Design and Implementation of Energy-Conscious Optimizations through Deep Reinforcement Learning for Edge Computing Scenarios

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Advisor: Patricia Arroba García

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MSc Thesis' Objective

Our research group works on

Data centers optimization, in which I've been involved the last two years in:

- New cooling systems.
- Resource allocation optimization.

This MSc thesis' objective is

Energy-aware optimization in Edge Computing for resource allocation via:

- Two-phase immersion cooling systems.
- Deep Reinforcement Learning algorithms.

Demand for Novel Applications

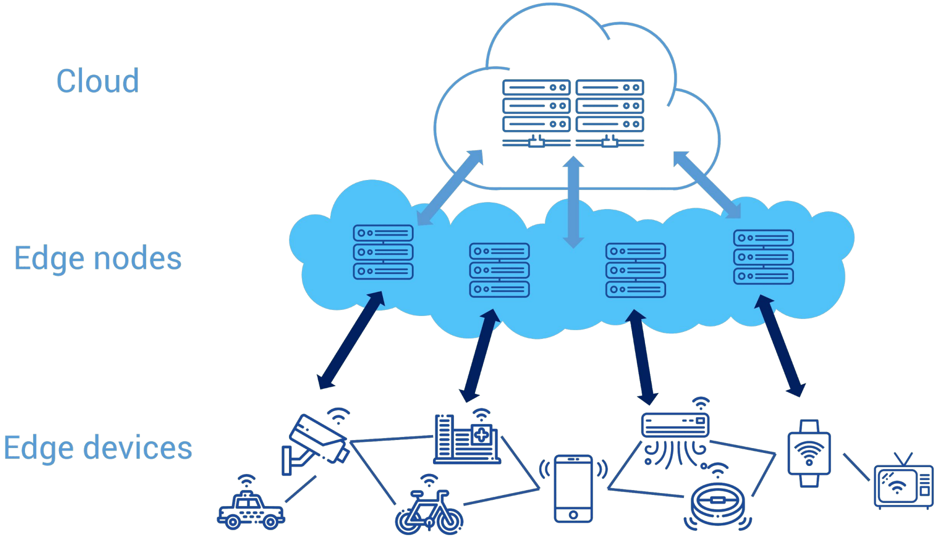
Current Computing Paradigm

Cloud Computing

Saturation

Delay

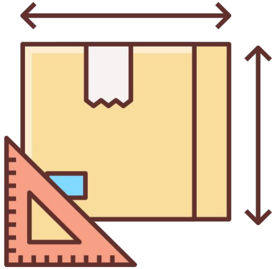
Edge Computing



Architecture

Edge Data Centers (EDCs)

Edge Computing Requirements

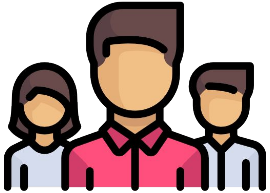


Small Areas

Low Cost

Location-Aware

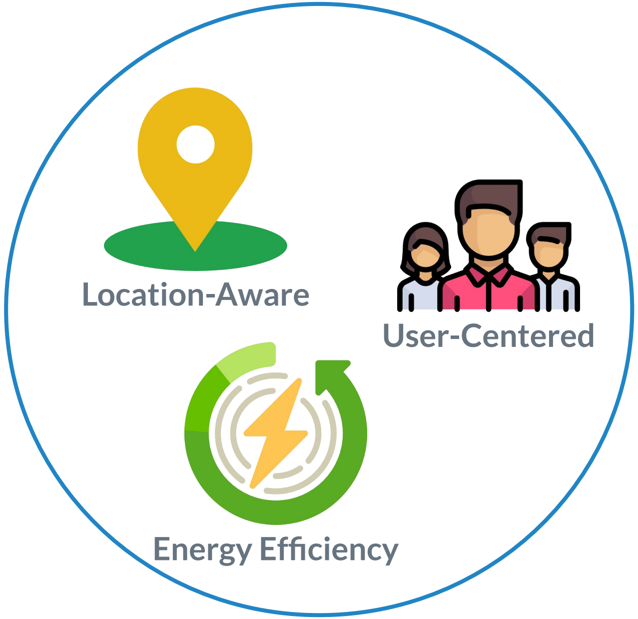
Energy Efficiency



User-Centered

Optimization in Edge Data Centers

EDC's* Cooling System

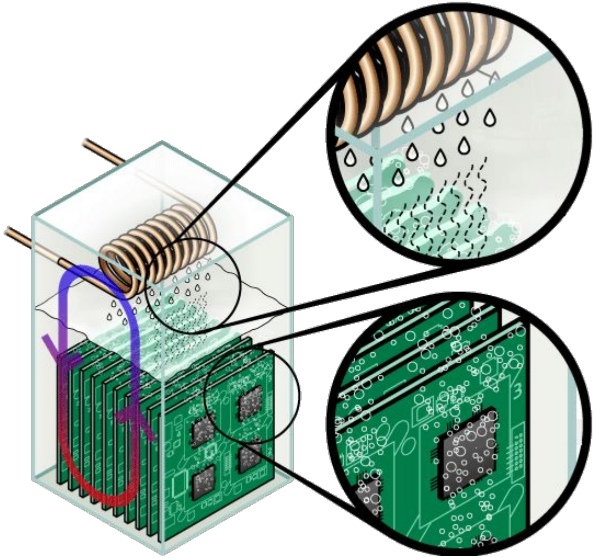


EDC* Management

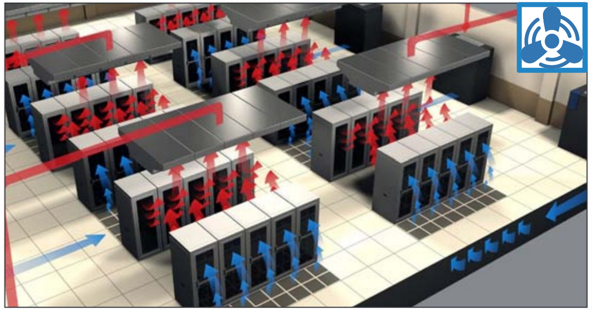
*Edge Data Center: EDC

Optimizing Cooling Systems

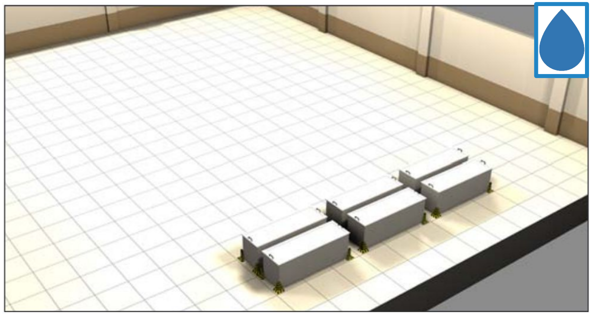
Two-Phase Immersion Cooling



NOVEC 7100



Conventional air-cooled system



Two-phase immersion system

Cooling Consumption

↓ 95%

Power Density per Rack

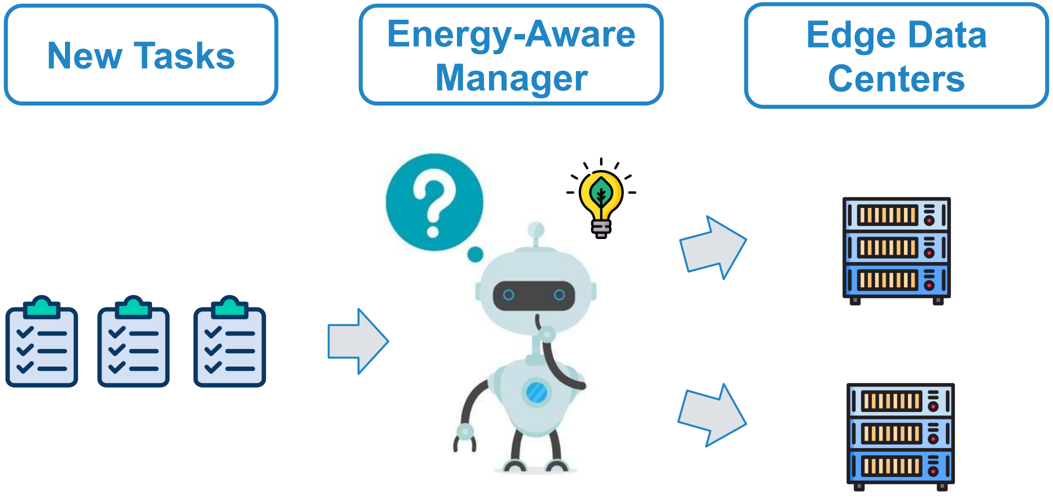
↑ x6.25

Physical Footprint

↓ x10

Optimizing EDC Management

Deep Reinforcement Learning (DRL)



Our Goal

Energy-aware dynamic allocation of resources in Edge Data Centers.

Why DRL?

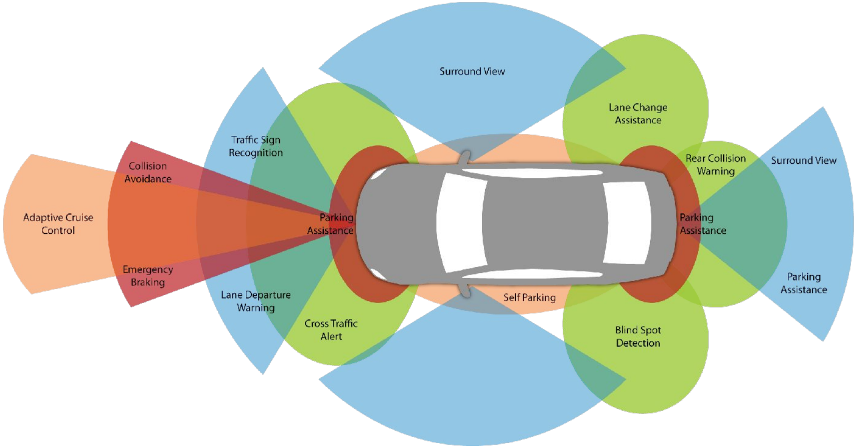
Technology suited for optimizing highly-complex dynamic environments.

