BITS Pilani

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Model-Assisted Optimal Control for Split Air Conditioners (ACs)

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Cooling Systems in Buildings

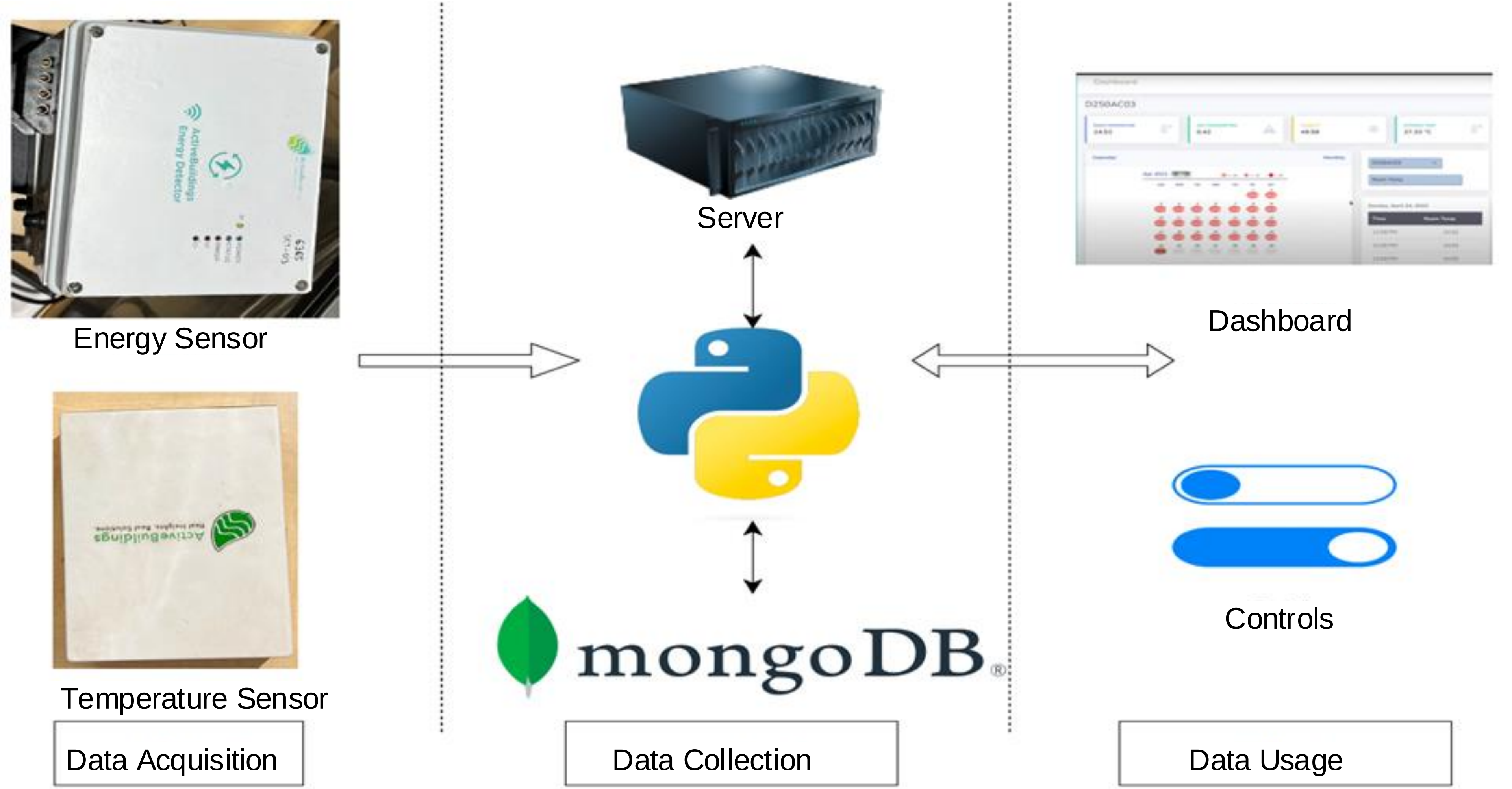
1. Cooling systems provide thermal comfort to humans which improves their productivity
2. Global warming is a reason of ever-increasing demand for cooling systems
3. Cooling systems consumes more than 40% of overall buildings' energy
4. Two types of cooling systems are available for use —
   a. Ducted-centralized cooling systems
   b. Ductless-split cooling systems

