“ENTRY TO THE STOCKHOLM JUNIOR WATER PRIZE 2025”

# EFFECTIVE WATER USAGE WITH DEEP REINFORCEMENT LEARNING IN DATA CENTRE

BY

**SAMANYU SRIVASTAV**

**INDIA**

# TABLE OF CONTENTS

# LIST OF TABLES



# LIST OF FIGURES

# ACKNOWLEDGEMENT

I would like to convey my sincere gratitude to Sh. Sunil Gupta, CEO Yotta Data Services Private Limited and Ms. Hema Jain, Computer Science faculty, DPS R K Puram, New Delhi for their invaluable guidance, constant encouragement, and support throughout this work. No amount of words can really be adequate in expressing my sincere thanks to them. Without their unremitting support, this work would have never been completed.

At this moment of accomplishment, I would like to say a heartfelt thanks to my parents for all their blessings and encouragement to pursue this project research.

I would finally like to thank my relatives and friends and all those, directly and indirectly, involved in the making of this thesis and my research work.

**(Samanyu Srivastav)**


# BIOGRAPHY

I am an enthusiastic and dedicated scholar with a deep interest in STEM. I have a great passion for learning and have strong commitment for academic excellence. Currently I am a student of Class XI, studying in Delhi Public School, R K Puram New Delhi, India. I have a strong academic record with consistent outstanding performance throughout my academics journey. Some notable achievements of me are –a near perfect SAT score of 1570/1600, earned High Distinction in International Chemistry Quiz conducted by Royal Australian Chemical Institute, top 10 performers in Class X in school, have earned State scholarship, earned DELF certification in French, recipient of several award and certificates in International/National Science, Mathematics Olympiad, have represented School on several competitive platforms and have won honors for school.

I have been a representative of High School in Student Council and recipient of meritorious 'Red Blazer' award. I have deep passion for Computer and Electronic research projects and have thorough knowledge of Python, C++, and Arduino. I have published articles in leading science magazines, blogs and have successfully completed several science projects. I am an active member in various academic clubs and activities at school. I have deep passion for playing piano and have earned Diploma from Trinity College London. I am fond of playing basketball, and badminton. I am determined to build a strong academic foundation with career aspiration in research.

**(Samanyu Srivastav)**

# SUMMARY

Data centers have been water guzzlers owing to heavy-duty cooling and energy requirements. Globally, very limited efforts have been made in water conservation and water utilization effectiveness (WUE) in data centers (DC). The industry standard for WUE is 1.8 L/kWh. This novel research is based on water conservation principle by improvising the WUE in DC. To achieve this objective this work proposes an efficient smart water cooling modeling framework that leverages the simulation software EnergyPlus (Open source platform) coupled with Sinergym (Open source framework) based on Deep Reinforcement Learning (DRL).

In this study, a realistic DC has been leveraged to fully test the simulated solution for summer design days. The smart water cooling model optimizer has been trained using a Deep reinforcement learning (DRL) that minimizes the total water consumption. A comparison of the study (with or without DRL) infers that merely deploying the simulation software does not efficiently assist in improvising the WUE. It's the DRL approach using DDPG algorithm that has improvised the WUE industry standard by 20.64%. With this integrated solution, being tested in the real time DC, the resultant WUE has outperformed the industry standard.

**Keywords:** Water usage effectiveness, Deep reinforcement learning, Data centers, Water conservation, Smart water cooling modeling framework.

# LIST OF ABBREVIATIONS AND ACRONYMS

| **Abbreviations and Acronyms** | |
|---|---|
| A3C | Asynchronous Advantage Actor-Critic |
| AI | Artificial Intelligence |
| API | Application Programming Interface |
| ASHRAE | American Society of Heating, Refrigerating and Air-Conditioning Engineers |
| CSP | Cloud Service Provider |
| DC | Data Center |
| DCP | Data Center Provider |
| DDPG | Deep Deterministic Policy Gradient |
| DRL | Deep Reinforcement Learning |
| EMF | Electro Magnetic Force |
| EMS | Energy Management System |
| ESG | Environmental Social and Governance |
| GPT | General Pre-trained Transformer |
| HVAC | Heating Ventilation and Air conditioning |
| KWH | Kilo Watt Hour |
| PPO | Proximal Policy Optimization |
| RL | Reinforcement Learning |
| SAC | Soft Actor-Critic |
| SFA | Server Farm Area |
| TR | Ton of Refrigeration |
| WUE | Water Usage Effectiveness |

## 1. Introduction

Globally, Data centers are rapidly increasing in number due to data explosion, and consequently their negative impact on environment is increasing especially in terms of water demand. These data center facilities are humongous repositories of hardware such as servers, storage, network, routers, switches that run uninterruptedly to meet an ever-evolving requirements of cloud computing, digital storage, movies & music streams, artificial intelligence, online gaming, data analytics, and other services. These data centers (DC) are huge energy guzzlers that require a large amount of water for cooling purposes.

In a typical data centers (DC), around 30~40% of the energy is spent on the cooling system *(Xianyuan et al. 2025)*, thereby posing a pressing need for developing new efficient cooling optimization technologies for DC. With the advent of Artificial Intelligence, the computing and data centers consume a large amount of freshwater for cooling. Power hungry and energy-intensive GPUs, accelerators, and other specialized AI data center hardware produce significant heat, thereby creating a critical challenge for data center operations.

Data centers are notorious for their massive energy usage and water consumption. As per the study it is estimated that downloading 1GB of data may require up to 200 liters of water *(Ristic et al. 2015)*. As per *(Shumba et al. 2024)*, the water consumption of two large language models namely Llama-3-70B and GPT-4 was studied and the findings revealed that writing a 10-page report using Llama-3-70B can consume about 0.7 liters of water, while the water consumption by GPT-4 for the same task may go up to about 60 liters.