Successful Areas

Resource management, robotics, economics, chemistry, games, etc.

Edge as an ADAS Enabler

Advanced Driver Assistance Systems (ADAS)



Goal

Reducing human-related road accidents (93% of the total[1]).

Requirements

Critical latency constraints.

Data-Intensive services[2].

Computationally expensive.

Location-aware service.

[1]Source: Virginia transportation research council.

[2]Up to 4TB per vehicle every 1:30 hours. Source: Intel.

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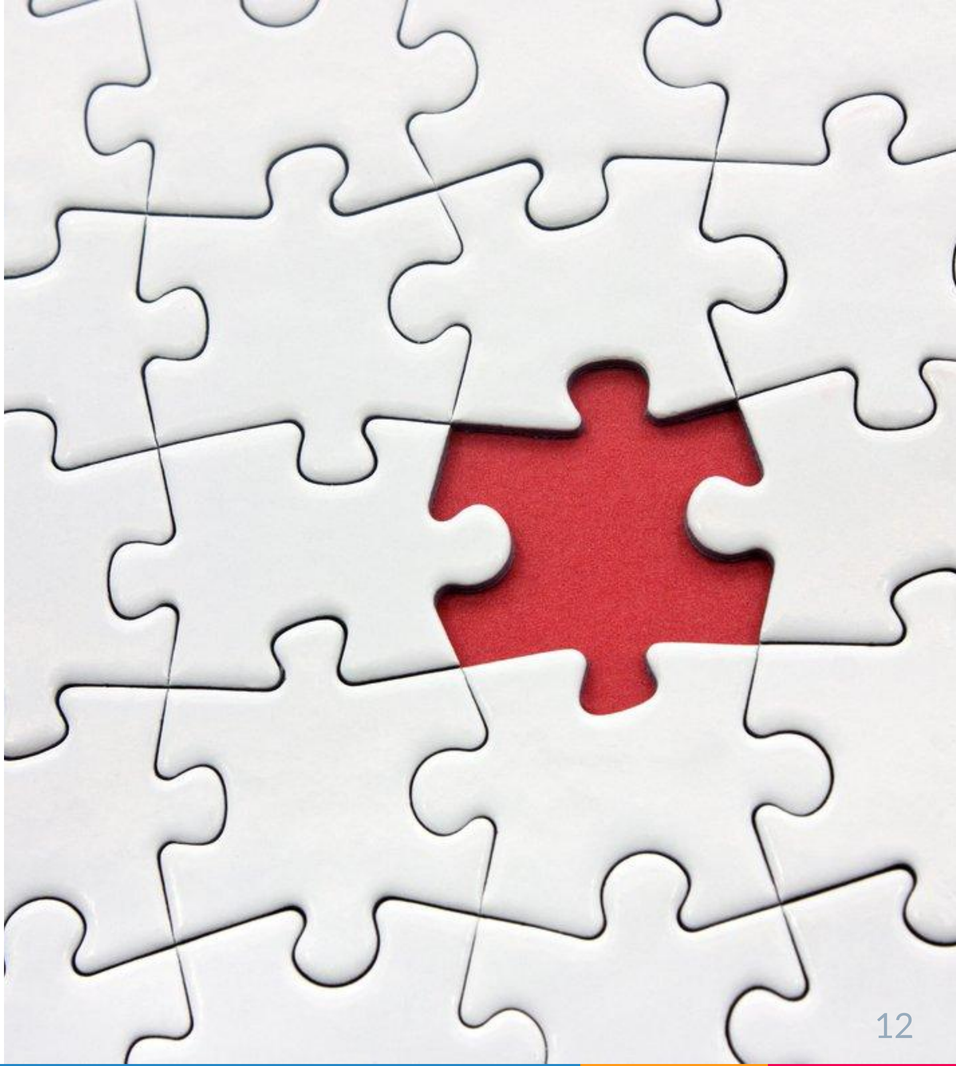


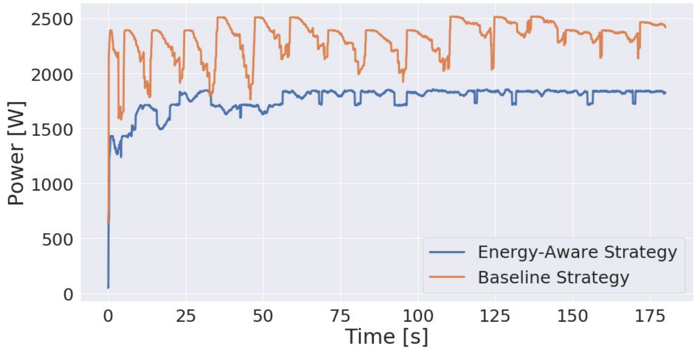
Contributions to the State of the Art

Energy-aware Edge Data Center modeling:

- Of conventional and **two-phase immersion** systems.
- Using **real hardware** prototypes.
- And a real Edge Computing application (**ADAS***).

Energy-aware resource management:

- Of Realistic **Edge Computing scenarios**.
- Using **Deep Reinforcement Learning**.
- And Mercury, a 5G-Edge simulator.



*Advanced Driver Assistance Systems: ADAS

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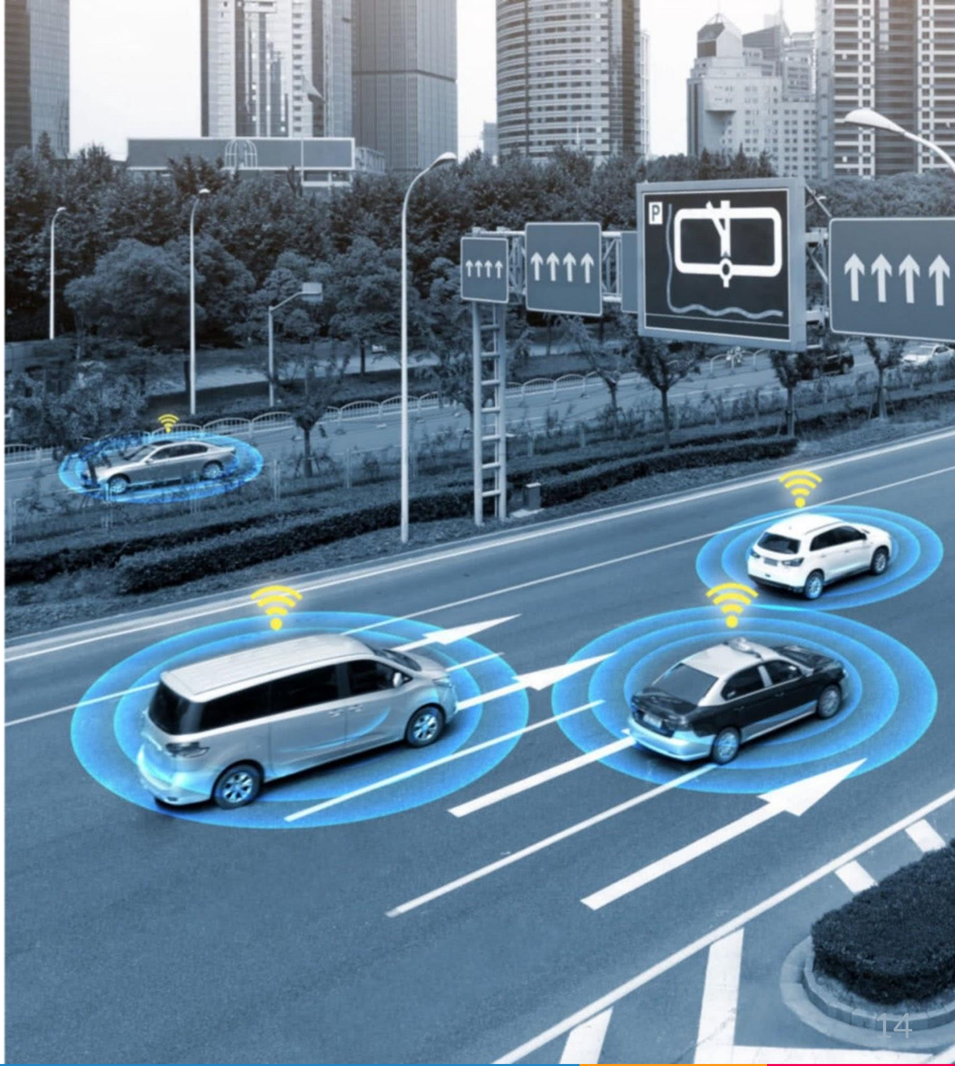
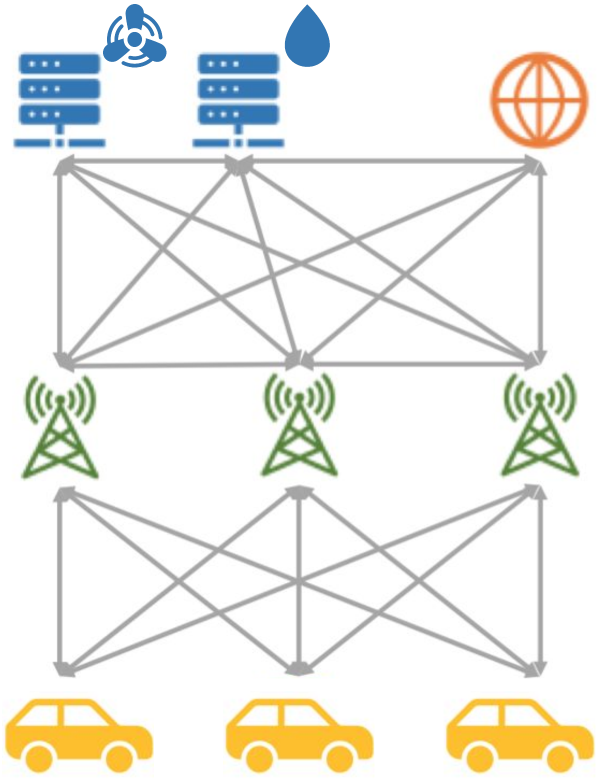