Ducted and Ductless

1. In Ducted-centralized cooling systems, we have a compressor that distributes air to multiple Individual Cooling Systems (ICSes)
2. In Ductless-split cooling systems, each ICS is associated with an independent compressor unit
3. The challenges in optimal control of Ductless-split cooling systems
   a. Presence of multiple ICSes in a room
   b. Independent controls and their impacts
   c. Variable heat load for each ICS

IoT-enabled Ductless-split Cooling Systems

Data Collection



Problem Statement

1. The cooling systems follows a cooling cycle with certain max ON and min OFF periods
2. Relationship between energy consumption and change in room temperature, i.e., efficiency of the ICS, is dynamic
3. We need a technique to find
   a. The efficiency of each ICS
   b. Based on the efficiencies, compute a schedule for the operations of the ICS

Existing Solutions

1. Linear scheduling techniques for optimization of cooling systems requires prior knowledge of the efficiencies of each cooling system deployed in the room; however, the efficiencies of cooling systems keeps changing depending on factors like the time of the day

2. Reinforcement Learning-based solutions are capable to learn the efficiencies of the cooling systems, but these approaches are slow to converge

Energy as a Function of Execution Time

- The energy consumption of cooling systems follows a linear behavior with the time for which it is executed
- To optimize energy consumption, we propose to minimize the cooling system's total execution time
- The function that calculates the cooling system's execution time is a convex function of efficiency of the ICS
- We use the max-min solver with Bayesian predicting capabilities to solve the defined convex optimization problem
- This gives us a long-term optimal control trajectory for the ICS

$$E_c = \sum_{i=1}^{n} f_i(g_i(C_T, \tau, x) + b_i)$$

Theorem 1. *The function* $g(C_T, \tau, x) = \frac{C_T}{1+\tau * x}$ *is a convex function for all feasible values of* τ *and* x. *Here, feasible means the ability of the cooling system to cool the room.*

Estimating Efficiencies of ACs

- We use time series data of efficiency calculated using temperature and energy sensors corresponding to each ICS
- Once we have efficiency data for each ICS, we use the time series fitting method to identify the distribution with the least Sum of Squared Error (SSE)
- The Bayesian Regression technique allows us to estimate the future efficiencies of each ICS, which is required to predict a long-term control trajectory

MaOC Algorithm

1. Estimate efficiencies of each ICS present in the room
    - Learning the probabilistic distribution of time series characteristics of cooling systems
2. We propose to use probabilistic regression to generate a long-term control trajectory
    - We use the probabilistic distribution with regression to estimate the long-term efficiency of each ICS
    - We use max-min solver to identify the most efficient ICS for execution
    - To maintain the execution cycle of the cooling system, we use an automaton that checks the availability of the cooling system for execution

Evaluation

- We evaluate the proposed solution in both experimentation and simulation
  - We use a well-known simulator called EnergyPlus for this purpose
- We compare the solution with CLA (Linear Scheduling) and OCSRL (Reinforcement Learning)
- We consider the following metrics for evaluation
  1. Estimation of efficiencies
  2. Energy consumption
  3. Temperature maintained and time taken to cool the room

