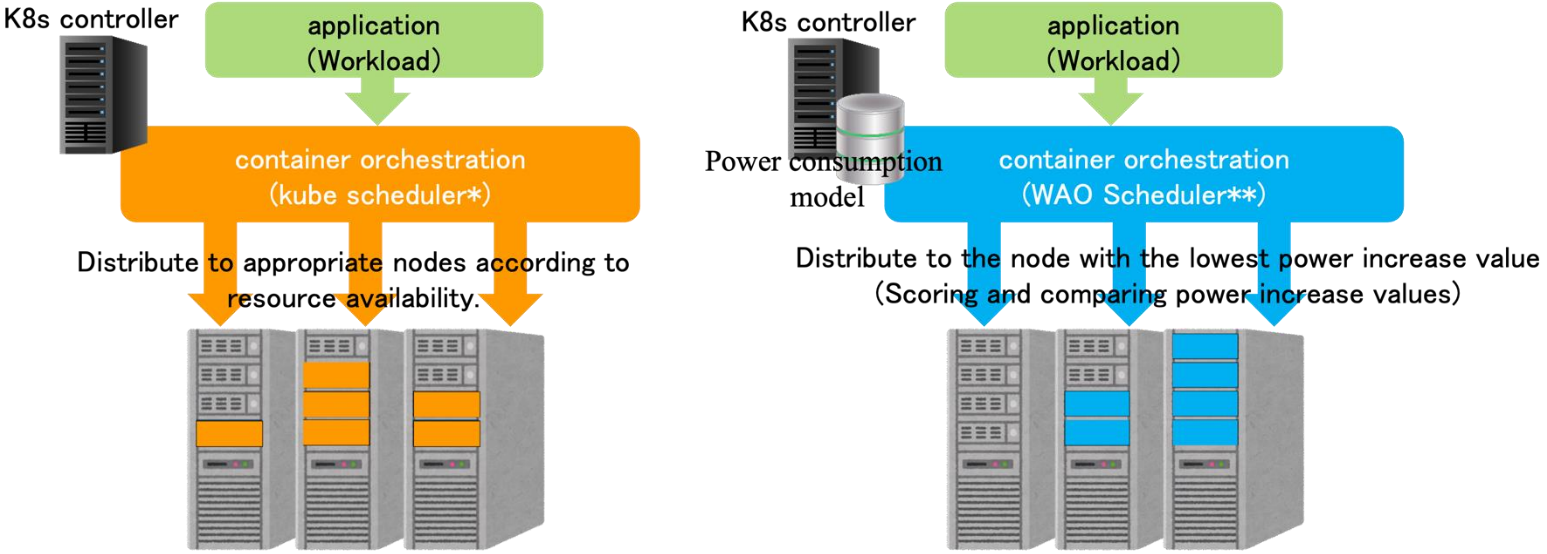
Data Center energy saving with Workload Allocation Optimizer (WAO on Kubernetes)