Problem Description



We want to optimize Edge Computing scenarios not deployed yet

We need

Simulations of the scenario

We need

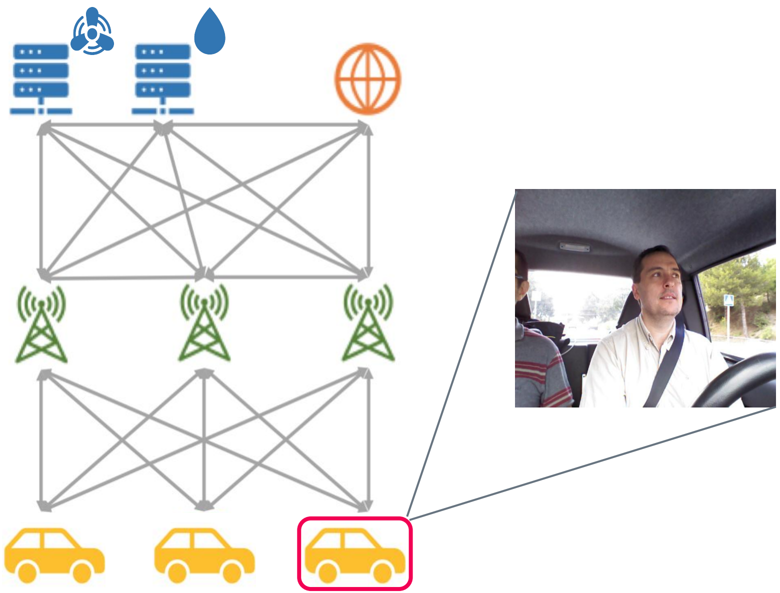
To model the elements of the scenario

We need

A real Edge Computing application

Edge Computing Application

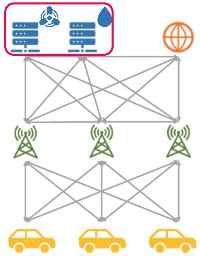
Driver Tracking Service



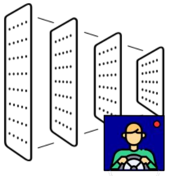
- **ADAS application** for enhancing drivers' attention to the road.
- DrivFacce dataset: **realistic video footage** from cameras inside cars.
- **A vehicle's session is a CNN*** model that is trained in the EDCs.
- It's **used for modeling EDCs**' IT equipment.

*Convolutional Neural Network: CNN

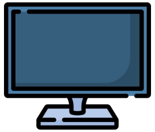
Edge Data Center Modeling



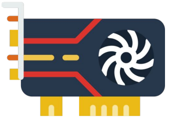
IT Equipment Modeling



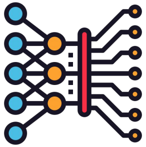
1. CNN-ADAS implementation



3. GPU monitoring (power, clocks…)

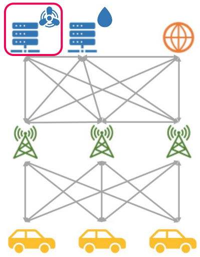


2. CNN-ADAS execution in GPU



4. FFN* power consumption model

*FeedForward Neural Network: FNN



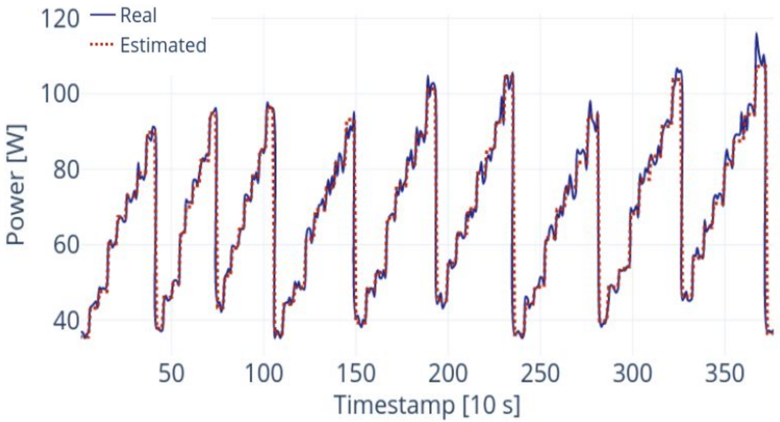
Air-cooled EDC

IT Equipment

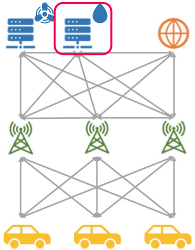
Hardware

Sapphire Pulse Radeon
RX580 GPU

Model Results



NRMSD	2.45%
R^2	99.01%



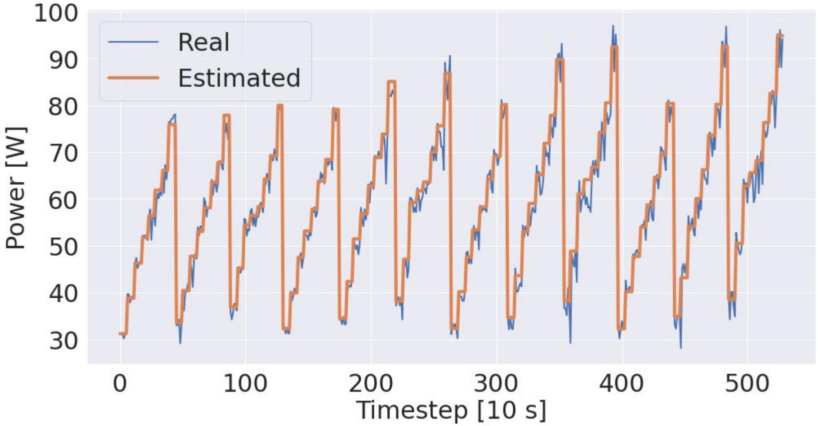
Immersion-Cooled EDC

IT Equipment

Coolant: NOVEC 7100

GPU model: Sapphire Pulse Radeon RX570

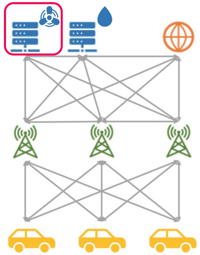
Model Results



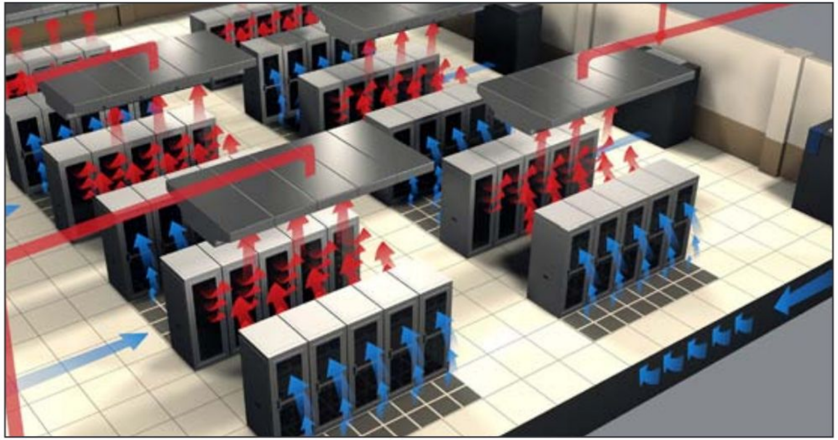
NRMSD	3.15%
R^2	97.97%

Air-Cooled EDC

Cooling System



Layout



Hot Aisle/Cold Aisle

SotA Model*

$$P_{cooling} = \frac{P_{IT}}{0.0068 \cdot T_{inlet}^2 + 0.0008 \cdot T_{inlet} + 0.458}$$

where:

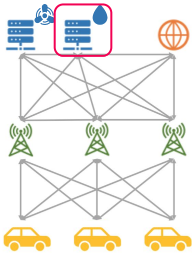
P_{it} ≡ IT power consumption

$P_{cooling}$ ≡ cooling power consumption

T_{inlet} = 20 ºC ≡ inlet temperature

(ASHRAE Recommendation: 18-24ºC)

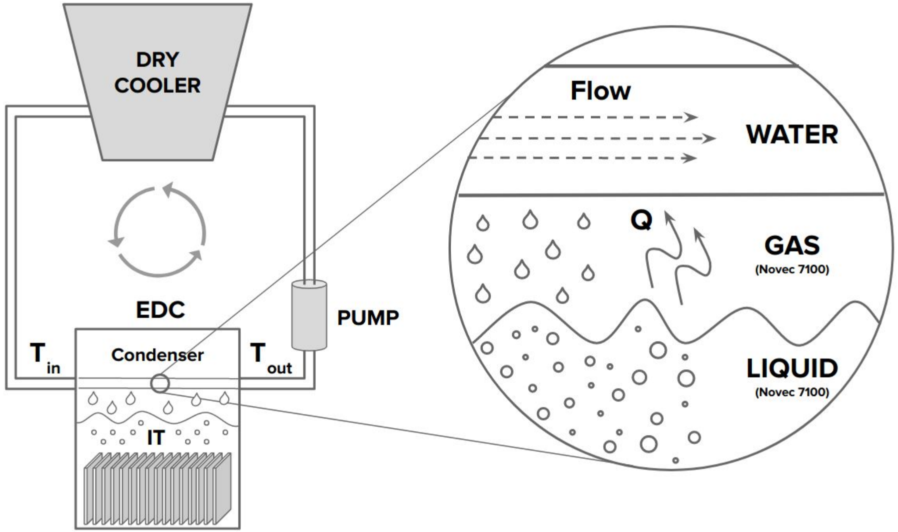
*J. D. Moore et al. “Making scheduling” cool”: Temperature-aware workload placement in data centers.,” USENIX, 2005.