Globally, only one third of the DC monitor water utilization and for rest water conservation is not a prioritized area (Mytton, 2021). Major Data center providers/Cloud service providers (CSP) do not publish any water efficiency metrics which indicates that the sustainability efforts by these DCP/CSPs are far too low in comparison to the damage done by these water-guzzling infrastructures.

To address the efficient water utilization, a crucial parameter Water Usage Effectiveness (WUE) is studied that ensures the effective water consumption in DC. The novel idea of the project is to improvise WUE in data centers wherein it proposes an efficient smart water cooling modeling framework that leverages the simulation software EnergyPlus (Open source platform) coupled with Sinergym framework based on Deep Reinforcement Learning (DRL). This work endeavors to lower the WUE from the industry standard of 1.8L per kWh. *(NREL, 2003; ESG report,2023; Rutberg,2012)*.

### 1.1 Objective of the study

The objective of this research is to develop a smart water cooling modeling framework that has better WUE than the industry standard average of 1.8L per kWh.

### 1.2 Problem statement

In a typical Data center, cold water generated from chillers and evaporative cooling towers is sent to the server rooms to provide cold air for servers. This continuous supply of cool air generated from water is not put to efficient use, thus resulting in poor WUE. Some of the factors that results in the inefficient WUE are first even when the servers and chips are either idle or working with limited loads, secondly frequent changing server loads and last but not the least that physical locations of servers produce complex and dynamic temperature fields inside the server room resulting in the strong thermal impressions and deep heat pockets.

As mentioned above, these conditions leads to an in-effective water utilization, that calls for an optimized control of air cooling in the server farm area by improvising WUE and for better sustainability of DC operations.

While the energy efficiency of DCs has been researched extensively, however the water utilization efficiency (WUE) has so far received little to no attention. This article endeavors for reducing the water footprint in Data centers and thus improvising WUE.

## 2. Definitions and terminologies *(Ref: ASHRAE,2024)*

*Adiabatic process*- It is a thermodynamic process during which no heat is extracted from or added to the system.

*Air changes per hour*- Ventilation airflow divided by room volume. It indicates how many times, during one hour, the air volume from a space is replaced with outdoor air.

*Air conditioning*- The process of treating air to meet the requirements of a conditioned space by controlling its temperature, humidity, cleanliness, and distribution.

*Air spread*- The divergence of an airstream after it leaves an outlet.

*Air temperature* -The temperature of the air measured at a test point.

*Artificial Intelligence*- Artificial intelligence (AI) is intelligence demonstrated by machines, as opposed to the natural intelligence displayed by humans or animals.

*ASHRAE*- The American Society of Heating, Refrigerating and Air-Conditioning Engineers is an American professional association seeking to advance heating, ventilation, air conditioning and refrigeration systems design and construction.

*Cooling coils*- An arrangement of pipes or tubes, not enclosed in a pressure vessel, that can be used either with refrigerant or secondary coolant to provide cooling or cooling with dehumidification.

*Data center*- A data center is a physical facility that organizations use to house their critical applications and data.

*Dew point temperature*- Temperature at which water vapor has reached the saturation point (100% relative humidity). Temperature of the air at which it must be cooled at constant barometric pressure for water vapor to condense.

*Dry bulb temperature*- Temperature of air indicated by an ordinary thermometer shielded from solar and long wave radiation

*Energy plus*- It is a free open source and cross platform solution for building energy simulation programs.

*HVAC systems*- The equipment, distribution systems, and terminals that provide, either collectively or individually, the processes of heating, ventilating, or air conditioning to a building or portion of a building.

*Temperature sensor*- A sensor located in the fluid that is capable of producing a signal (output) that is related to the temperature.

*Water foot print*- It is a measure of the quantity of freshwater consumed and polluted. The water footprint of a product is the volume of freshwater used to produce the product, measured over the full supply chain *(Water footprint manual, 2011)*

*Water Usage Effectiveness (WUE)*- is a key metric for measuring data center sustainability, defined as the ratio of water consumption to the total equipment energy consumption.

## 3. Background and Related work

**3.1 How Data Center Water Cooling Works.** Water cooling involves channeling water through pipes surrounding IT hardware. The liquid absorbs heat from processing units before being transported to radiators, where fans dissipate the heat. A reservoir may store additional water to stabilize thermal fluctuations. Anti-fouling agents are often added to prevent microbial growth within the system. Water cooling systems are generally classified into open-loop systems that are customizable solutions designed by users to accommodate specific data center needs, while closed-loop systems are preconfigured, self-contained cooling units that provide reliability and ease of maintenance.

**3.2 Water usage effectiveness (WUE).** A lower Water usage effectiveness (WUE) signifies a more water-efficient facility, with the industry average being 1.8L per kWh (industry standards). The lower a data center's WUE ratio is, the more efficient its use of water resources is. WUE = Water Consumption (L) / IT equipment Energy Consumption (kWh)