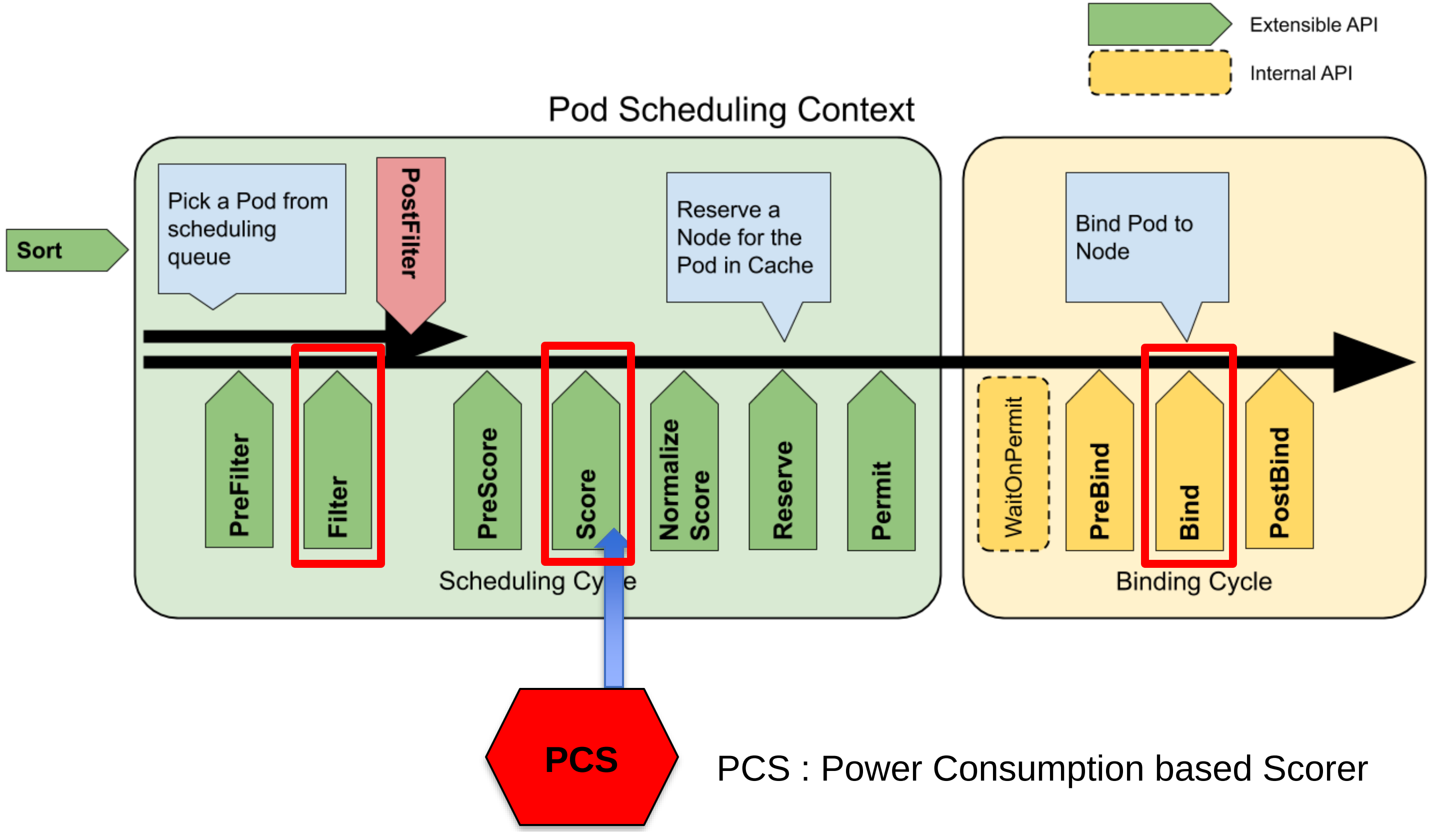


Existing Technology
*Least Requested Priority

Proposed Technology
**Add power consumption increase to the kube scheduler
Add scoring function