Immersion-Cooled EDC

Cooling System

Layout



Pump

Wilo IPL 50/115-0,75/2
(Installed in our real-sized prototype)

Power Model

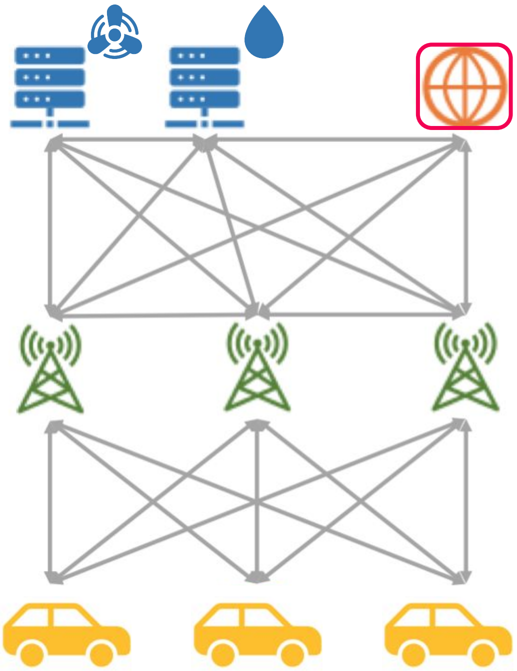
$$Q = m \cdot C_p \cdot \Delta T$$

+

Pump's datasheet

Resource Allocation Management (i)

Resource Allocation Manager



Goal

Dynamic resource allocation

Solution

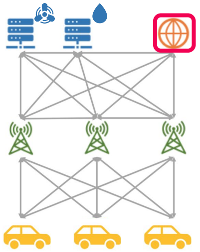
Deep Reinforcement Learning

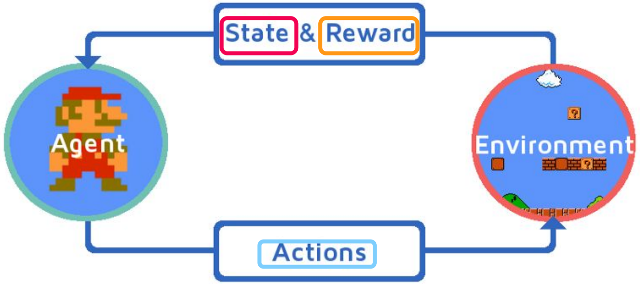
Model

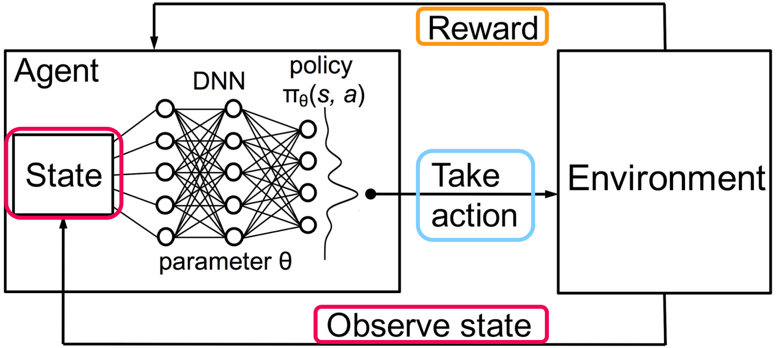
Synchronously parallelized
Advantage Actor-Critic (A2C)

Resource Allocation Management (ii)

Reinforcement Learning (RL) Formulation







Goal

Based on EDCs' energy status, **select the best EDC to assign new incoming sessions** energy-wise.

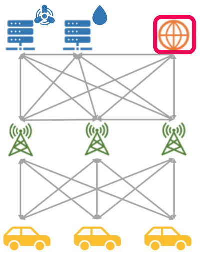
RL Elements

State
EDCs' energy status

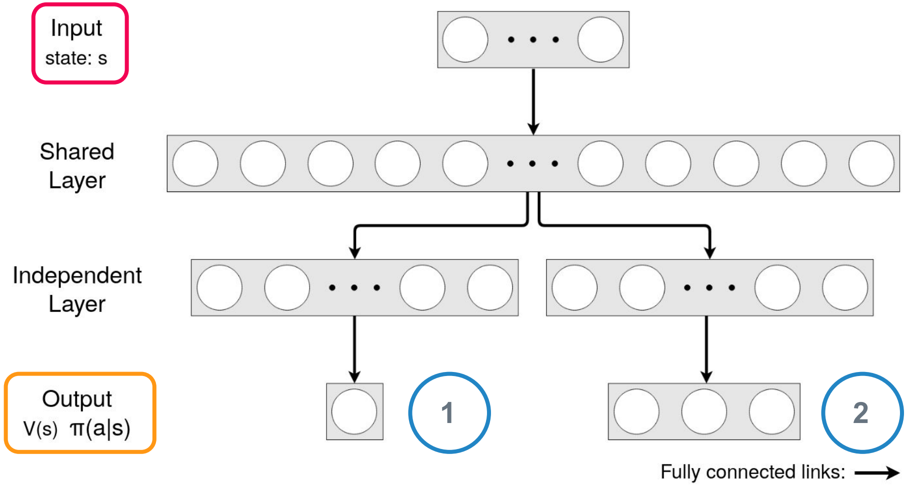
Action
Choosing an EDC

Reward
Minimize EDCs' energy consumption

Resource Allocation Management (iii)



Model Architecture and Training



Two-Headed FNN*

$$
\begin{aligned}
\min \mathscr{L}_t = & -log(\pi(a_t \mid s_t, \theta_\pi)) \cdot (R_t - V(s_t)) \\
& - \beta \cdot \pi(A_t \mid s_t, \theta_\pi) \cdot log(\pi(A_t \mid s_t, \theta_\pi)) \\
& + 0.5 \cdot (R_t - V(s_t))^2
\end{aligned}
$$

Loss Function

*FeedForward Neural Network: FNN

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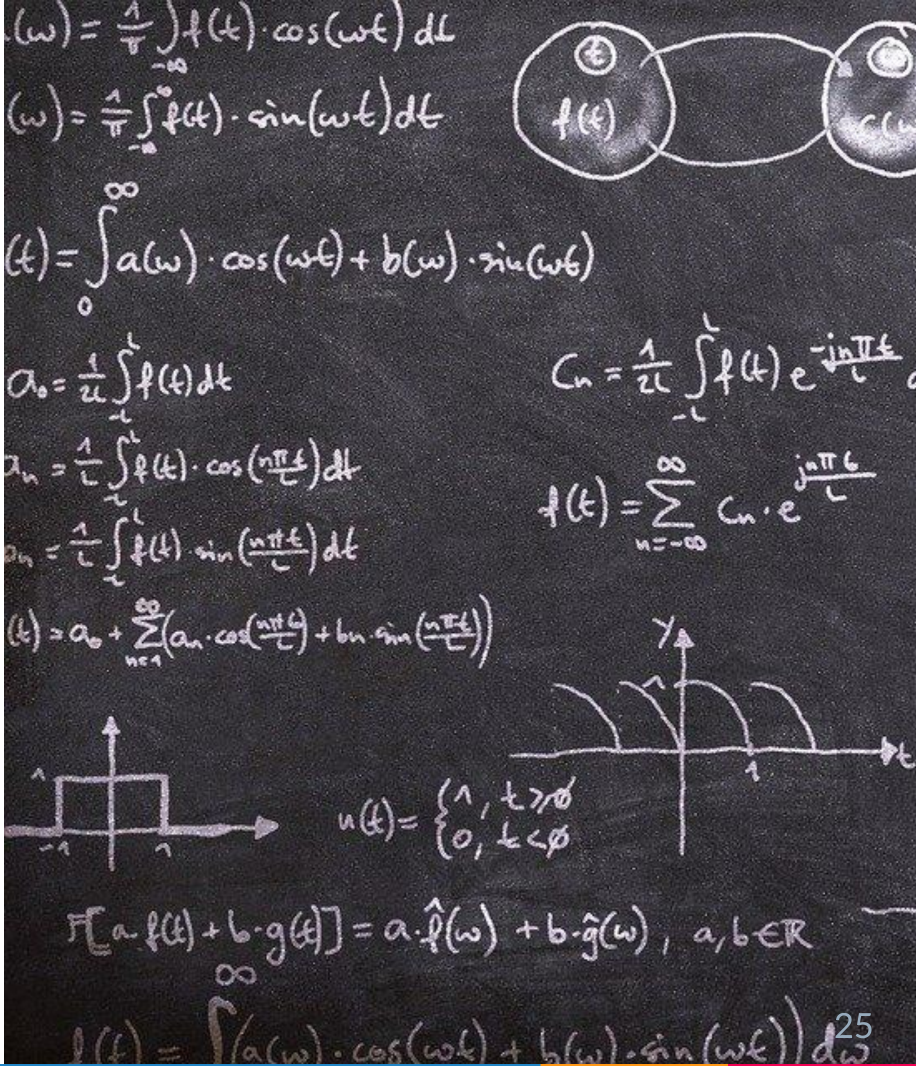
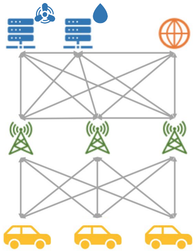
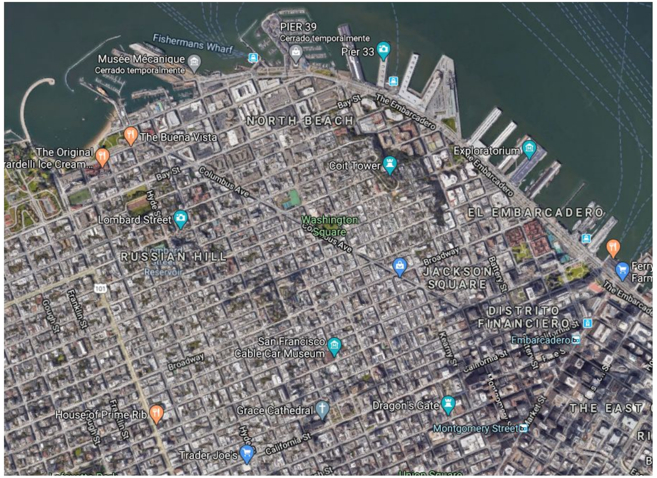
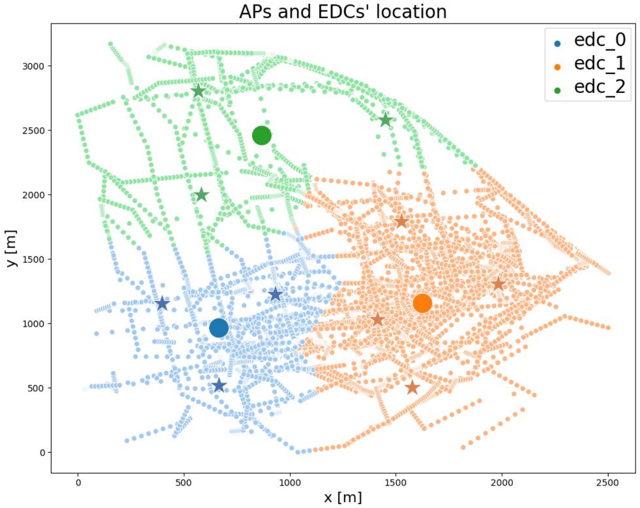