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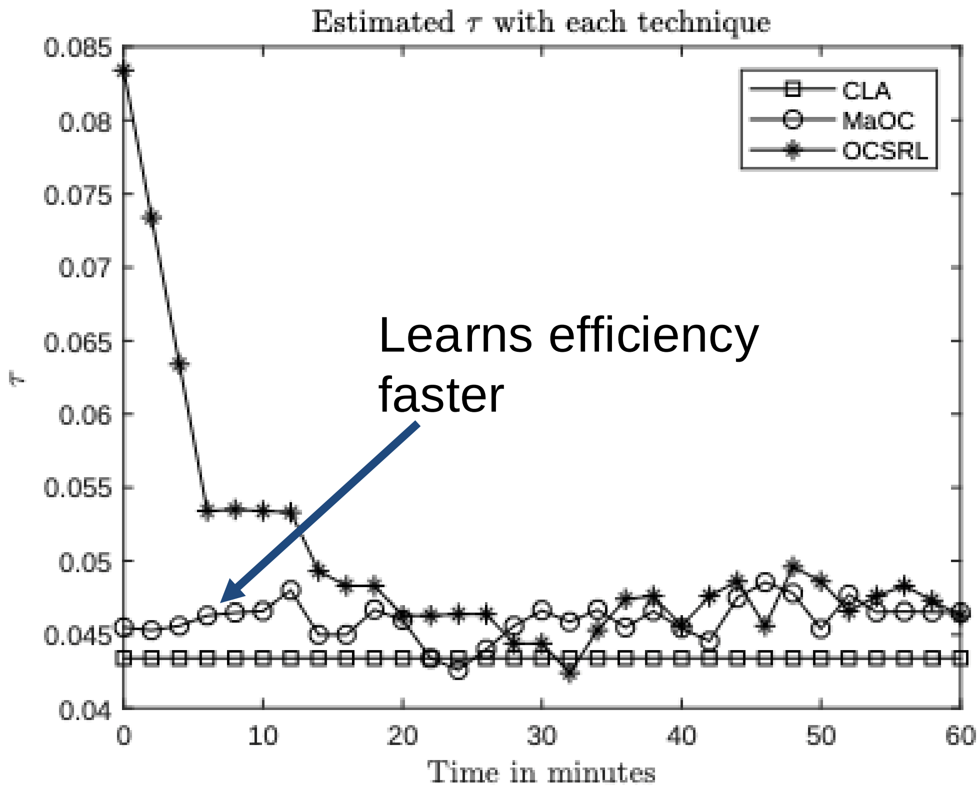
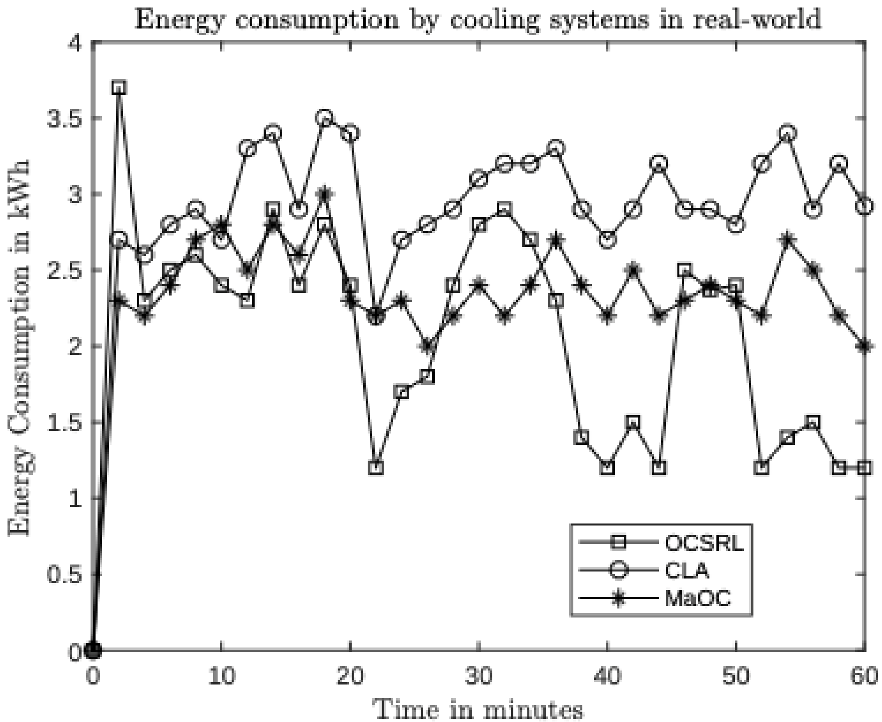
Evaluation— Experimentation