WAO:Workload Allocation Optimization

WAO Algorithm in K8s



PCS : Power Consumption based Scorer

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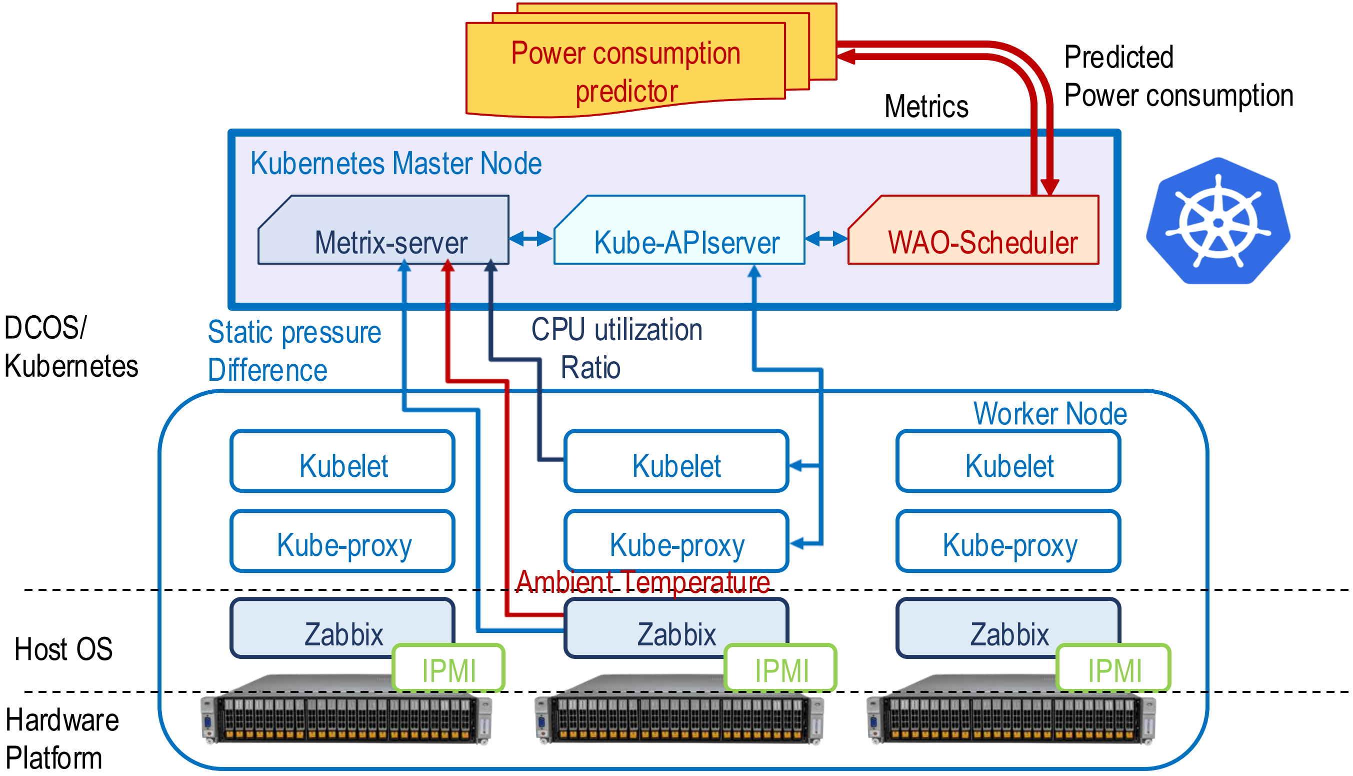
Operation flow of WAO on Kubernetes



WAO implementation (GitHub repository)

Scan me!

waok8s/**wao-core**
https://github.com/waok8s/wao-core

waok8s/**wao-metrics-adapter**
https://github.com/waok8s/wao-metrics-adapter

Scan me!

waok8s/**wao-scheduler**
https://github.com/waok8s/wao-scheduler

Scan me!