Scenario Configuration (i)








3 EDCs

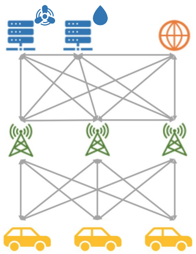

10 APs


50 vehicles

San Francisco's Bay Area

Location-Aware Baseline

Scenario Configuration (ii)



A) Air-Based Scenario

x3 

B) Immersion-Based Scenario

x3 

C) Heterogeneous I Scenario

x2  x1 

D) Heterogeneous II Scenario

x1  x2 

Main Evaluation Metrics

$$P = P_{fed} = \sum P_{IT} + P_{cool}$$

Goal

Total energy efficiency

SotA values

Depends on the scenario

$$PUE = \frac{\sum P_{IT} + P_{cool}}{\sum P_{IT}}$$

Goal

Cooling energy efficiency

SotA values

1.60-2.50 (air)

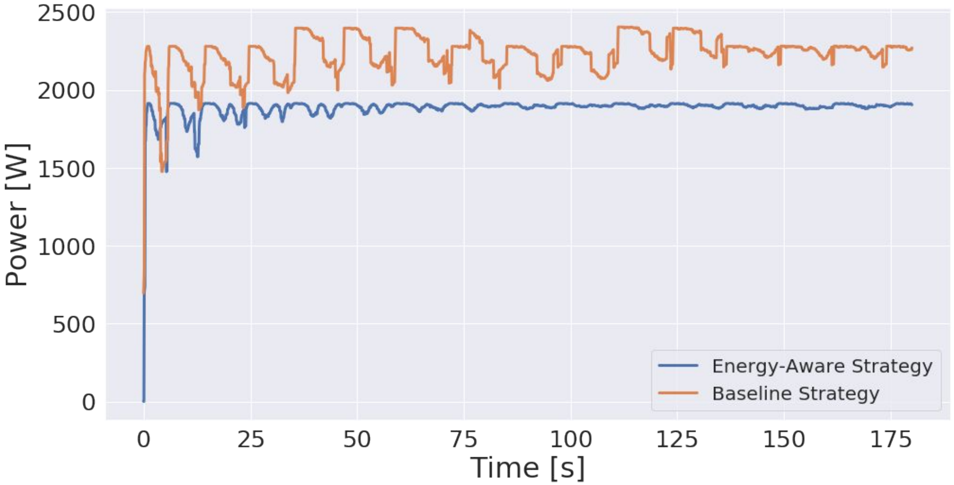
1.01-1.05 (immersion)

A) Air-Based Scenario

x3 

Strategy	GPUs*	P [kW]	[%]	PUE	[%]
Baseline	5	1.86	-13.1	1.31	0.00
Energy		1.61		1.31	
Baseline	10	2.23	-15.5	1.31	0.00
Energy		1.88		1.31	
Baseline	15	2.22	-6.19	1.31	0.00
Energy		2.09		1.31	

Hot Standby Results



10-GPU Strategy Comparison

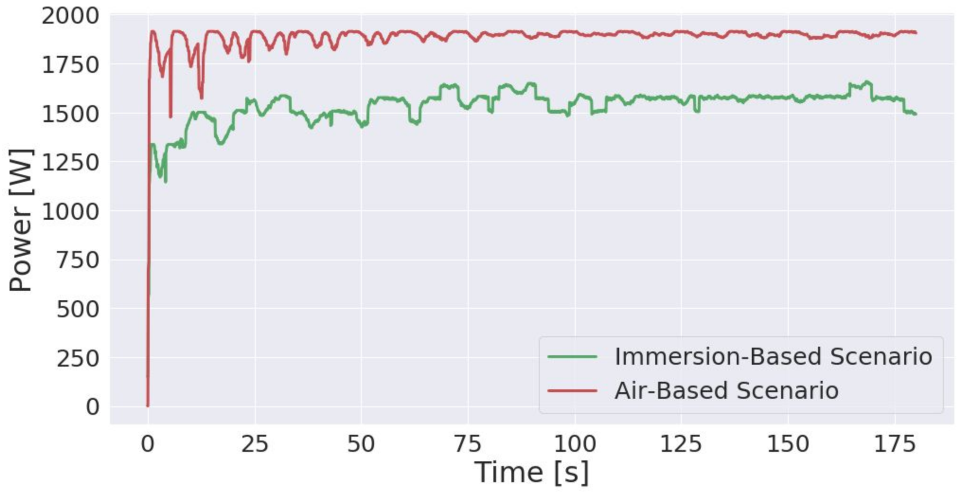
Considerable energy savings respect to the baseline (**~12%**).

*GPUs per EDC

B) Immersion-Based Scenario x3

Strategy	GPUs*	P [kW]	[%]	PUE	[%]
Baseline	5	1.33	-4.87	1.02	+0.24
Energy		1.26		1.03	
Baseline	10	1.64	-6.60	1.05	+1.61
Energy		1.53		1.06	
Baseline	15	1.72	-0.56	1.10	-1.36
Energy		1.72		1.09	

Hot Standby Results



10-GPU Scenario Comparison

Immersion-cooled solutions yields savings of **18.3%** in contrast to air-cooled ones.

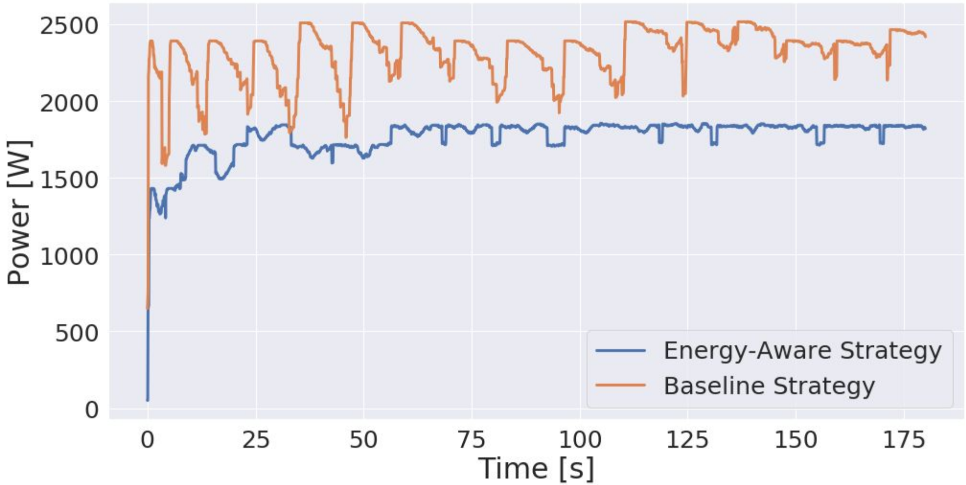
*GPUs per EDC

C) Heterogeneous I Scenario

x2 x1

Strategy	GPUs*	P [kW]	[%]	PUE	[%]
Baseline	5	1.80	-7.67	1.24	-1.84
Energy		1.67		1.22	
Baseline	10	2.31	-23.8	1.27	-10.3
Energy		1.77		1.14	
Baseline	15	2.34	-22.6	1.29	-14.9
Energy		1.81		1.10	

Hot Standby Results



10-GPU Strategy Comparison

Scenarios with the highest savings respect to the baseline (up to **23.8%**).