**3.3 Types of cooling.** The Data centers generally have following types of cooling that are illustrated in Figure 1.

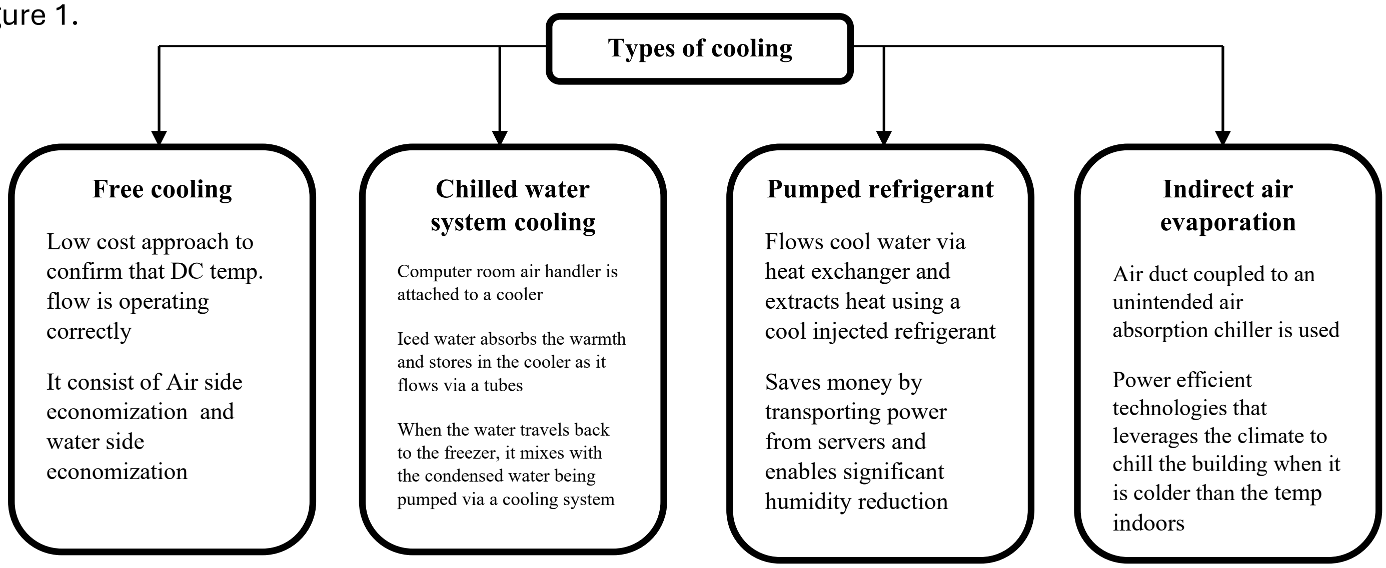


**Figure 1: Types of cooling in Data centers**

Basis, the various types of cooling practiced in DC, the scope of this study is limited to the chilled water system cooling, as this cooling is the most commonly used deployed solution in DC and has heavy utilization of water. Data centers employ different water cooling methodologies based on infrastructure needs that are discussed as below-

i. *Evaporative Cooling*: Uses large fans to pull warm air through water-saturated pads, cooling the air through evaporation.

ii. *Rear-Door Water Cooling*: Implements heat exchangers at the rear of server cabinets to absorb and expel heat efficiently.

iii. *Waterborne Data Centers*: Floating data centers leverage nearby water bodies to dissipate heat via an open-loop cooling process.

**3.4 Data center cooling controls.** The cooling distribution of a typical Data Center comprises of water section and air section. The water section consists of chillers and cooling towers wherein water is cooled, while the air section circulates the cold water through the ducts in the server room. Through air-water heat exchange, the cooled air is blown in the server room, resulting in the air temperature regulation. The generated warm water is repeatedly sent back to the chillers and cooling towers for re-cooling.

### 3.5 Dynamic workloads

The dynamic workloads are the varying degree of computing tasks that cause fluctuations in the amounts of heat generation from servers. Temperature sensors, humidity sensors and measurement probes properly installed at the rack level to measure tiniest fluctuation at the chip level can serve as an input to simulation platform. This will help in analyzing the fluctuating workloads at the chip level.

## 4. Methodology

To improve WUE, and to have efficient water cooling technique, a model has been developed that comprises of EnergyPlus, and Python based Deep Reinforcement Learning (DRL) Sinergym framework. The WUE in the DC has been calculated using EnergyPlus without DRL and again using EnergyPlus with DRL. The WUE results for both the outputs have been compared and discussed in the subsequent section. This section discusses workflow, system architecture, various input variables, details of simulation platform EnergyPlus, and Deep Reinforcement Learning (DRL) Sinergym. The methodology is shown in Figure 2.