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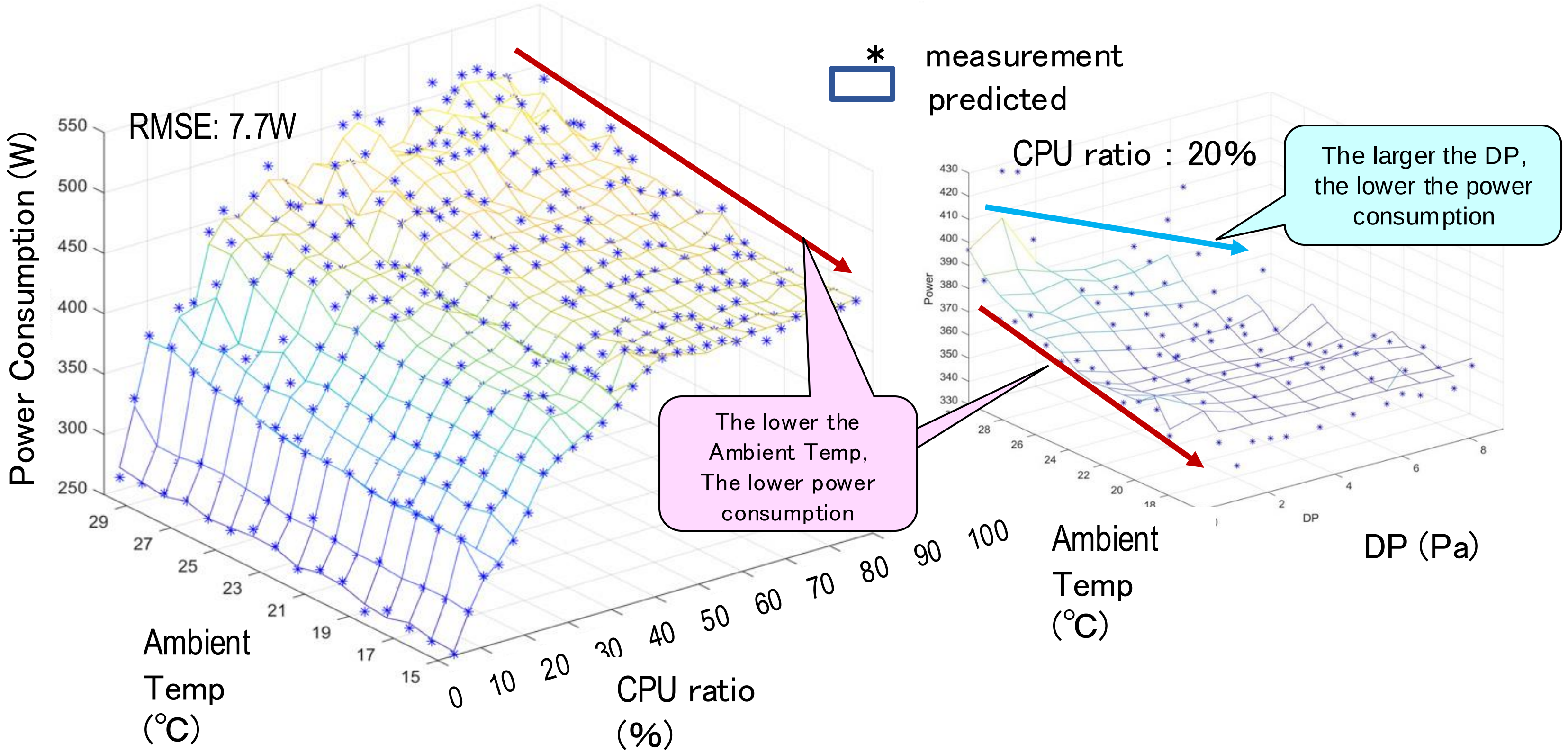