1. Estimation of efficiencies



Evaluation— Experimentation

2. Energy consumption



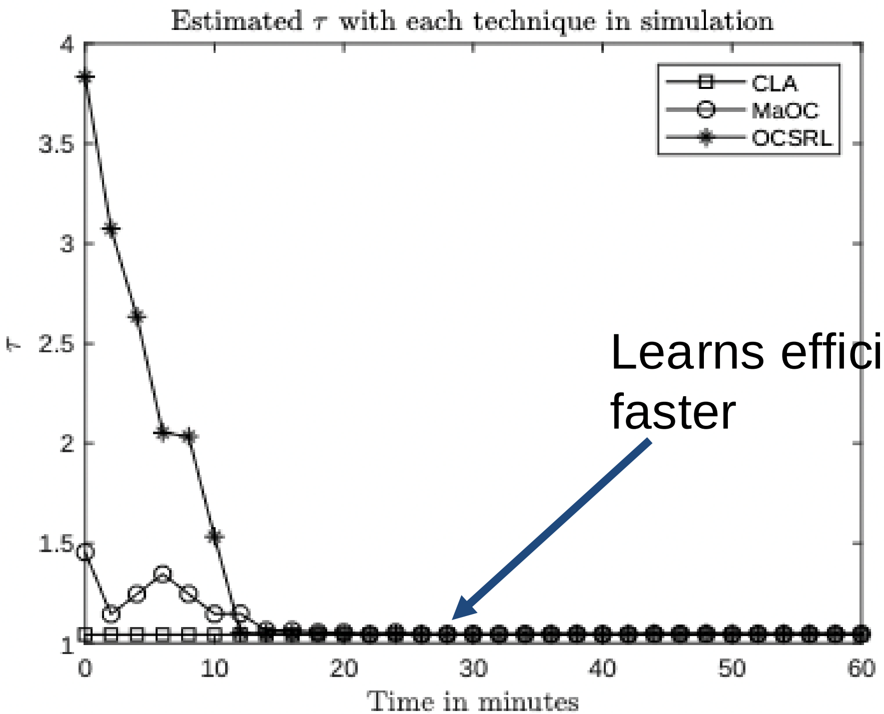
Evaluation— Experimentation

3. Temperature maintained and time taken
   - The desired temperature is 23º C

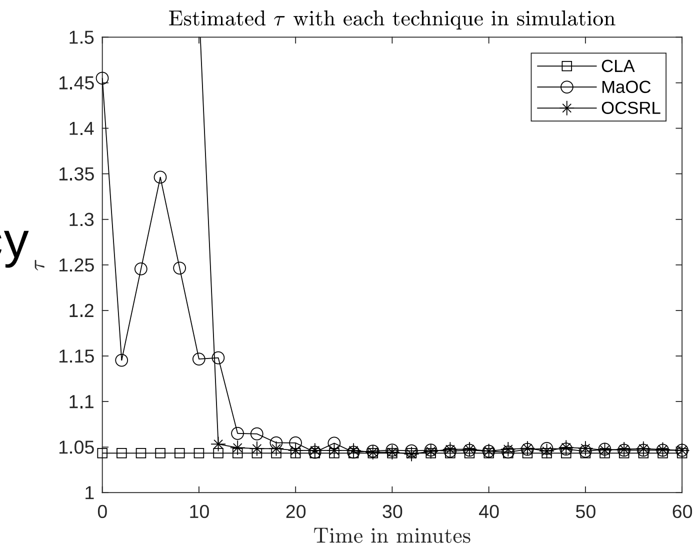
Algorithm	Time to reach desired temperature (in minutes)	Average temperature maintained (in $^{\circ}C$)
CLA	12	23.8
OCSRL	18	23.5
MaOC	12	23.3

