Technical Description

Subject: *Using machine learning to efficiently cool data centers*
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Problem Statement

30-40% of power costs in a data center goes to cooling. Average PUE of data centers in India is over 1.7. Though data centers have state of the art cooling systems from best companies, they can be managed more efficiently. We think these inefficiencies happen due to following:

1. Data centers are notoriously difficult to model, thus there is no place to experiment with new settings, such as setpoints. But data centers can be modelled using past sensory and control data. These models are highly accurate and can predict effects of changing setpoints and other controls
2. Cooling policies are coarse grained and localised, often set to work against peak IT load capacity, not taking into account the effect one cooling system has on another
3. Cooling policies are reactive or static. E.g. when the temperature of a zone rises, AC's are switched to lower temperature. By using dynamic policies, these scenarios are managed automatically and in real time

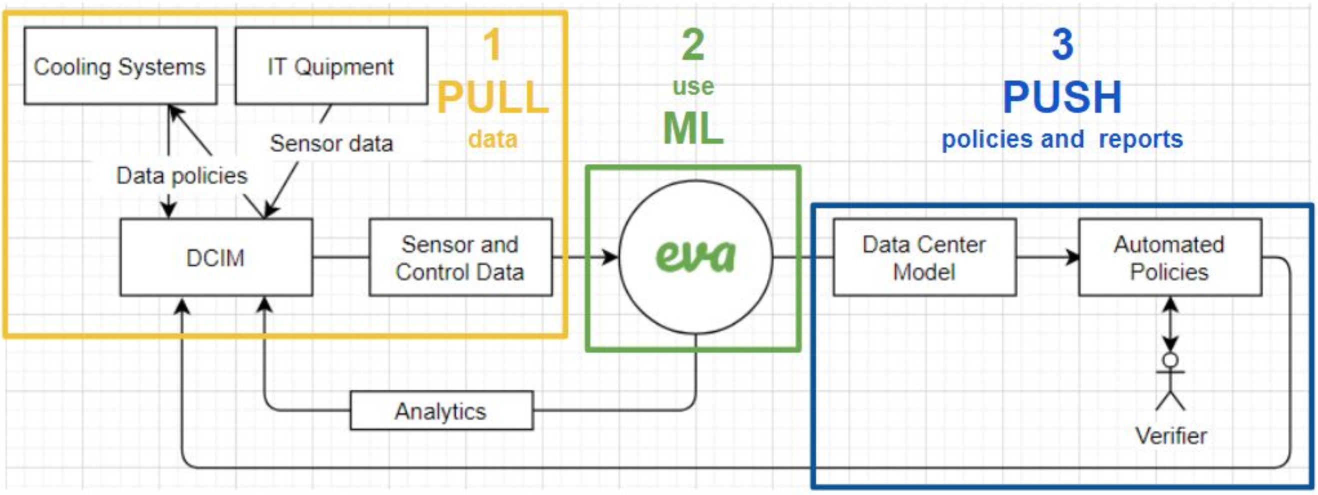
Introduction

Data centers can be modelled using past sensors and control data. These models are highly accurate and can predict changes caused by moving setpoints. These models can then be used to test new policies or generate policies automatically.

Background

Google (link) successfully deployed machine learning based systems to control cooling in their data centers. This saved them 40% of cooling costs and now they have some of the lowest possible PUEs of all data centers (1.06).

Our Methodology



Using data to model and then control

1. Modelling

Data centers log their data to monitor equipment performance. Most of DC equipment is connected by Modbus or SNMP and feeds data to a DCIM or similar data extraction softwares. E.g. temperature across various racks, current IT load, fan speeds for different AHUs etc. We use this data to model the data center using deep neural networks. Neural networks are known to be capable of modelling very complex nonlinear functions and these models are typically highly accurate. Neural networks are also being used across industries where feature design is complex. Our model is a function of different setpoints and sensory data and outputs power usage of the cooling system. The network is trained using time series modelling techniques which are also used for stock market prediction. We optimize for accurate aggregate prediction of energy usage in the next 1 hour.

2. Model as proxy

Let us say, we want to know what would be the PUE if one of PACs setpoint is increased by a degree. Since data centers are mission critical, one cannot just modify the setting and check its impact. Such experiments can lead to downtime and are hence extremely risky. The model we trained above is used to do such experiments virtually, as it can predict PUE without touching the real data center. We use this model as a proxy for experiments and exploration.

3. Model testing

We deploy this model in a containerized environment on cloud or on premise. Then it can be used by existing data center personnel, to experiment with new policies and reduce PUE. This is a risk free deployment, as the personnel only use the model for testing.