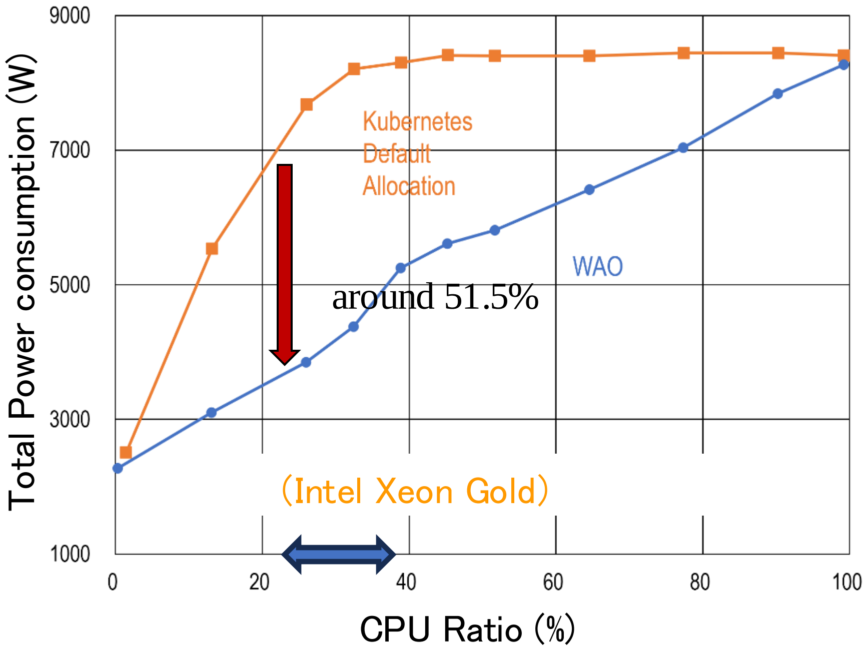
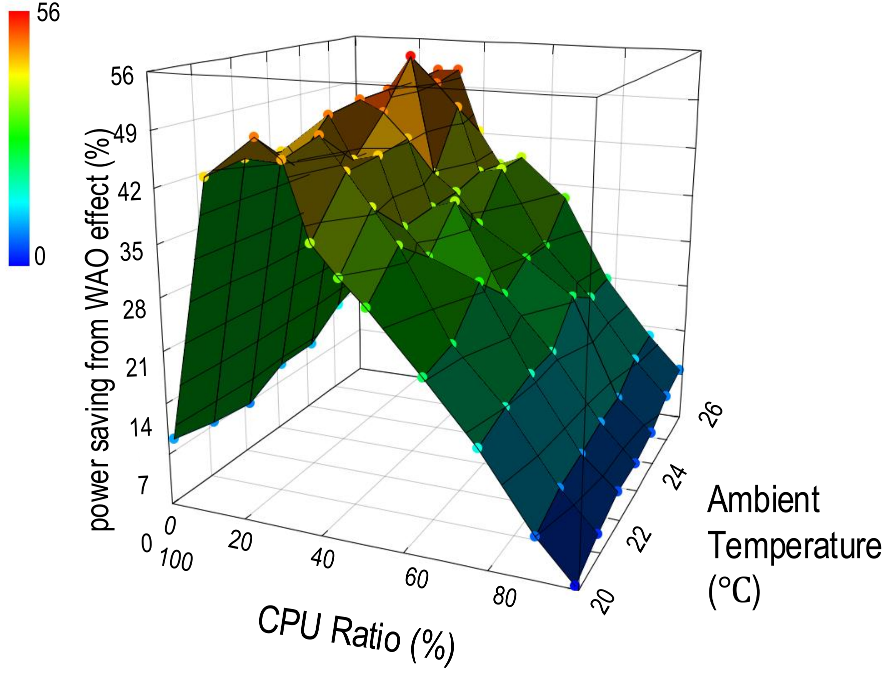
Server Power Prediction Result:

case of Xeon Gold CPU server



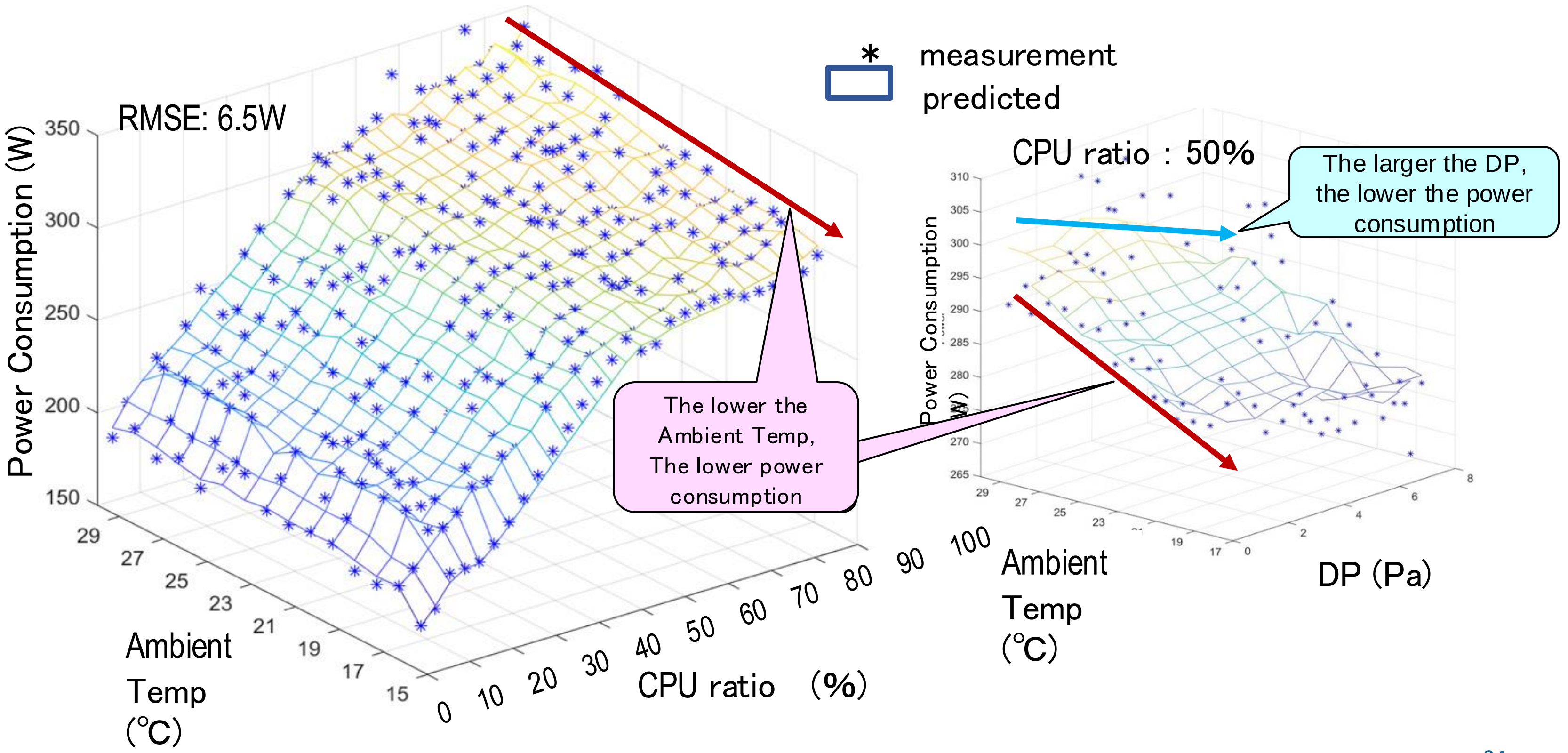
Power saving result:
case of Xeon Gold CPU server



