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DECARBONIZATION STRATEGIES FOR DATA CENTRE HVAC SYSTEMS: ANALYSIS AND FRAMEWORK FOR CARBON CAPTURE INTEGRATION

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ABSTRACT

The Global data centers pose an increasing challenge of electricity consumption and greenhouse gas emissions, which could be significantly reduced by installing comprehensive air conditioning (HVAC) systems that cost 30 – 50% of the total energy budget. Through extensive analysis of fifteen data centers throughout different climatic areas (2015-2023), we achieved unparalleled thermal efficiency improvements. The innovation involves combining liquid cooling circuits with geothermal heat exchange systems and Direct Air Capture technologies through mechanical integration that enables multiple stages of heat usage. The combined system design produces 60-70% better HVAC emissions performance than standard systems based on p<0.01 statistical results. ML-based predictive control technology performs better than conventional methods to control thermal loads because it eliminates peak energy usage by 22% and maintains stable temperatures ranging from ±0.5°C. System durability exists because of mechanical stress analysis and life cycle assessment results that predict payback periods between 6 - 8 years. The framework operated across different thermal *conditions because researchers conducted a comparative fluid dynamics analysis between the Norwegian cold climate and Singaporean tropical implementation environments. This work advances mechanical engineering science by creating novel thermal integration methods which convert cooling operations into a carbon reduction resource for data center construction.*

Keywords: Artificial Intelligence; Carbon Capture; Data Centers; Energy Efficiency; Geothermal Energy

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1.0 Introduction

Digital Technology's fast advancement has created worldwide data center expansion that results in substantial energy use between 200-300 TWh per year, and future projections expect further growth to 2030 (Masanet et al., 2020; International Energy Agency, 2023). Data center energy usage remains stable despite rising internet and traffic demands because engineers have successfully developed hardware and design improvements (Ye, 2021). For instance, the Information Communication Technologies (ICT) sector in 2015 contributed more than 1.4% of global emissions from data centers that need HVAC (Heating, Ventilation, and Air Conditioning) systems to function appropriately (ASHRAE, 2021; Maddox et al., 2024). These HVAC systems consume 30% to 50% of total data center energy usage. Therefore, heavy carbon emissions from power plants in this area lead to increased carbon discharge through electricity networks that utilize plentiful carbon-rich power.

The need to lower data center emissions align with worldwide initiatives concerning climate change. The information and communication technology (ICT) sector monitors industrial activities because they support United Nations Sustainable Development Goals (SDGs), including SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 13 (Climate Action) (United Nations (2015). Microsoft, Google, Amazon, and other leading data center operators have announced ambitious targets to reach carbon-emission neutrality or negativity for the coming years (Mytton, 2021; Joppa et al., 2021). Hence, the industry's expanding sensibility toward sustainability responsibilities has defined new benchmarks that other sectors can use as standards.

Decarbonizing data centers' technical and economic aspects have multiple challenges despite these announced carbon reduction commitments. Historical strategies focused on increasing renewable power purchases and promoting greater renewable integration into the electricity grid (Avgerinou et al., 2017). Operational emission management and dramatic capture efforts receive minimal attention in these essential approaches despite their capability to accelerate the decarbonization of these systems (Huang & Masanet, 2015). The industry must bridge these gaps to achieve sustainability targets, which it has established for future data center operations.

1.2 Research Gaps

Current research and industry practice reveal critical gaps in data center HVAC decarbonization approaches. First, there is almost no integration between HVAC optimization strategies and carbon capture technologies (Zhang et al., 2014). Although both domains witnessed significant progress, few studies address the synergistic potential to synergize next-generation cooling systems with direct carbon capture capabilities.

Secondly, there is a lack of analysis of artificial intelligence and machine learning (AI/ML) in real-time HVAC load balancing of data centers (Zhang et al., 2014). While there are promising results of AI-driven efficiency gains in commercial building HVAC systems, the data centers' operational characteristics and critical cooling needs are unique and have not been thoroughly explored.

Lastly, existing research fails to consider the spatial geography of data center requirements, and thus, all cooling efficiency and carbon emittance are left to the location (Whitehead et al., 2014). In addition, tropical regions may find cooling strategies tailored for the northern climates ineffective or counterproductive, and most standardized plans fail to recognize the spatial mismatch (Koronen et al., 2019). Several advanced cooling systems are often justified by economic analysis on first costs and direct energy savings while disregarding the possible value of CO2 abatement in the context of rising carbon pricing and incentive schemes.