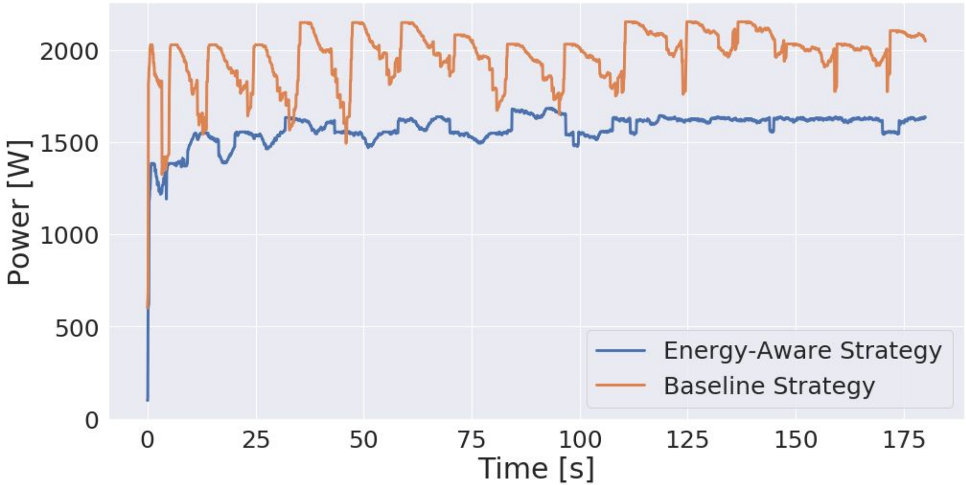
*GPUs per EDC

D) Heterogeneous II Scenario

x1 x2

Strategy	GPUs*	P [kW]	[%]	PUE	[%]
Baseline	5	1.57	-8.93	1.14	-2.58
Energy		1.43		1.11	
Baseline	10	1.97	-20.2	1.16	-7.70
Energy		1.57		1.07	
Baseline	15	2.00	-12.3	1.19	-8.31
Energy		1.76		1.09	

Hot Standby Results



10-GPU Strategy Comparison

Scenarios with the highest savings respect to the baseline (up to **20.2%**).

*GPUs per EDC

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MSc Thesis' Summary

Literature Review

Smart Cities, Cloud & Edge Computing, ADAS, Cooling Systems, Resource Allocation, and Deep Reinforcement Learning.

Theory

Mercury Simulator, Optimization, Neural Networks, Advantage Actor-Critic (A2C), and Thermodynamics Fundamentals.

Hardware

GPUs for Neural Networks,
Air and Two-Phase Immersion Systems,
and the AMD-ROCm Backend.

Software

VS Code, Jupyter, Collectd, Kafka, Cassandra, and Python: Mercury, TensorFlow, Keras, PyTorch, NumPy, Pandas, Seaborn...

Conclusions

The **two-phase immersion cooling EDC** consumed less energy than the conventional air-based EDC with **mean energy savings of 18.3% and a maximum of 28.5%**.

The most complex scenarios, **the heterogeneous scenarios**, yielded the best results compared to the baseline, obtaining **energy savings up to 33.6%**.

Our research on modeling and optimization would help with the gradual deployment and operation of Edge Computing solutions, and thus, **a more scalable, sustainable, and greener future**.

Future Work

New RL Models

A3C, DQN...

New DL Models

CNN, RNN...

New Edge Applications

e-Health, Cryptocurrency...

New IT Equipment

NVIDIA GPUs, Cloud Servers...

New Baselines

Evolutionary Algorithms

Multi-Objective Optimization

Power-delay-cost balance

More Realistic Scenarios

Smart-Grid & Economic Viability

Improved EDCs

Thermal-Aware EDC Modeling

Our Project

Publications

J. Pérez, S. Pérez, J. Moya, and P. Arroba, "Thermal Prediction for Immersion Cooling Data Centers Based on Recurrent Neural Networks," IDEAL 2018.

S. Pérez, J. Pérez, P. Arroba, R. Blanco, J. Ayala, and J. Moya, "Predictive Gpu- Based Adas Management in Energy-Conscious Smart Cities," IEEE ISC2, 2019.

Funding

▷ HDC–NOVEC: Refrigeración de servidores de centros de datos de alta densidad por inmersión en fluido refrigerante bi-fase (CDTI IDI-20171194).

▷ GRID-E: Sistema integral para la gestión óptima coordinada de recursos en centros de datos de altas prestaciones (*Retos Colaboración* RTC-2017-6090-3).

Awards

EnerTIC Award 2019 in Power & Cooling Category.

Real-sized Prototype

Partners

3M
TEIMMERS
aeon ingeniería
Adam
imesAPI

Literature Review

1. Smart Cities
- 1.1 Growth & concerns
- 1.2 Cloud & Edge
- 1.3 ADAS applications

2. Cooling Systems
- 2.1 Current methods
- 2.2 Two-phase immersion
- 2.3 Dielectric coolants

3. Resource Allocation
- 3.1 Current methods
- 3.2 Deep RL theory
- 3.3 Edge & Deep RL

Solution

1. Edge Modeling
- 1.1 ADAS application
- 1.2 Air & two-phase prototypes
- 1.3 IT & cooling models

2. Edge Optimization
- 2.1 A2C theory & design
- 2.2 Implementation in Mercury
- 2.3 Scenario layout

3. Optimization Results
- 3.1 Four scenarios tested
- 3.2 Two EDC modes tested
- 3.3 Three configurations tested

Project

1. Publications
- 1.1 IDEAL 2018
- 1.2 IEEE-ISC2 2019
- 1.3 Working on an article

2. Industry Prototype
- 2.1 EDC with 100 kW
- 2.2 Partners: 3M, Adam...

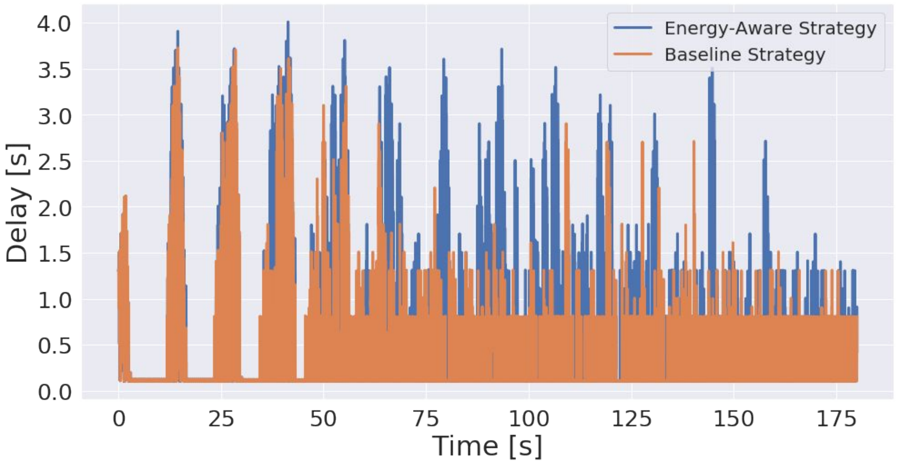
3. Funding
- 3.1 IDI-20171194
- 3.2 RTC-2017-6090-3

4. Awards
- 4.1 EnerTIC Awards 2019

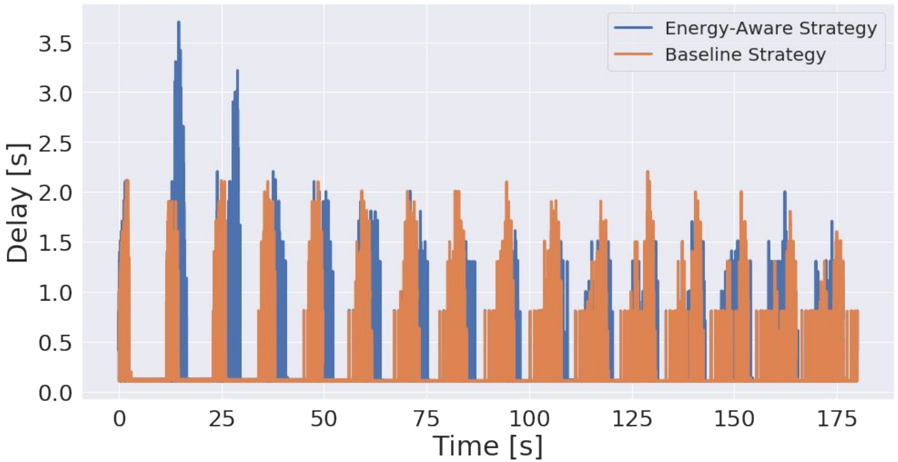
Thanks! **Any questions?**

BACKUP

Delay Analysis



WITHOUT Hot Standby



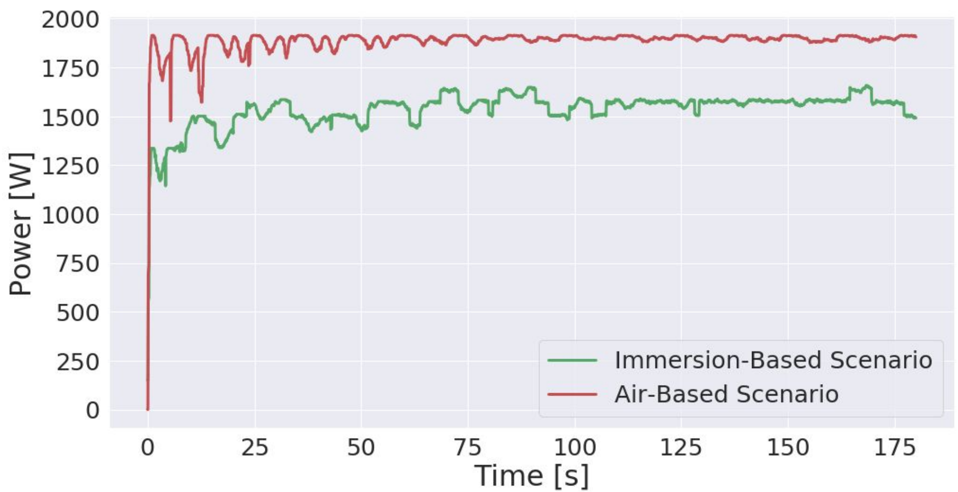
WITH Hot Standby

Air vs. Immersion

Scenario	GPUs*	P [kW]	[%]	PUE	[%]
Air	5	1.86	-28.5	1.31	-22.1
Imm.		1.33		1.02	
Air	10	2.23	-26.5	1.31	+19.8
Imm.		1.64		1.05	
Air	15	2.22	-23	1.31	-16.0
Imm,		1.72		1.10	