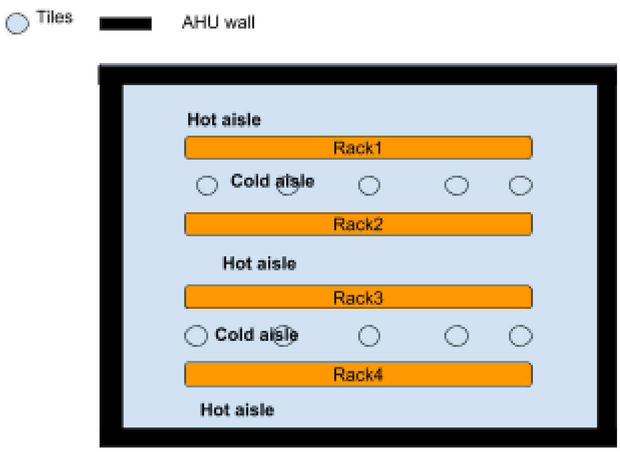
4. Generating policies

In this step, we generate automatic strategies to cool the DC for specific scenarios. These policies are derived using reinforcement learning algorithms (used in trading and self driving cars). We reward the algorithm for generating policies that reduce PUE and follow constraints. These policies are pushed to DCIM after generation and then either reviewed or deployed directly to control cooling systems.

Experiments

Strategy Simulations

Consider 4 racks arranged in a cold aisle, hot aisle arrangement shown below. Each rack sucks air from the cold aisle and throws it to the hot aisle. All tiles are controllable, with a fixed temperature setpoint of 0.1 (10% of max allowable temperature). All racks are at 0.9 (90% of max allowable temperature) in the beginning. The model is trained for a day with an objective to bring the rack temperature down to 0.8 using minimum time and energy.



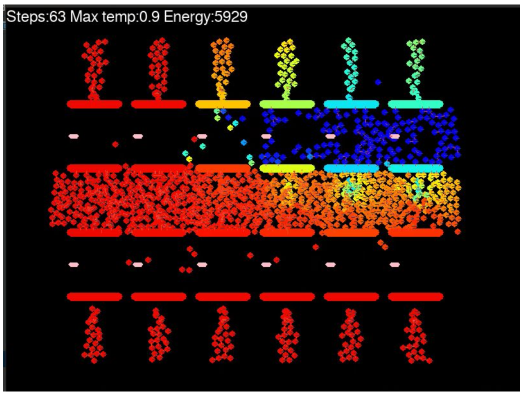


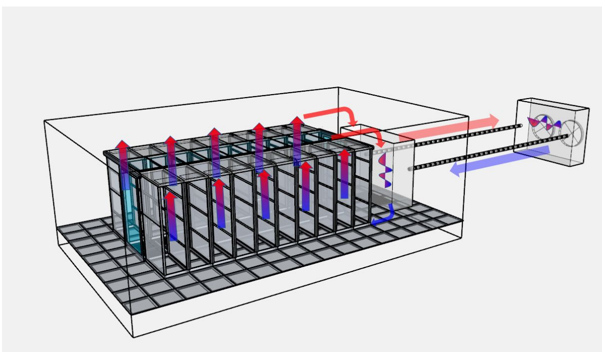
Figure : Simulated DC Floor

What does the model learn?

1. After 10000 iterations (video [here]), the model learns to:
    a. Cool some servers in Rack2
    b. Uses their cool air which is coming to middle hot aisle, to cool Rack3
    c. Choses suboptimal tiles and keeps them on
2. After 20000 iterations (video [here]), the model learns to:
    a. Switch tiles on and off
    b. Optimizes tile damping

EnergyPlus Simulations

EnergyPlus is a popular software used to simulate energy consumption in buildings. It comes with its own control systems which can be overridden. We are using EnergyPlus as simulation software and modelling existing data centers. EnergyPlus is used to obtain sensor and control data. This serves as an experimentation platform to design the backbone structure of our neural networks.



Simulated DC floor

Integration with DCIM

Since all we need for our base system to work is access to data, we can run on cloud, on a workstation in the data center, or on the DCIM as a plugin itself. We require access to data API's of a DCIM, or a portal where data can be uploaded by data center personnel.

Launch

Before launch, we will collect constraints DCs are currently required to follow (e.g. temperature at rack < 22C etc). All policies will ensure that these constraints are satisfied at all times.

Policy stage 1: In this stage, we will generate cooling policies and get them checked with DC SMEs. Approved policies are deployed on DCIM and continuously monitored. In this stage, policies are generated very slowly, once per 6 hours

Policy stage 2: In this stage, we move to generating policies faster, around 1 per hour. Policies will still require manual approval to go through

Policy stage 3: If stage 2 is successful, and leads to 99% of policies being passed through, we will move to automatically deploying policies on the DCIM. All policies will be verified once a day and monitored continuously.

Policy stage 4: In this stage, our system takes policy control and no manual verification is required. Team retains access to revert the systems back to original state in case of event occurrence

Performance monitoring: We will monitor all systems and constraints. Also, we will have a clear measure of how much energy is saved by these policies

Data Required for Modelling

- The following HVAC characteristic data from DCIM systems is used to model data centers. The list is for illustration purpose only. Non-availability and over availability of parameters do not have an impact on the overall savings result.
- Sensory data
  - Temperature and humidity data across racks (necessary)
  - Temperature and humidity of outside atmosphere (necessary but can be arranged from other sources if not available)
- Cooling system data
  - AHUs:
    - Setpoint
    - Return air temperature
    - Supply air temperature
    - Fan speed
    - Power consumption
  - Chillers, Condensers, Cooling towers and subsequent loops, if any:
    - Input and output temperature
    - Speeds of various fans and drives in each device
    - Power consumption
    - Any other state variables
- Overall metrics
  - PUE
  - IT load
  - Power distribution across AHUs, chillers, cooling towers etc.