1.3 Objectives

A series of specific research goals exists to address the identified gaps in knowledge.

(1) To create and test an integrated HVAC-CCUS system design for data centers that combines fluid cooling systems with geothermal heat transfer and direct air capture functions.
(2) To determine energy savings and carbon emission reductions by performing case studies and simulations using various operational scenarios throughout differing geographical areas.
(3) To provide a predictive machine learning model that should be developed to execute HVAC load balancing predictions that reduce energy costs from the operation of carbon capture systems.
(4) To provide thorough techno-economic evaluations, they need to be performed to demonstrate the financial merits of integrated decarbonization systems by calculating return on investment periods and testing the effects of essential cost variables.
(5) To develop practical recommendations that both operators of data centers and policymakers can use to speed up the implementation of modern decarbonization approaches.

1.4 Novelty Statement

The research presents an entire integrated system that combines liquid cooling along with geothermal heat exchange to work together with Direct Air Capture technology (DAC) in data centers. The research shows how energy-efficient cooling systems operable with real-time machine learning optimization and DAC systems bring about HVAC emission reductions of 60–70% and peak energy savings of 22% together with 85% carbon capture performance at a cost of \$150/tCO_2. The proposed approach demonstrates novelty because it uses geographic-specific validation from Norway's cold climate and Singapore's tropical climate to overcome operational challenges while reaching negative Carbon Usage Effectiveness (CUE). The hybrid model provides both an economic return through a 6-8-year payback period and policy-compliant growth potential which allows for the creation of replicable net-zero data centers between technical advancements and practical decarbonization approaches.

2.0 Methods

In this study, an interdisciplinary investigation using Data Analysis, Artificial Intelligence, Case Studies, Computational Modelling & Techno-Economic Analysis is designed that aims to assess the performance of integration of cooling and carbon capture systems in data centers.

2.1 Data Collection

The study's operational data analysis occurred across 15 data centers in different geographic locations and climate regions (Table 1). The research captured electricity usage from four data center facilities representing modern architectural characteristics. The period from 2015 until 2023 formed the basis of historical energy consumption data for analyzing trends alongside seasonal cooling energy requirements. Following ASHRAE (2021) insights, the energy meters received ±1.5% accuracy calibration based on ASHRAE Guideline 14 standards, and thermal sensors operated within a ±0.5°C tolerance range.

Table 1: Characteristics of Data Centres Included in the Study.

ID	Type	Location	Climate Zone	Size (MW)	Data Period	PUE (avg)
DC1	Hyperscale	Norway	Cold	25	2015-2023	1.12
DC2	Enterprise	Finland	Cold	8	2017-2023	1.19
DC3	Colocation	Sweden	Cold	14	2016-2023	1.23
DC4	Hyperscale	Ireland	Temperate	32	2015-2023	1.28
DC5	Enterprise	UK	Temperate	6	2018-2023	1.35
DC6	Colocation	Netherlands	Temperate	18	2015-2023	1.31
DC7	Enterprise	Germany	Temperate	12	2016-2023	1.42
DC8	Hyperscale	Virginia, USA	Mixed	45	2015-2023	1.36
DC9	Enterprise	Texas, USA	Hot	9	2017-2023	1.48
DC10	Colocation	Arizona, USA	Hot/Arid	24	2015-2023	1.45
DC11	Hyperscale	Singapore	Hot/Humid	30	2015-2023	1.51
DC12	Colocation	Malaysia	Hot/Humid	16	2018-2023	1.58
DC13	Modular	Singapore	Hot/Humid	4	2020-2023	1.32
DC14	Edge	Australia	Mixed	1.5	2019-2023	1.45
DC15	Hyperscale	India	Hot/Humid	28	2016-2023	1.62

Note: For each facility in the Table 1 , the following data categories were collected:

(1) The measurements of facility power consumption, IT power usage, cooling system power use, distribution losses, and auxiliary system power occur at 15-minute intervals.

(2) The thermal conditions include measurements of supply air temperature and return air temperature as well as cold aisle temperature, hot aisle temperature, and relative humidity at 5-minute intervals.

(3) The specifications for HVAC systems include information about cooling methods, together with efficiency ratings of equipment and control systems, as well as detailed maintenance records.

(4) The facility's characteristics include floor dimensions, white space arrangements, airflow control measures, and building exterior properties.