Hot Standby & Baseline Results

(The best ones)



10-GPU Scenario Comparison

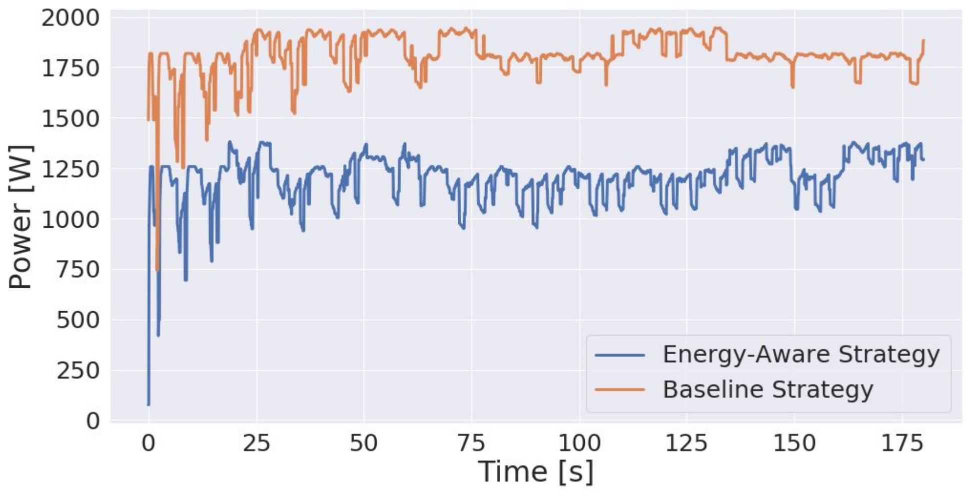
(Not the best one)

*GPUs per EDC

Best Results (Heterogeneous I)

Strategy	GPUs*	P [kW]	[%]	PUE	[%]
Baseline	5	1.69	-19.2	1.26	-4.86
Energy		1.36		1.20	
Baseline	10	1.78	-27.4	1.20	-15.0
Energy		1.30		1.10	
Baseline	15	1.81	-33.6	1.31	-20.5
Energy		1.20		1.05	

NO Hot Standby Results



15-GPU Strategy Comparison

*GPUs per EDC

EXTRA

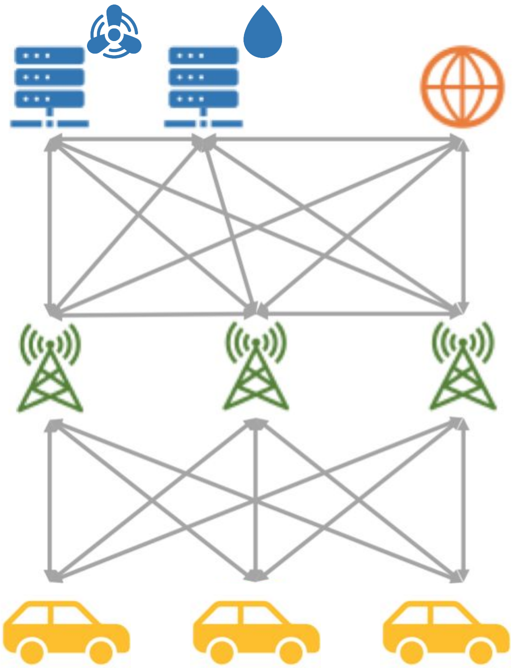
*Edge Data Center: EDC

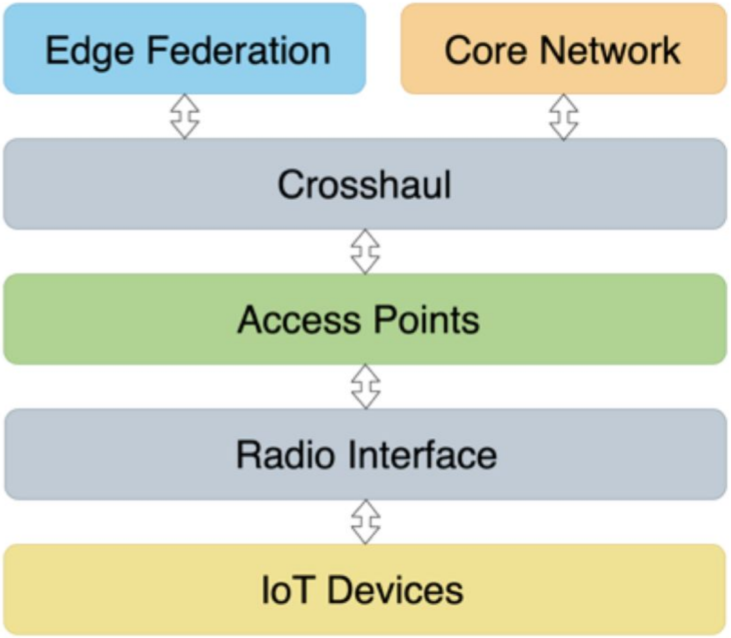
Contributions to the State of the Art

The **energy-aware EDC* modeling** of a conventional and a two-phase immersion system using real hardware prototypes and a real Edge Computing application.

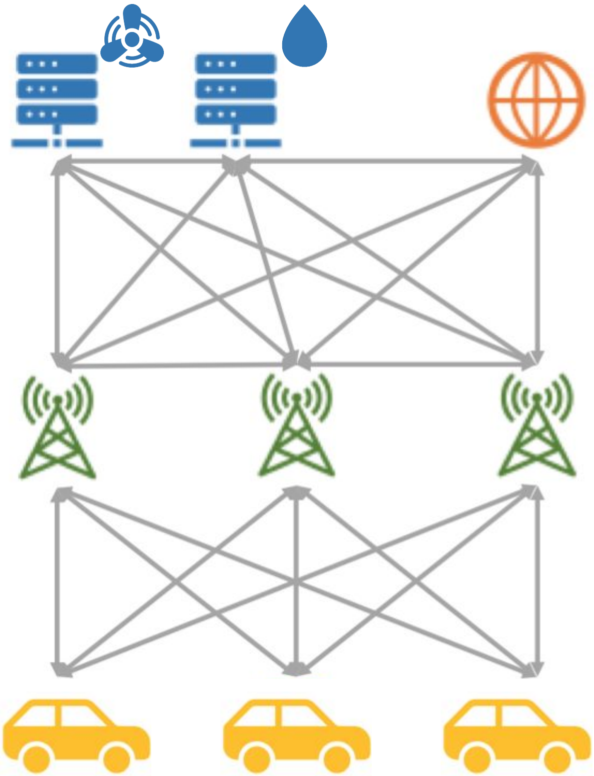
The **energy-aware resource optimization** of realistic Edge Computing scenarios using Deep Reinforcement Learning and Mercury, a 5G-Edge simulator.

Solution: Scenario Description





Problem Description



A real Edge Computing service

We need

Realistic models of the scenario

We need

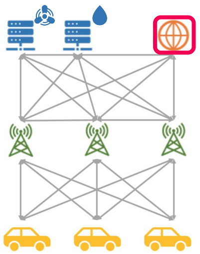
Simulations

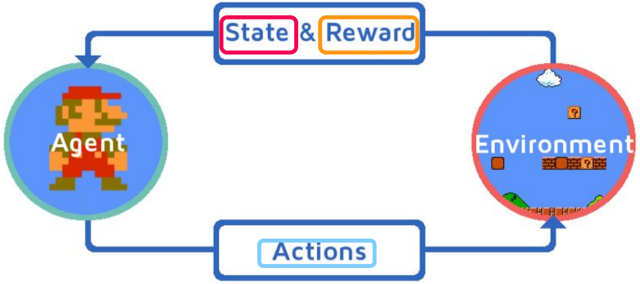
We need

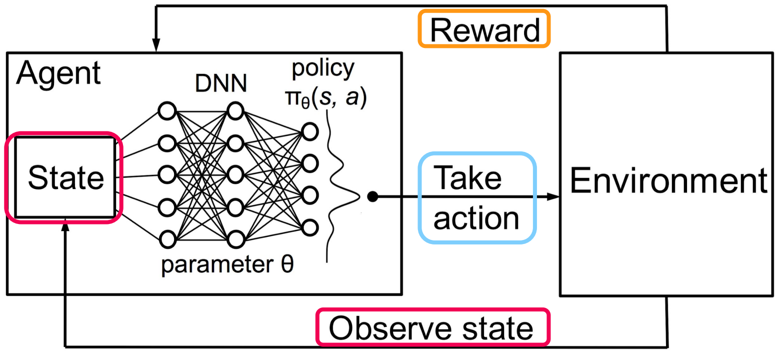
We want to optimize Edge Computing scenarios not deployed yet