Evaluation— Simulation

1. Estimation of efficiencies



Learns efficiency faster



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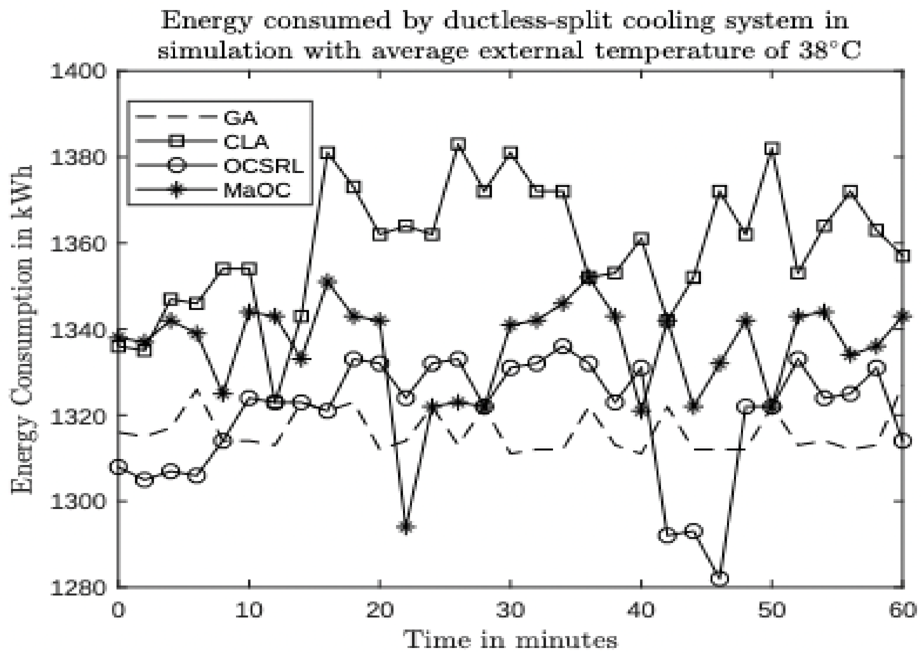
Evaluation— Simulation

2. Energy consumption
   - Greedy Algorithm (GA) is optimum possible
   - GA's average energy consumption is the minimum



Evaluation— Simulation

3. Temperature maintained and time taken

Algorithm	Time to reach desired temperature (in minutes)	Average temperature maintained (in $^\circ C$)
CLA	40	24.2
OCSRL	52	24.6
MaOC	45	24.3
GA	92	24.9