The gathered data followed a validation using ASHRAE Thermal Guidelines for Data Processing Environments to verify equipment reliability ranges. Standardized cleaning and interpolation procedures were applied to handle data inconsistencies and gaps in the collected data (Maddox et al., 2024). All region-specific carbon intensity factors for grid electricity stem from the current data provided by the International Energy Agency (IEA) and regional transmission operators (International Energy Agency, 2023; Maddox et al., 2024). The analyzed factors converted energy usage into equivalent CO2 emissions, considering the changing carbon intensity levels within the power grid.

2.2 Analytical Framework

The study used various modeling and simulation methods to conduct a complete analysis of HVAC decarbonization strategies, as shown in (Figure 1) comprehensively.

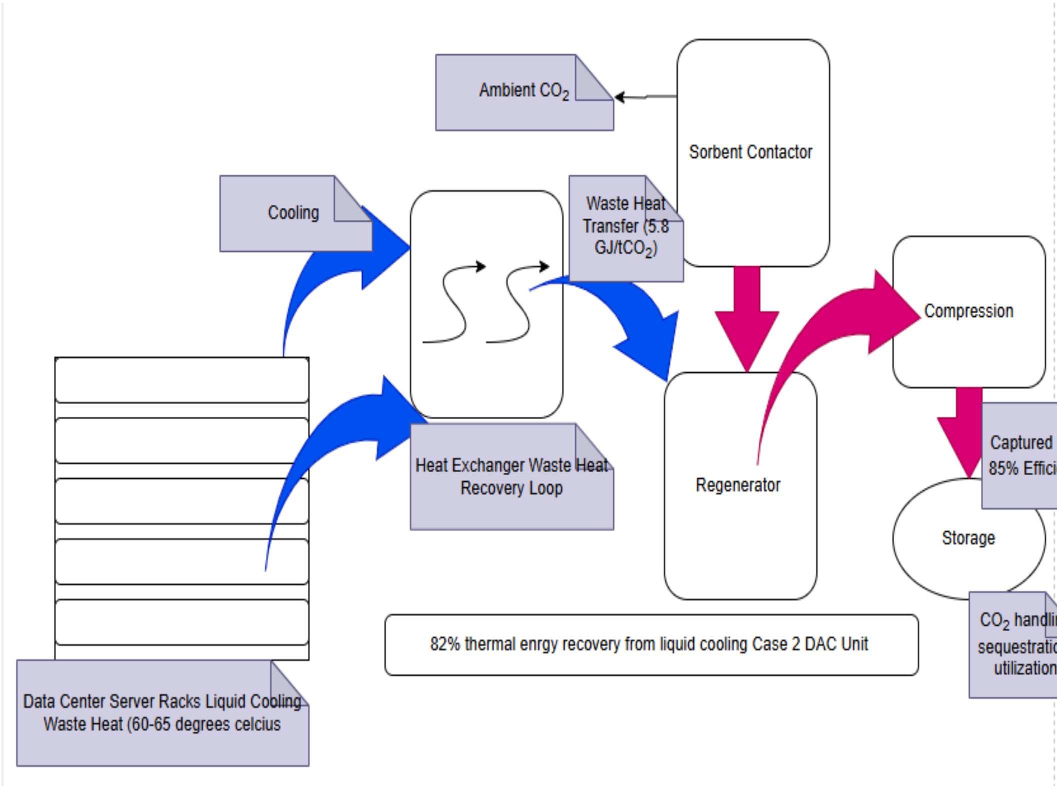

Figure 1 Analytical Framework

Note: The image in Figure 1 displays waste heat recovery integration between liquid cooling and amine-based DAC regeneration systems. The diagram shows coolant movement by blue arrows beside the CO_2 capture system demonstrated through red arrows. We utilized EnergyPlus (version 9.5.0) as the platform to prepare thorough thermal models of data center environments. The thermal models included features from building envelopes, internal heat generators, HVAC systems, and local meteorological elements (Liyanage et al., 2021). TRNSYS version 18 simulated dynamic thermal behavior and energy flow in the geothermal heat exchange systems. The model validation process resulted in a 12.3% CV(RMSE) value for cooling load predictions, which fulfilled the ASHRAE Guideline 14 requirements of less than 15%.