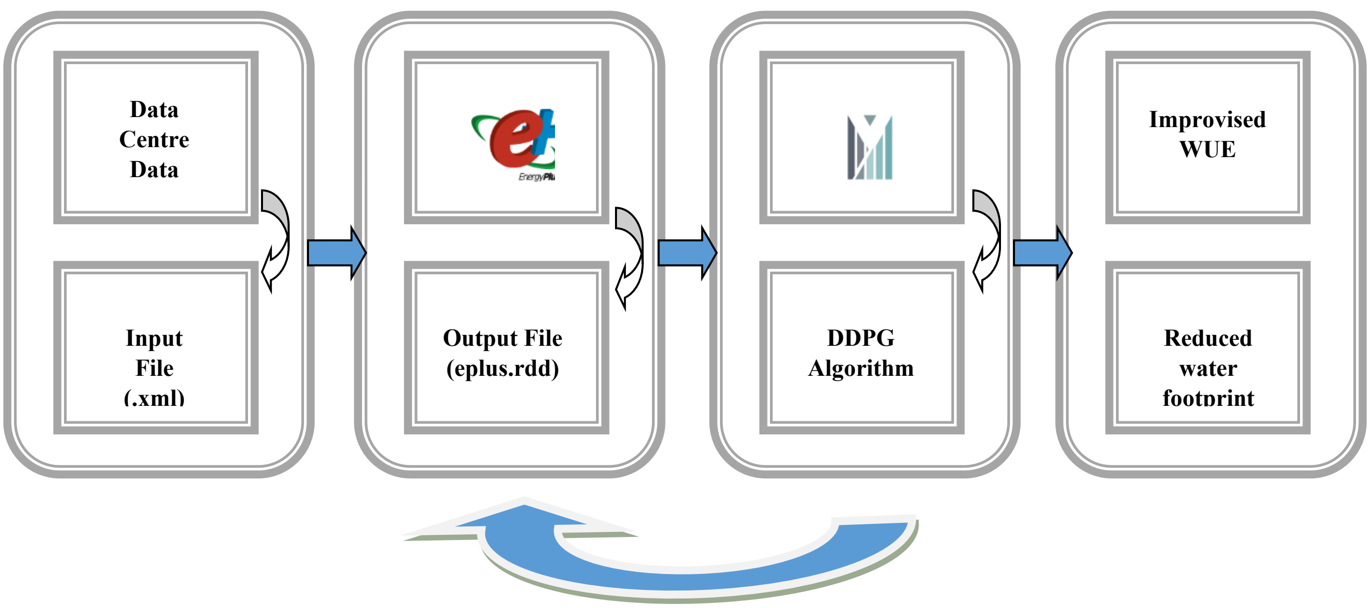


**Figure 2: Methodology work flow**

### 4.1 System architecture

The system architecture comprises of namely four basis blocks that are input functions, smart water cooling engine, Data centre and its outcome on water usage effectiveness, and reduced water footprint.

**4.2 Input Functions-** The function block in the framework comprises of variables, dynamic workloads, HVAC, and geometry that are discussed in the subsequent section.

### *4.2.1 Variables*

The literature review suggested that there are some modeling tools available for design and controlling that allows for reinforcement learning (RL) based controllers. For the ease of use, this research work used EnergyPlus version 24.2.0 (Energyplus) which is a free open source and cross platform solution for building energy simulation programs. Fundamentally, some important variables used in the simulation platform for exchange of information from sensor to the actuator are discussed as below-

i. *Sensor variables*- These variables have global scope and are used to get time-varying input data from elsewhere in the simulation model. It comprises of inputs from temperature sensors installed in server rooms e.g. thermistors, resistance temperature detectors, thermocouples.
ii. *Actuator*- The actuator variable has the role opposite to that of the sensor variable. Sensor variables are used to get the state of building systems; actuator variables are used to set the state of building systems. Some important sub variables under this category are temperature set point (both minimum and maximum), humidity ratio, mass flow rate set point, cooling coils, thermal storage coils, surface boundary conditions.
iii. *Global variables*- Global variables can be used to store intermediate results that span across the simulation platform.
iv. *Built-in variables*- The EMS system automatically declares a set of built-in variables with predefined names. These variables have global scope. Some of the built in functions are dry bulb temperature, humidity ratio, barometric pressure, wet bulb temperature, enthalpy of moist air, dew point temperature.
v. *Internal variables*- The input object declares a user defined variable and maps it to a variable elsewhere. Variables so declared have global scope and are used to get static input data from elsewhere in simulation platform. The internal variable comprises of the factors such as zone geometry, zone air volume ($m^3/s$), air changes per hour, zone floor area, sensible load request, HVAC, air mixer controller, chiller capacity. All these mentioned parameters in the variables have to be chosen in the framework.

### 4.3 Simulation platform- EnergyPlus

EnergyPlus is a building energy simulation program that is used to model both energy consumption—for heating, cooling, ventilation, lighting and plug and process loads and water use in buildings. Figure 3 shows the overall simulation software structure. It has three basic components namely: Simulation Manager, Heat Balance Simulation module, and Building Systems Simulation module. The Simulation Manager controls the entire simulation process, the Heat Balance Simulation module calculates thermal and mass loads, and the Building Systems Simulation Manager handles communication between the heat balance engine and the HVAC water and air loops and their attached components such as coils, boilers, chillers, pumps, fans *(Crawlie et al., 2000)*.

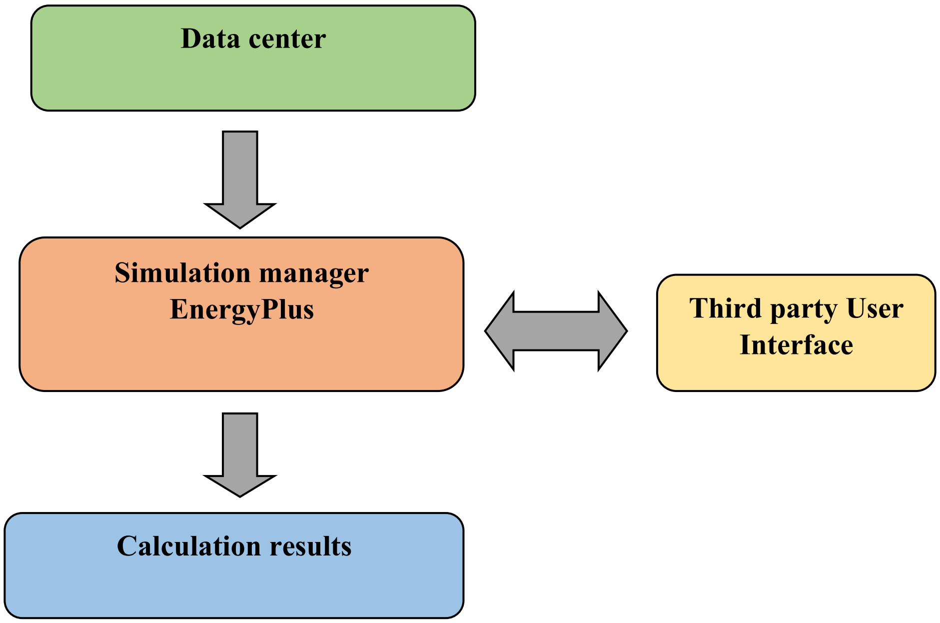


**Figure 3: EnergyPlus simulation manager**

### 4.4 Deep Reinforcement learning (DRL)

Reinforcement learning (RL) is learning from experience. An agent interacts with its environment through an action and this action is followed by a positive RL signal or negative RL signal *(Wang & Hong, 2020, Khan et al. 2012)*. By using Deep Learning, Reinforcement Learning (RL) agents can learn directly from raw input data, such as images, sensor readings, without the need for manual feature engineering. For this work Open source Deep Reinforcement Learning Sinergym framework has been used. It is an open source Python-based virtual test bed for large-scale building simulation. The objective of Sinergym is to create an environment for simulation engines for building control using deep reinforcement learning. The main functions of Sinergym are data collection, continuous control, and experiment monitoring, benchmarking environments, ability to integrate with different simulation engines, automatic building models configuration and data visualization.