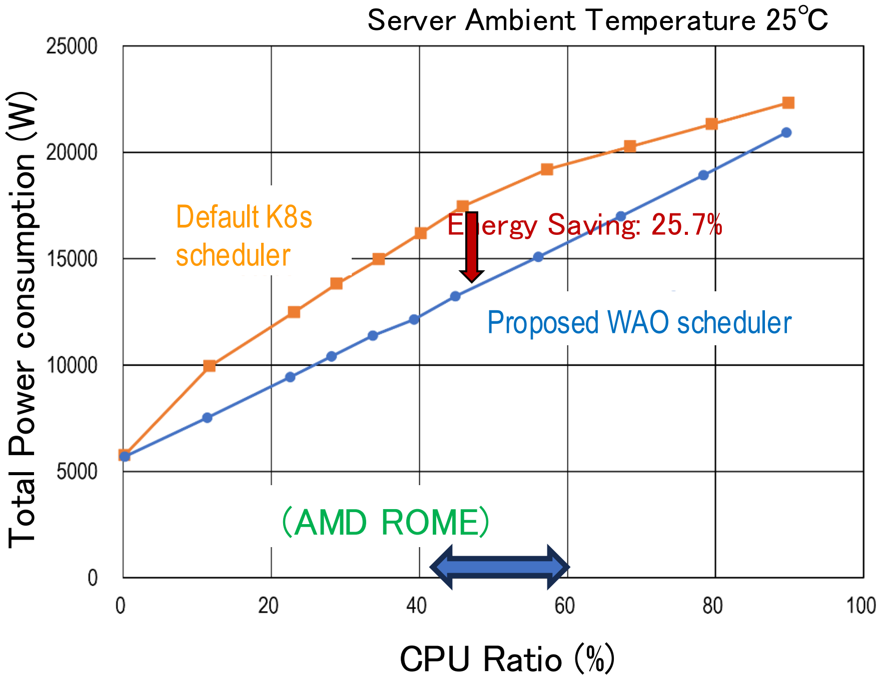


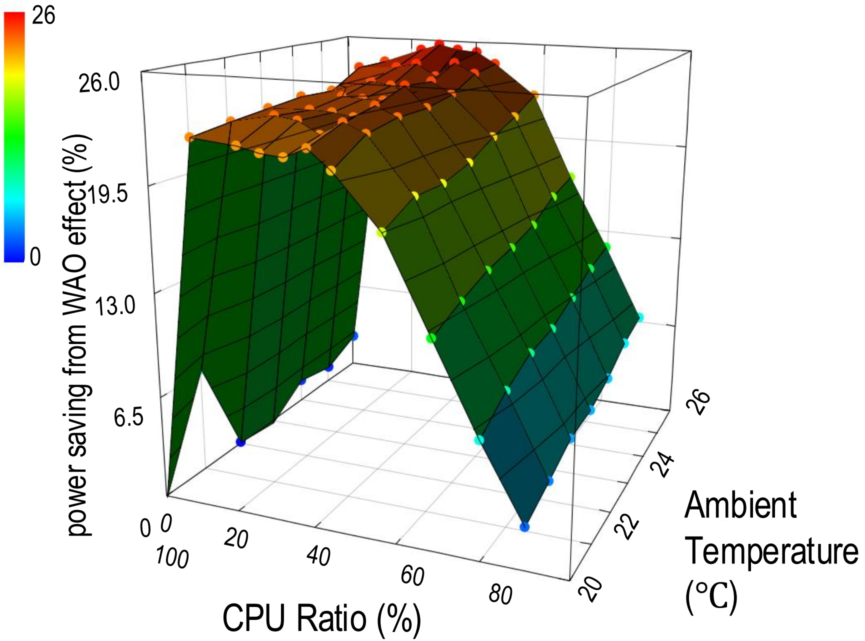
Server Power Prediction Result:

case of AMD ROME CPU server



Power saving result:
case of AMD ROME CPU server





WAO:Workload Allocation Optimization

Summary

- Discuss about optimizing workload allocation with HVAC considerations for sustainable data center operations.
- Incorporated **static pressure differences (DP)** to assess HVAC impact on server efficiency, enhancing prediction accuracy.
- Developed highly accurate **generic server power prediction models** using over 20 algorithms.
- Introduced a **K8s-based workload allocation optimization (WAO)** algorithm extending Kubernetes API to realize energy efficiency in the data centers.
- Conducted experiments in a real-world test-bed data center with over 200 servers of varying CPU capabilities.
- Achieved significant energy savings: 51.5% with Intel Xeon Gold CPU servers and 25.7% with AMD ROME CPU servers.

Acknowledgment

New Energy and Industrial Technology Development Organization

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Thank you

Any Questions?