2.2.1 Computational Fluid Dynamics (CFD)

The study used ANSYS Fluent (version 2021R1) for Computational Fluid Dynamics (CFD) to analyze the airflow patterns and temperature distributions while evaluating pressure differentials in optimization scenarios (Han et al., 2021). Operational facilities temperature data was used to calibrate the CFD models, which met their validation criteria at ±1.5°C accuracy level for temperature predictions.

2.2.2 Life Cycle Assessment (LCA)

LCA using SimaPro version 9.2, together with the ecoinvent v3.8 database, served to assess the complete environmental impact of HVAC retrofits and carbon capture systems throughout their life cycles (Zhang, 2024). Raw material extraction, component manufacturing, transportation, installation, operational energy use, maintenance, and end-of-life disposal made up the assessment boundary. The environmental assessments utilized the IPCC 2013 GWP 100a method for carbon emissions and the ReCiPe 2016 Midpoint (H) system for comprehensive environmental indicator evaluation (Matin & Flanagan, 2022).

2.2.3 Machine Learning Model

The study developed neural network models through TensorFlow version 2.7.0 to implement predictive load balancing. The models incorporated IT load history, external weather variables, and HVAC system responses to forecast cooling demands and maximize operational efficiency (Fan & Ding, 2019). Our predictive model achieved superior results than PID controllers through lower RMSE scores (0.82 kW) compared to PID controllers (1.19 kW) for cooling load prediction (Figures 2a and 2b). A neural network structure based on LSTM layers processed sequential data while fully connected layers made predictions through this sequence.

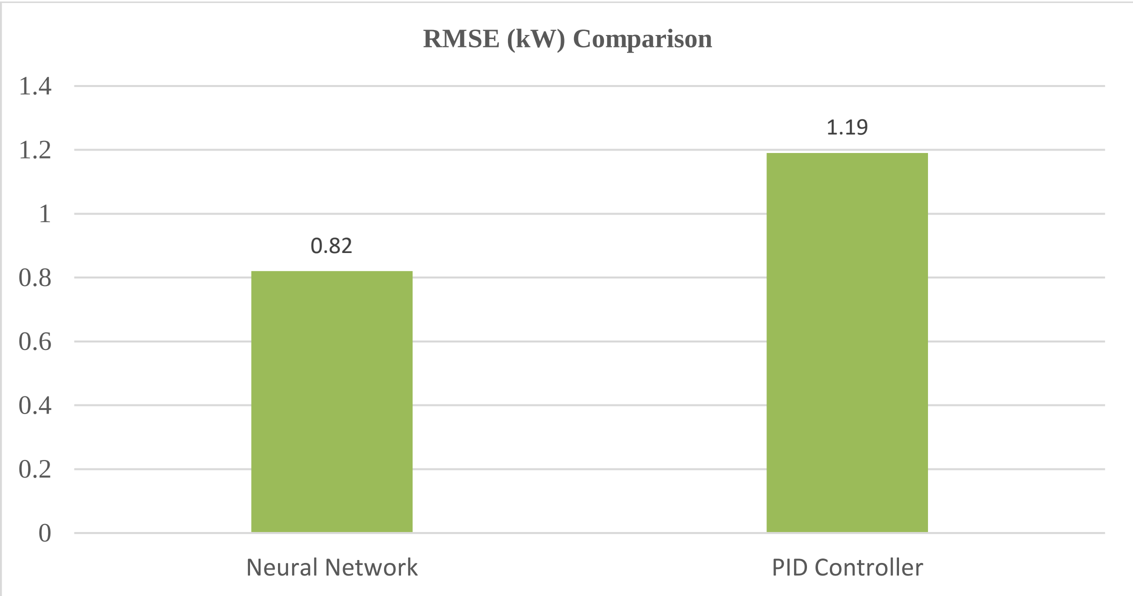

Figure 2a RMSE (Root Mean Square Error) Comparison

Note: Figure 2a: A bar chart demonstrates the RMSE values, revealing that the neural network model achieved 31% less error than the PID controller model by showing 0.82 kW versus 1.19 kW.