Resource Allocation Management (ii)

Reinforcement Learning Formulation







State

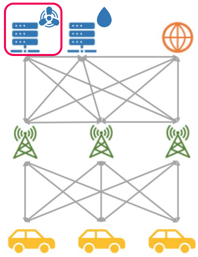
EDCs' energy status

Action

Choosing an EDC

Reward

$$r = -P_{fed} = -\sum P_{EDC} = -\sum P_{IT} + P_{cool}$$



Solution: Air-cooled EDC (i)

IT Equipment

Hardware

Sapphire Pulse Radeon RX580 GPU

Model

Type

FeedForward Neural Network

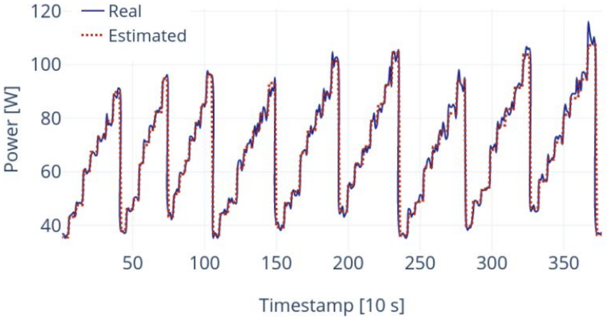
Input

Main and memory clocks, and ADAS sessions.

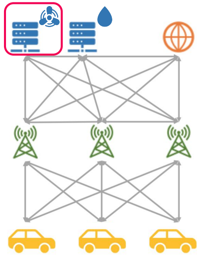
Output

Power Consumption

Results

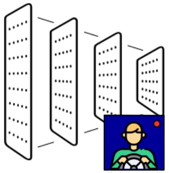


NRMSD	2.45%
R^2	99.01%

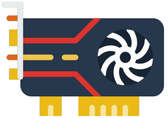


Air-Cooled EDC (i)

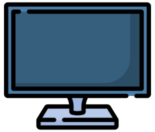
IT Equipment Modeling



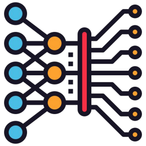
1. CNN-ADAS implementation



2. CNN-ADAS execution in GPU
   (GPU model: Sapphire Pulse Radeon RX580)

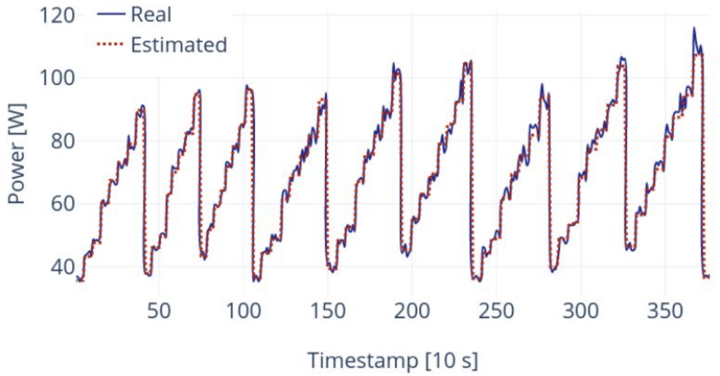


3. GPU monitoring (power, clocks…)



4. FFN* power consumption model

5. Model results



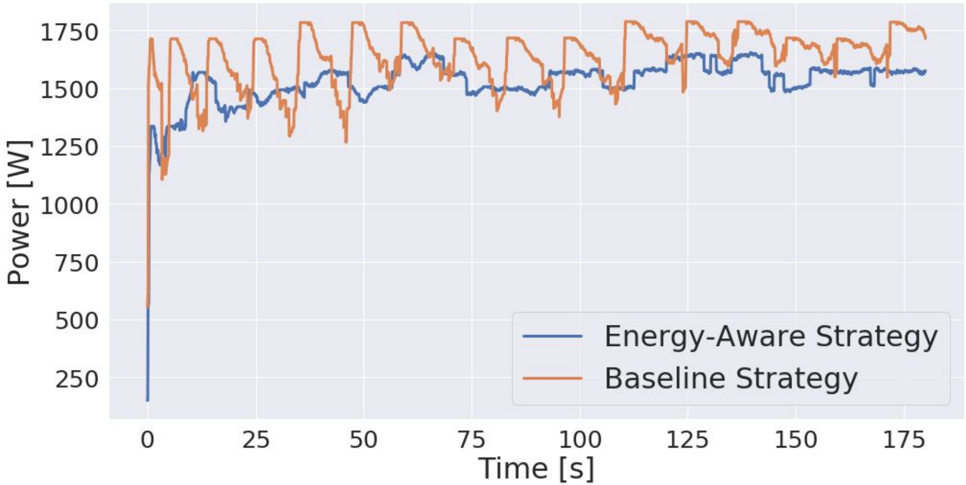
NRMSD	2.45%
R^2	99.01%

*FeedForward Neural Network: FNN

B) Immersion-Based Scenario x3

Strategy	GPUs*	P [kW]	[%]	PUE	[%]
Energy	5	1.33	-4.87	1.02	+0.24
Baseline		1.26		1.03	
Energy	10	1.64	-6.60	1.05	+1.61
Baseline		1.53		1.06	
Energy	15	1.72	-0.56	1.10	-1.36
Baseline		1.72		1.09	

Hot Standby Results



10-GPU Model Comparison

Immersion-cooled solutions yields savings of **18.3%** in contrast to air-cooled ones.

*GPUs per EDC

Our Project

Publications

J. Pérez, S. Pérez, J. Moya, and P. Arroba, “Thermal Prediction for Immersion Cooling Data Centers Based on Recurrent Neural Networks,” International Conference on Intelligent Data Engineering and Automated Learning (IDEAL), 2018.

S. Pérez, J. Pérez, P. Arroba, R. Blanco, J. Ayala, and J. Moya, “Predictive Gpu-Based Adas Management in Energy-Conscious Smart Cities,” IEEE International Smart Cities Conference (ISC2), 2019.

Awards

Primer premio EnerTIC Awards 2019 en la categoría Potencia y Refrigeración

enerTIC

Industry-Ready Prototype

Commercial Partners

3M

aeon ingeniería

TEIMMERS

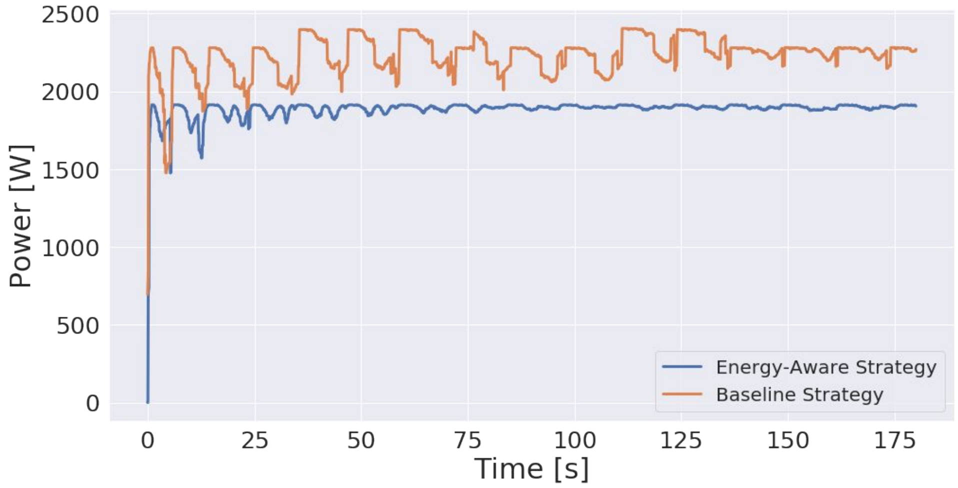
imesAPI

Adam

Air-Based Scenario x3

Considerable energy savings respect to the baseline.

Strategy	GPUs*	P [kW]	[%]	PUE	[%]
Energy	5	1.86	-13.1	1.31	0.00
Baseline		1.61		1.31	
Energy	10	2.23	-15.5	1.31	0.00
Baseline		1.88		1.31	
Energy	15	2.22	-6.19	1.31	0.00
Baseline		2.09		1.31	



Hot Standby Results

10-GPU Model Comparison

*GPUs per EDC

MSc Thesis' Summary

Literature Review

1. Smart Cities
- 1.1 Growth & concerns
- 1.2 Cloud & Edge
- 1.3 ADAS applications

2. Cooling Systems
- 2.1 Current methods
- 2.2 Two-phase immersion
- 2.3 Dielectric coolants

3. Resource Allocation
- 3.1 Current methods
- 3.2 Deep RL theory
- 3.3 Edge & Deep RL

Theory & Hardware

1. Theory
- 1.1 Mercury simulator (DEVS)
- 1.2 Neural networks
- 1.3 Optimization
- 1.4 Advantage Actor-Critic
- 1.5 Thermodynamics

2. Hardware
- 2.1 GPUs for neural networks
- 2.2 AMD & ROCm backend
- 2.3 Air-cooled prototype
- 2.4 Two-phase prototype
- 2.5 NOVEC 7100

Software

1. Simulator
Mercury (Python module)

2. Neural Networks & RL
Keras, TensorFlow, PyTorch

3. Data Processing
Numpy, SciPy, Pandas

4. Data Visualization
Seaborn, Plotly, Matplotlib

5. Monitoring System
Collectd, Kafka, Cassandra

6. Code Editor
VS Code, Jupyter, VIM

Thanks!

Any questions?