### 4.5 Learning model

In this paper, the improvisation of water usage effectiveness in Data center is pursued. In order to achieve this, Energyplus coupled with Sinergym has been deployed in the smart cooling model framework. It uses learning algorithm is to adapt the deep neural network parameters that represent the controller to successfully map the input water usage to output optimized temperature in SFA. The Deep Reinforcement Learning controller has inputs from sensor readings that indicate the water usage, temperature in the SFA and a reward signal based on the evaluation of the cooling control applied. The output signal is used to dynamically send the signals to cooling actuators resulting in effective and intelligent temperature spread.


**Figure 4: Sinergym general architecture**

The Figure 5 shows how the learning algorithm interfaces with the smart cooling modeling framework that stores past experiences in a memory buffer, maps current states to actions (learns the policy), and computes the gradients based on the received rewards to update the network parameters. The learning algorithm is evaluated based on the control effort required to efficiently cool the SFA by minimizing the water usage, time to go from the initial to the final configuration, and number of iterations required to train the learning algorithm to achieve the best performance.

## 4.6 Algorithms

Deep Reinforcement Learning is a rapidly advancing field that combines the power of Deep Learning with the principles of reinforcement learning. Various types of algorithm for DRL are Deep Q-Learning (DQN), Policy Gradient Methods, Deep Deterministic Policy Gradient (DDPG), Asynchronous Advantage Actor-Critic (A3C), Soft Actor-Critic (SAC), Proximal Policy Optimization (PPO), and Sample Efficiency. However for the experiment purposes Deep Deterministic Policy Gradient (DDPG) is leveraged as it is flexible, economical, robust and efficient *(Fangzhou et al. 2025, Xiangfei et al. 2022)*.

### *4.6.1 Deep Deterministic Policy Gradient (DDPG)*

**Deep Deterministic Policy Gradient** is an off-policy algorithm.

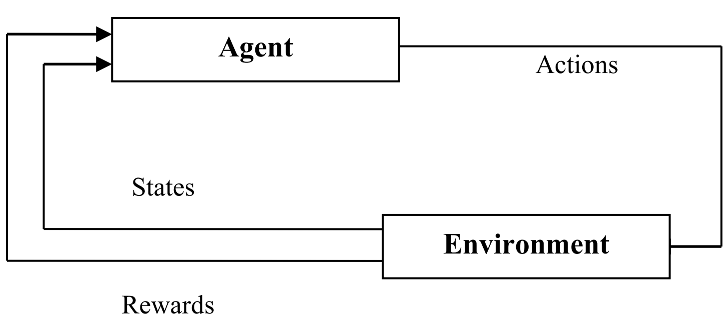


**Figure 5: Reinforcement learning w.r.t agent and environment** *(Ref: Vinicus et al.)*

It integrates ideas from Deterministic Policy Gradient and Deep Q-Network. It is based on actor-critic method based on Deterministic Policy Gradient. The algorithm uses two neural networks, one for the actor and one for the critic and leverages the benefits of both the value based and policy based. The actor preserves a policy. The policy gets a state in the form of input and produces an action as its output *(Ashraf et al. 2021)*.

## 5. Results

### 5.1 Experiment and environment settings

A hyperscale data center of total server farm area of 402.54 sq mt. located in National Capital Region of Delhi was chosen as the environment set up.

| Timestamp | Temperature (°C) | Humidity (%) | Dry Bulb Temp (°C) | Wet Bulb Temp (°C) | Dew Point (°C) | Pressure (hPa) |
|---|---|---|---|---|---|---|
| 01-09-2024 00:00 | 25.2 | 60 | 25.2 | 20.1 | 16.8 | 1012 |
| 01-09-2024 01:00 | 24.8 | 62 | 24.8 | 19.9 | 16.5 | 1012 |
| 01-09-2024 02:00 | 24.5 | 63 | 24.5 | 19.7 | 16.3 | 1011 |
| 01-09-2024 03:00 | 24.1 | 65 | 24.1 | 19.5 | 16.1 | 1011 |
| 01-09-2024 04:00 | 23.8 | 66 | 23.8 | 19.3 | 15.9 | 1010 |
| 01-09-2024 05:00 | 23.6 | 67 | 23.6 | 19.2 | 15.8 | 1010 |
| 01-09-2024 06:00 | 24 | 65 | 24 | 19.6 | 16.2 | 1011 |
| 01-09-2024 07:00 | 25 | 62 | 25 | 20 | 16.7 | 1012 |
| 01-09-2024 08:00 | 26.3 | 58 | 26.3 | 21.1 | 17.5 | 1013 |
| 01-09-2024 09:00 | 27.5 | 55 | 27.5 | 22 | 18.2 | 1014 |
| 01-09-2024 10:00 | 28.8 | 52 | 28.8 | 22.9 | 18.9 | 1015 |
| 01-09-2024 11:00 | 30.2 | 49 | 30.2 | 23.8 | 19.6 | 1016 |
| 01-09-2024 12:00 | 31.5 | 45 | 31.5 | 24.6 | 20.1 | 1016 |
| 01-09-2024 13:00 | 32 | 43 | 32 | 25 | 20.3 | 1015 |
| 01-09-2024 14:00 | 32.4 | 41 | 32.4 | 25.3 | 20.4 | 1014 |
| 01-09-2024 15:00 | 32.1 | 42 | 32.1 | 25.1 | 20.3 | 1013 |
| 01-09-2024 16:00 | 31 | 44 | 31 | 24.3 | 19.9 | 1012 |
| 01-09-2024 17:00 | 29.5 | 48 | 29.5 | 23.2 | 19.2 | 1012 |
| 01-09-2024 18:00 | 28 | 52 | 28 | 22 | 18.4 | 1011 |
| 01-09-2024 19:00 | 27 | 55 | 27 | 21.3 | 17.9 | 1011 |
| 01-09-2024 20:00 | 26 | 58 | 26 | 20.5 | 17.3 | 1011 |
| 01-09-2024 21:00 | 25.5 | 60 | 25.5 | 20.2 | 17 | 1011 |
| 01-09-2024 22:00 | 25 | 62 | 25 | 19.9 | 16.7 | 1011 |
| 01-09-2024 23:00 | 24.7 | 63 | 24.7 | 19.7 | 16.5 | 1011 |