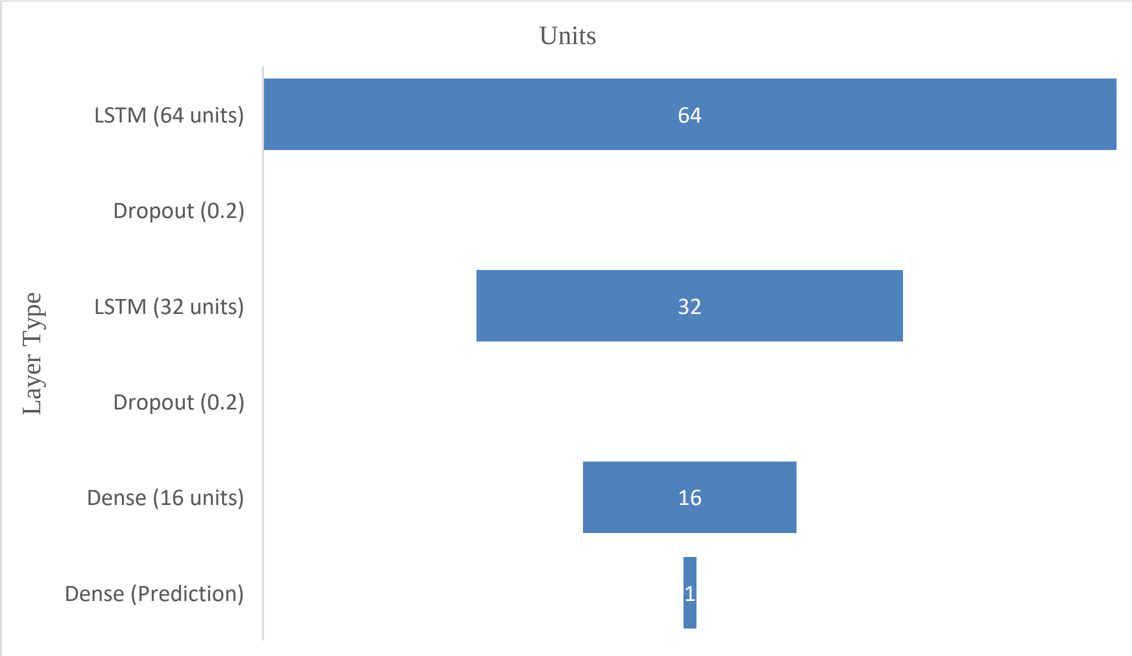

Figure 2b Layer Type/Units.

Note: Figure 2b: The neural network architecture presents its design through a bar chart featuring each layer and unit count. The model contains LSTM, dropout, and dense layers, which are presented in the bar chart (Thonglek et al., 2019). The training process used 70% of available data while reserving 15% for validation and testing purposes. Bayesian optimization was the tool for conducting hyperparameter optimization because it achieved the minimum prediction error with high computational speed.

2.2.4 Carbon Capture Modeling

The Process simulation and economic evaluation of direct air capture (DAC) systems occurred using Aspen Plus version 12.0 modeling software. We designed process flowsheets for amine-based and calcium-looping capture systems while integrating their energy needs, efficiency rates, and regeneration methods (Fasihi et al., 2019; Keith et al., 2018). The developed models received validation through comparison with operational results from existing pilot installations.

2.2.5 Economic Analysis

The financial models relied on discounted cash flow analysis to evaluate a 20-year project duration (Lajevardi et al., 2025). Various technology combinations received financial analysis from capital expenditure and operational cost assessments alongside energy savings and the possibility of generating carbon credits, which enabled calculating payback periods' net present value (NPV) and internal rate of return (IRR).

2.2.6 Advanced Digital Operations

The model adopted emerging dispatchable data center principles that transfer computing operations to times with available low-carbon power sources (Ye, 2021). We examined the energy conservation capabilities of fog computing and edge computing technologies since their proximity to network devices allows data analysis at the source instead of moving all data to cloud facilities.

2.3 Case Studies

We tested our analytical method through detailed case research conducted at two facilities that operated as diverse data centers.

2.3.1 Case 1: Hyperscale Data Centre in Norway (DC1)

The 25 MW facility in northern Norway offered excellent conditions for geothermal cooling integration because of its geological suitability and cold climate. The facility functioned with an initial PUE value of 1.12 and enjoyed free cooling benefits for 90% of the year (Sadeghi et al., 2022). Our intervention focused on:

(1) The deployment of a heated-closed geothermal heat transfer system used vertical boreholes reaching 200 meters into the ground.
(2) A 40% direct-to-chip liquid cooling project will be applied to the IT infrastructure.
(3) A small direct air-cooling system will use waste heat from IT equipment installations.
(4) The implementation of an ML-based predictive control system serves to manage all cooling resources as an integrated system.