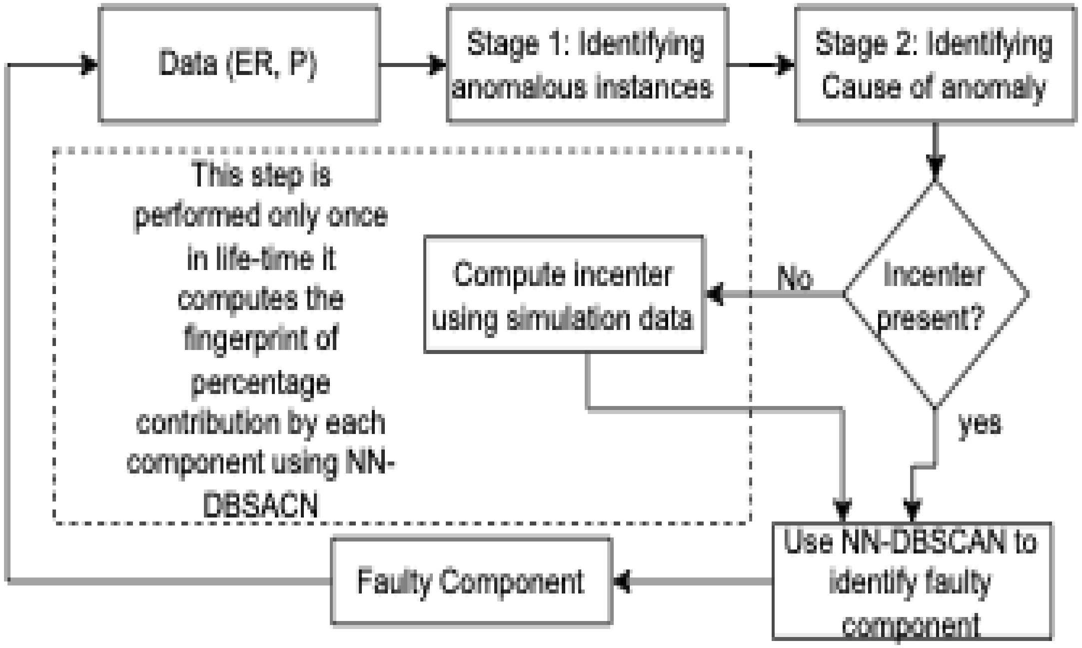
Algorithm	t_exec of AC1 (in minutes)	t_exec of AC2 (in minutes)	t_exec of AC3 (in minutes)	Execution Time (in minutes)	Environment (in $^\circ C$)
CLA	640	640	640	1920	38
GA	1430	632	0	2062	
OCSRL	640	480	548	1668	
MaOC	640	520	536	1696	
CLA	560	560	560	1680	32
GA	1440	420	0	1860	
OCSRL	624	403	510	1537	
MaOC	610	418	520	1548	
CLA	480	480	480	1440	26
GA	1440	20	0	1460	
OCSRL	534	360	480	1374	
MaOC	540	364	500	1404	

Conclusion of MaOC Work

1. We introduced possibility of learning dynamical efficiencies of cooling systems using probabilistic techniques
2. Probabilistic techniques combined with optimization framework can be used for an optimal control
3. We presented that the probabilistic techniques helps us in attaining optimality comparable to the computationally expensive Reinforcement Learning
4. We observed using domain knowledge can help in saving more than 30% of energy using cooling systems

Problem of Identifying Anomalies

1. Occurrences of faults/anomalies in cooling systems are frequent
2. These faults cost more than 45% of energy wastage in the entire execution lifetime of a cooling system