**Table 1: Output data from the Data Centre**

The said DC was having an HVAC system consisting of air economizers, evaporative coolers, cooling coils, and chillers. The main source of heat comes from the hosted servers in the 42U racks. The building is simulated with EnergyPlus platform. The experiment was run in the month for September 2024. The sample output file

(.xml) from Data centre served as an input through 'Data transfer' API to the EnergyPlus that has Python Plugins as well. EnergyPlus is modular in its actual filling in the details for the simulation. Because of this modularity, each module is responsible for getting its own input. It receives this input from the input processor from APIs connected to Data centre. The input data file is the primary file that EnergyPlus uses to create the water effectiveness simulation. The various input files thus created in EnergyPlus are- ZoneAirCooled.idf, Chillers.idf AirflowNetworkVent.idf, RoomAirflowNetwork.idf, HybridVentilationControl.idf, Refrigeration Cases.idf, FluidPropertiesRefData.idf etc.

```
Program Version,EnergyPlus, 24.2.0, 10/02/2024/11:02:17,IDD_Version 24.2.0
Var Type (timestep per hour, 6
Zone,Average,Site Outdoor Air Drybulb Temperature,35C
Zone,Average,Site Outdoor Air Dewpoint Temperature, 28C
Zone,Average,Site Outdoor Air Wetbulb Temperature, 32C
Zone,Average,Site Outdoor Air Humidity Ratio, 48%
Zone,Average,Site Outdoor Air Relative Humidity, 66%
Zone,Average,Site Outdoor Air Barometric Pressure, 100000Pa
Zone,Average,Site Sky Temperature, 37C
HVAC,Average,System Node Temperature, 23C
HVAC,Average,System Node Mass Flow Rate, 27kg/s
HVAC,Average, Site WaterMainsTemperature, 35C
HVAC,Average,System Node Setpoint Temperature, 23C
HVAC,Average,System Node Setpoint Humidity Ratio, 41%
HVAC,Average,System Node Wetbulb Temperature, 24C
HVAC,Sum, Zone Mechanical Ventilation No Load Heat Removal Energy, 857J
HVAC,Sum,Zone Mechanical Ventilation Cooling Load Increase Energy,12000J
HVAC,Average,Zone Mechanical Ventilation Mass Flow Rate, 0.8kg/s
HVAC,Average, Zone Mechanical Ventilation Standard Density Volume Flow Rate, 4.5m3/s
HVAC,Sum,Zone Mechanical Ventilation Standard Density Volume, 130m3
HVAC,Sum,Zone Mechanical Ventilation Mass, 190kg
HVAC,Average,Zone Mechanical Ventilation Air Changes per Hour,50ach
HVAC, Facility Water Use Volume, 200m3
HVAC, Cooling tower heat rejection, 340.9TR
HVAC, Condenser flow delta, 10C
HVAC, Chilled Water Supply, 15C
HVAC, Chilled Water Return, 25C
HVAC, Evaporation Rate, 6.5GPM
HVAC, Hot water equipment load, 2400kw
HVAC, Blow down rate, 1.1m3/s
HVAC, Make up water flow rate, 7.9m3/s
ElectricEIRChiller Climaventa NX2WG06 34.5kW/2.67COP
HOT WATER LOOP ,1,0.1062471,11942.67,0.2586269,Yes ,7.324432E -004,2.586533E-004,Yes,1.0000,0.646862,4197.9300,999.8980
CHILLED WATER LOOP ,1,1.1222815,17614.26,0.6290764,Yes ,1.197307E -003,1.122396E-003,No,1.0000,6.256652E-002,4197.9300,999.8980
Coil:Cooling:Water, MAIN COOLING COIL 1,37219.64,24969.42,12250.22,0.67,4202.30,42.62
```

**Figure 6: Sample output file from EnergyPlus**

Based on the input parameters, simulation has been run for summer design days and the output file eplusout.rdd file is mentioned in Figure 6. The simulation graph has been generated by using Python Notebook for the data captured from EnergyPlus and is illustrated in Figure 7. The simulation exhibit is a graph between load (MW) and water consumption for the entire month of September 2024. The output file from EnergyPlus served as an input for the Sinergym framework that is using DDPG algorithm.

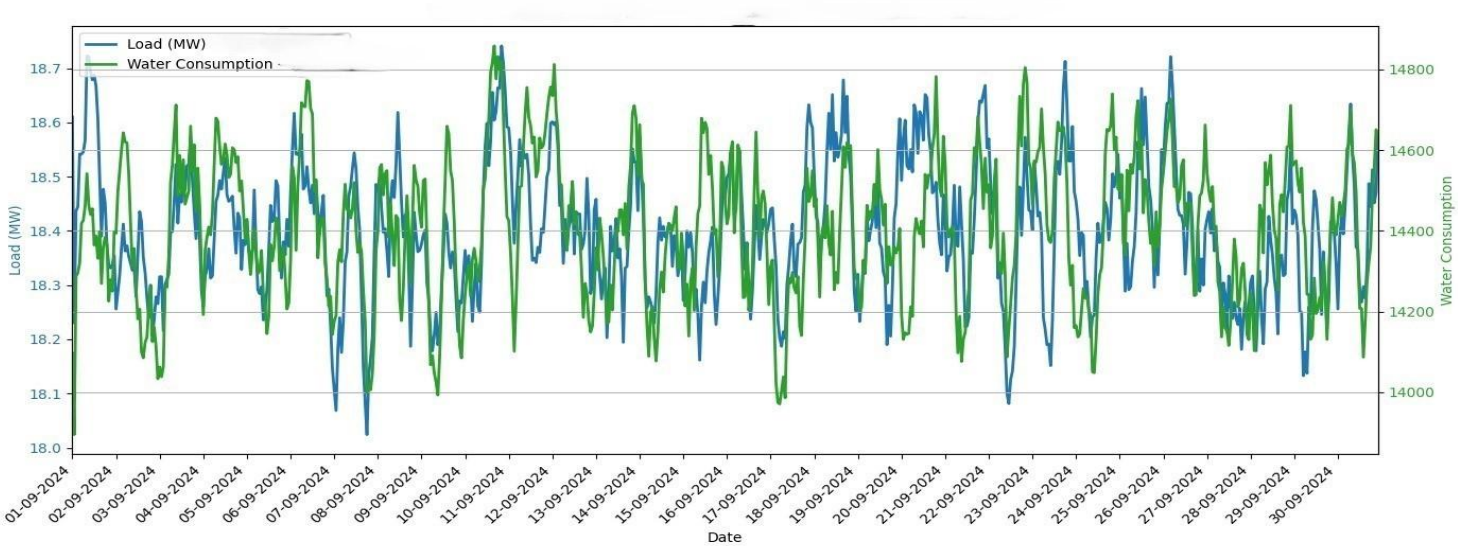


**Figure 7: Simulation from EnergyPlus**

The WUE values calculated using Sinergym framework with hyper parameters using DDPG algorithm along with the values are mentioned in Table 2. Both actions and critic values are normalized using Sinergym wrappers. Actions are performed every ten minutes, which maps to six time-steps per hour.

| **Hyperparameters** | **Value** |
|---|---|
| Actor learning rate | 0.0001 |
| Critic learning rate | 0.001 |
| Discount factor | 0.9 |
| Batch size | 64 |
| Target update rates (Episodes) | 100 |
| Target update factor | 0.005 |

**Table 2: Hyperparameters and values for DDPG**

## 5.2 Comparison of WUE results

WUE is calculated for the month of September 2024 with EnergyPlus and EnergyPlus with DRL using DDPG algorithm. The data is captured in Table 3. The WUE result for EnergyPlus on daily basis has been compared with the results when EnergyPlus is used with DRL. For a typical data center design, smart water cooling model optimizer has been trained using a Deep Reinforcement Learning algorithm that minimizes the total water consumption, when benchmarked against the industry standard of 1.8L/kwh.

| Days of Month (Sept.) | EnergyPlus (Without DRL) | EnergyPlus (with DRL) | Days of Month (Sept.) | EnergyPlus (Without DRL) | EnergyPlus (With DRL) |
|---|---|---|---|---|---|
| 1 | 1.93 | 1.48 | 16 | 1.86 | 1.51 |
| 2 | 1.90 | 1.44 | 17 | 1.80 | 1.56 |
| 3 | 1.88 | 1.52 | 18 | 1.82 | 1.52 |
| 4 | 1.81 | 1.49 | 19 | 1.85 | 1.56 |
| 5 | 1.95 | 1.45 | 20 | 1.88 | 1.52 |
| 6 | 1.91 | 1.44 | 21 | 1.91 | 1.49 |
| 7 | 1.80 | 1.49 | 22 | 1.96 | 1.48 |
| 8 | 1.82 | 1.50 | 23 | 1.92 | 1.44 |
| 9 | 1.75 | 1.44 | 24 | 1.88 | 1.42 |
| 10 | 1.79 | 1.45 | 25 | 1.91 | 1.46 |
| 11 | 1.87 | 1.49 | 26 | 1.85 | 1.45 |
| 12 | 1.91 | 1.47 | 27 | 1.86 | 1.46 |
| 13 | 1.90 | 1.48 | 28 | 1.86 | 1.58 |
| 14 | 1.86 | 1.46 | 29 | 1.81 | 1.50 |
| 15 | 1.83 | 1.53 | 30 | 1.87 | 1.52 |