Stage 1 – Identifying Anomalous Instance

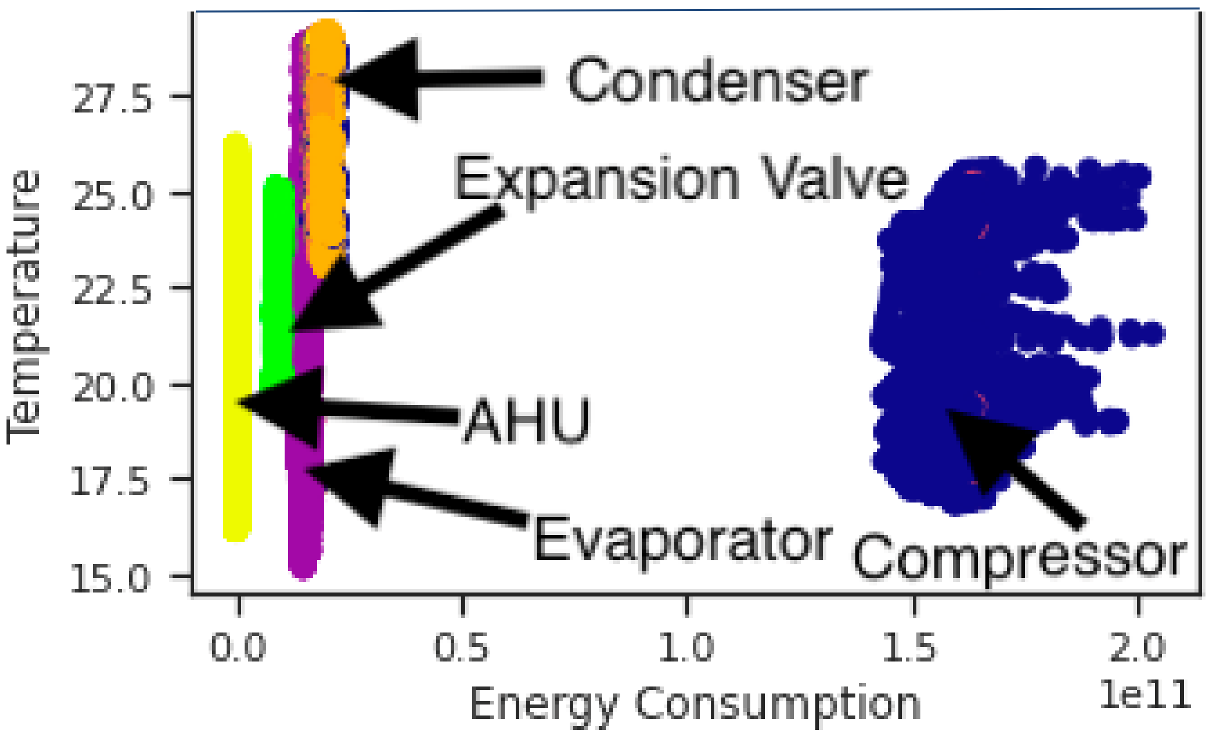
- We propose to use domain-driven time series analysis to identify instances of anomalies in cooling systems
- We use the moving average to identify the anomalous event
- When the energy consumption of cooling systems deviates by 5% from its Energy Rating we classify the instance as anomalous
- The space and time complexities of our solution are O(n)

Stage 2 – Identifying the Type of Anomalies

- We classify the anomalies into three categories—
  - Anomaly Cause 1: Wrong set temperature
  - Anomaly Cause 2: Technical fault
  - Anomaly Cause 3: Cooling requirements are not satisfied

Anomaly Cause	Rule No.	Rule	Conclusion
$AnomalyCause_1$	Rule 1	$T_{room} < T_{goal}$	T_{set} of AC is high — Change T_{set}
	Rule 2	$T_{goal} < T_{room}$	T_{set} of AC is low — Change T_{set}
$AnomalyCause_2$	Rule 3	$\Delta T_{external} < \Delta T_{room}$	Cooling in T_{room} is less than $T_{external}$ — Identify faulty part
	Rule 4	$\Delta T_{room} < 0$	Unable to cool — Identify faulty part
	Rule 5	$PA > 4$	More than 4 continuous anomalies — Identify faulty part
$AnomalyCause_3$	Rule 6	$T_{room} < T_{set}$	No need to cool — Turn OFF cooling system
	Rule 7	$\Delta T_{room} \leq 0$ && $T_{set} = minimum$ && $T_{room} \leq T_{goal}$	Unable to reach the T_{goal} — Cooling system not sufficient