**Table 3: Calculation of water utilization efficiency comparison**

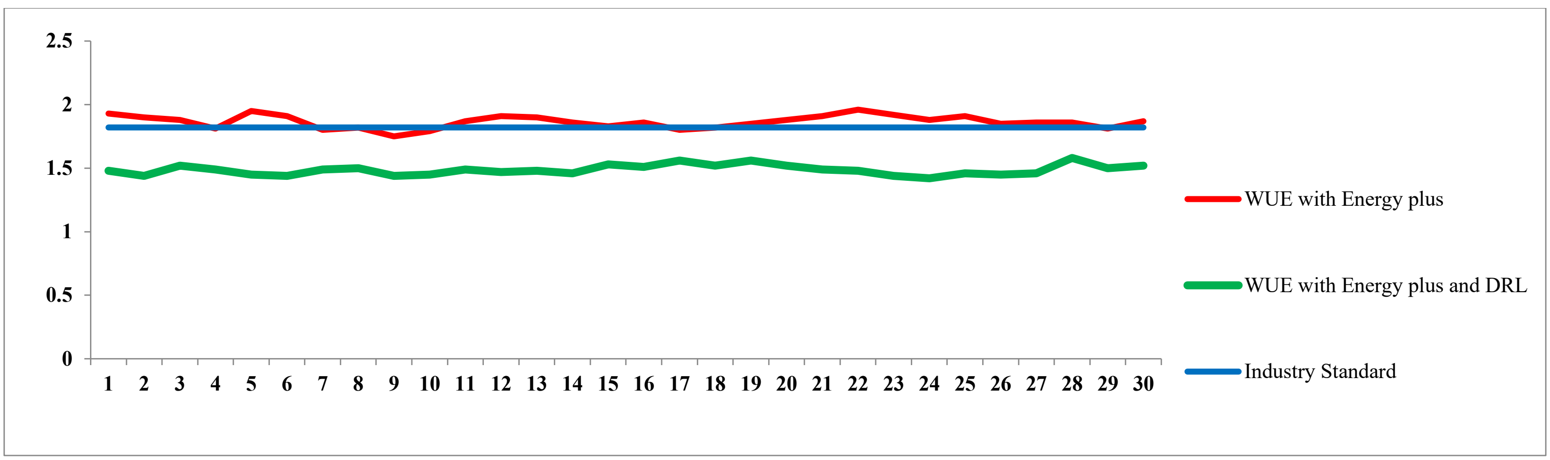


**Figure 8: Comparison of WUE results**

A comparison of the study (with or without DRL) infers that merely deploying the simulation software does not efficiently assist in improvising the WUE. It's the DRL approach using DDPG algorithm that has improvised the WUE industry standard by 20.64% as illustrated in Figure 8.

## 6. Conclusions

This work presented a smart water cooling modeling framework based on Deep Learning Reinforcement. The DRL based solution integrated with Sinergym and EnergyPlus (simulation platform) improvised the water utilization efficiency. A realistic Data center environment has been leveraged to fully test the simulated solution for summer design days. With this integrated solution, being tested in the real time Data center, the resultant WUE has outperformed the industry standard. The results illustrates that the water cooling presents a viable solution for modern data centers, enhancing cooling efficiency and sustainability.

As a future research direction, it is proposed that as the DC evolve, integrated water-efficient solutions will be essential for optimizing energy usage and minimizing environmental impact.

## 7. References


1. A multi-step predictive deep reinforcement learning algorithm for HVAC control systems in smart buildings, Energy, Volume 259, 2022
2. ASHRAE standards and guidelines.(2024). Available at https://www.ashrae.org/technical-resources/standards-and-guidelines
3. Ashraf NM, Mostafa RR, Sakr RH, & Rashad MZ. Optimizing hyperparameters of deep reinforcement learning for autonomous driving based on whale optimization algorithm. PLoS One. 2021 Jun 10;16(6):e0252754. doi: 10.1371/journal.pone.0252754.Available at https://api.semanticscholar.org/CorpusID:275921558
4. Crawley, D. B., Lawrie, L. K., Pedersen, C. O., & Winkelmann, F. C. (2000). Energy plus: energy simulation program. ASHRAE journal, 42(4), 49-56.
5. Energy plus, https://energyplus.net/
6. ESG Report, Scaling sustainability. (2023) Available at https://cologix.com/wp-content/uploads/ 2024/09/Cologix-2023-ESG-Report-English-Version-_-Updated-9.10.2024.pdf
7. Fangzhou,Guo., Sang woo, Ham., Donghun, Kim., Hyeun, & Jun Moon. (2025). Deep reinforcement learning control for co-optimizing energy consumption, thermal comfort, and indoor air quality in an office building, Applied Energy, Volume 377, Part A, 2025
8. J. Ansari et al. (Eds.): SMPS 2024, AISC 1458, pp. 273–280, 2024. https://doi.org/10.1007/978-3-031-65993-5_33
9. Khan, S. G., Herrmann, G., Lewis, F. L., Pipe, T., & Melhuish, C. (2012). Reinforcement learning and optimal adaptive control: An overview and implementation examples. Annual reviews in control, 36(1), 42-59.
10. Leng., Huiwen, Zheng., Chenhui, Liu., Tianshun, Hong., Yan, Liang., Yunxin, Liu., and Feng,
11. NREL, National Renewable Energy Laboratory. (2003). Consumptive Water Use for U.S Power Production, NREL/TP-550-33905, Available at https://www.nrel.gov/ docs/fy04osti /33905.pdf

12. Mytton, D. Data centre water consumption. npj Clean Water 4, 11 (2021). https://doi.org/10.1038/s41545-021-00101
13. Ristic, Bora & Madani, Kaveh & Makuch, Zen. (2015). The Water Footprint of Data Centers. Sustainability. 7. 11260-11284. 10.3390/su70811260.
14. Rutberg, Michael. (2012). Modeling water use at thermoelectric power plants.
15. Shumba, N., Tshekiso, O., Li, P., Fanti, G., & Ren, S. (2024). A Water Efficiency Dataset for African Data Centers. arXiv preprint arXiv:2412.03716.
16. Wang, Z., & Hong, T. (2020). Reinforcement learning for building controls: The opportunities and challenges. Applied Energy, 269, 115036.
17. Water foot print assessment manual, 2011. Available at https://waterfootprint.org/resources/TheWaterFootprintAssessmentManual_English.pdf
18. Xiangfei Liu, Mifeng Ren, Zhile Yang, Gaowei Yan, Yuanjun Guo, Lan Cheng, Chengke Wu, Xianyuan, Zhan., Xiangyu, Zhu., Peng, Cheng., Xiao, Hu., Ziteng, He., Hanfei, Geng., & Jichao, Zhao. (2025). Data Center Cooling System Optimization Using Offline Reinforcement Learning.