Opportunity of Identifying the Faulty Part



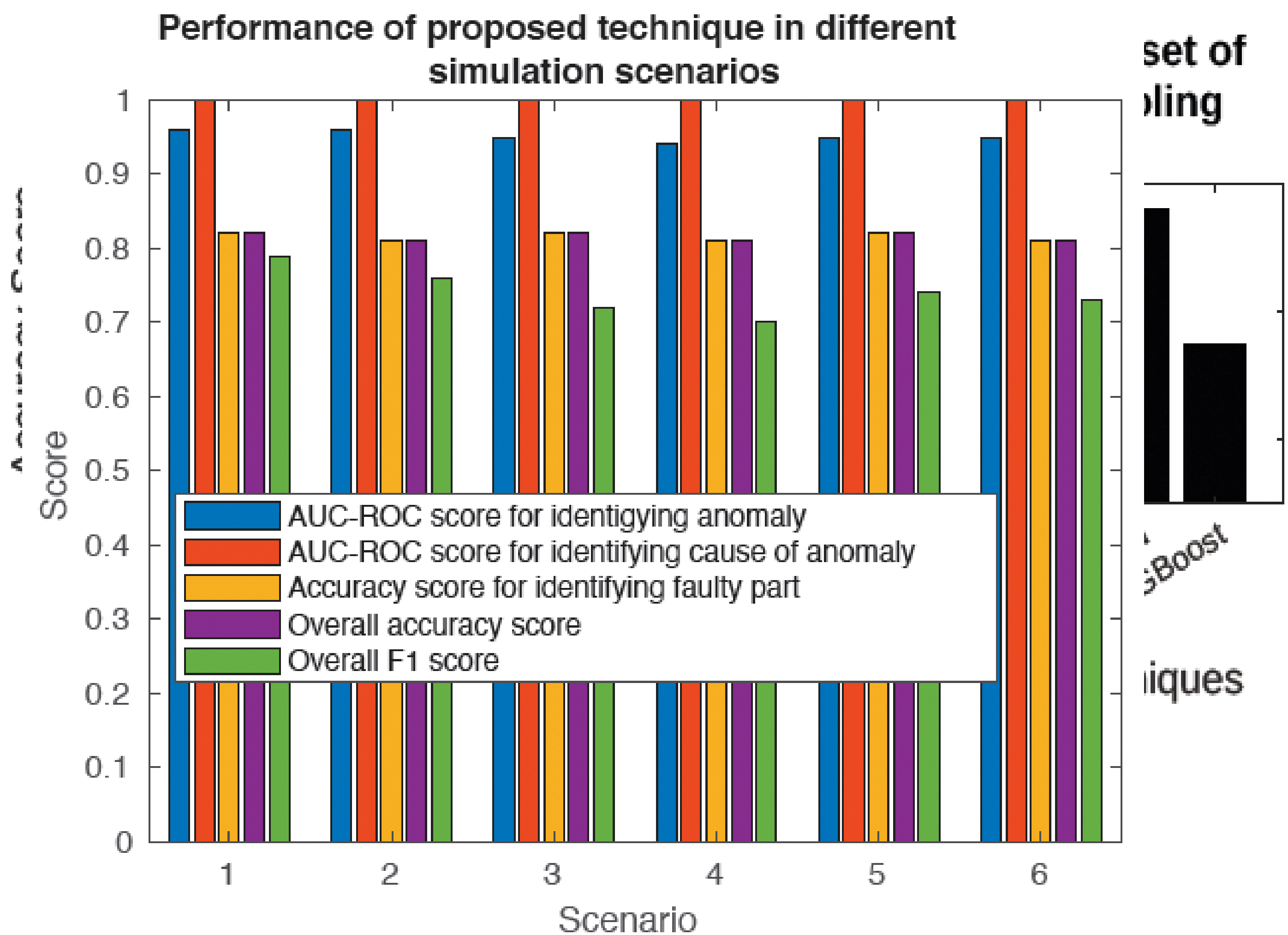
Stage 3 – Identifying the Faulty Part

- To identify the faulty part, existing solutions requires a lot of data
- Probabilistic causal models are infeasible to use because the occurrence of technical faults is rare in cooling systems
- Regression techniques require huge amounts of data to tune themselves for a new deployment
- To overcome these challenges, we propose Nearest-Neighbor Density-Based Clustering Applications with Noise (NN-DBSCAN)

NN-DBSCAN

- Estimate in-center for each of the five parts of cooling system
- To estimate the in-center, we use simulation data representing an equal number of faults for each part
- We approximate the percentage contribution of each part
- When the NN-DBSCAN is deployed to new deployments, it takes the Energy Rating to estimate the incenter of the new cooling system
- The initial identification of faults is performed by identifying the in-center Nearest-Neighbor
- Once min-Pts is attained for each cluster, it continues working as DBSCAN

Evaluation – Faulty Part



Data is Publicly Available

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