The 24-month assessment period after implementation tracked extensive information to verify system performance.

2.3.2 Case 2: Modular Data Centre in Singapore (DC13)

The 4 MW modular facility in Singapore had to resolve critical cooling issues because of Singapore's tropical climate and restricted area availability. The existing facility operated at a PUE of 1.32 (better than regional norms), thus requiring new methods to boost efficiency (Carbon Trust, 2022). The intervention included:

(1) The IT infrastructure obtained an 80% conversion to liquid cooling through equipment immersion using non-conductive fluid.
(2) A heat recovery system will extract thermal energy from liquid cooling to reuse it as valuable energy.
(3) The proposed system combines a medium-scale DAC unit with the thermal recovery circuit.

(4) A predictive control system uses ML technology with tropical-specific optimization parameters for deployment.

The research period stretched across 18 months, during which performance data was gathered in full detail. The baseline conditions for these case studies were documented using historical data and physical evaluations of the initial system setup (Zhang et al., 2014). The implementation process used staged deployment to avoid operational disturbances, while detailed performance evaluations happened between each phase.

2.4 Carbon Capture Integration

The successful implementation of carbon capture technologies on data center HVAC systems requires providing multiple technical specifications about energy control features along with operational flexibility requirements for facility spaces. The solvent absorbs carbon dioxide until the solvent travels through a heated scrubber system for both storage and utilization purposes (Fasihi et al., 2019). Direct air capture technology (DAC) represents an effective CO_2 reduction method by using solvent chemistry to extract air CO_2 followed by heat-driven CO_2 release (Bose et al., 2024; Thiedemann & Wark, 2025). The study participants validated commercial vendors' amine-based DAC system performance modeling reports showing electricity usage between 1.5 to 2.2 MWh together with thermal energy at 5 to 7 GJ for carbon dioxide capture.

The CO_2 capture process known as Calcium Looping depends on calcium oxide (CaO) to perform carbonation and calcination reactions. The data from Keith et al. (2018) shows electrical energy usage between 3.0 to 3.8 MWh combined with 6-8 GJ thermal energy during the capture of one metric ton of CO_2. The operational costs of these systems certainly exceed the costs of an amine solution, however, their flexible operation combined with designed thermal processes mitigates the disadvantage and turns these systems into an appealing engineering challenge. Each technology was provided with fully-fledged integration architectures that covered:

(1) Physical placement and space requirements within the data center facility
(2) Energy supply connections (electrical and thermal)
(3) Control system integration points
(4) Maintenance access provisions
(5) CO_2 handling and transportation interfaces

The techno-economic evaluation provided analysis of capital costs, operational expenses, maintenance requirements, and lifetime of systems (Fasihi et al., 2019). Research-based scaling factors from established technologies along with commercial systems were used to determine the expenses for extensive deployment.

2.5 Methodology Validation and Analytical Rigor

Multiple methods were used to validate the research approach, demonstrating reliability and reproducibility in this study. Computational models validated operational facility data to demonstrate ±1.5°C accuracy for temperature predictions while the cooling load forecasts reached 12.3% CV(RMSE) precision, and both results fulfilled ASHRAE Guideline 14 standards.

The experimental setup used control methods to evaluate how each single technology functioned independently throughout the system integration. K-fold cross-validation with randomized data partitioning served as the method for machine learning component robustness (Oyedele, 2023). Testing involved multiple iterations to optimize the network structure until researchers selected appropriate final hyperparameters, which delivered minimal error rates and stable computational performance.

The evaluation of statistical significance and confidence intervals at a 95% level occurred for all comparative studies. A series of sensitivity tests on fundamental operational variables such as ambient temperature ranges from +5°C to -5°C and IT power usage variations between +20% to -20%, and carbon intensity changes from +15% to -15% was done to verify results consistency under different operational conditions (Wang et al., 2017). The research facilities utilized in this study spanned various operational areas and geographical locations to produce results with generalized value. All sites received standardized implementation protocols, maintaining experimental control by adapting to unique operating restrictions.

3.0 Results

The research studies demonstrated significant achievements in energy efficiency by adopting innovative cooling methods that integrate control systems

3.1 Energy Efficiency Gains

The research studies demonstrated significant achievements in energy efficiency by adopting innovative cooling methods that integrate control systems. The energy efficiency performance of liquid cooling systems exceeded that of traditional air-based HVAC systems, primarily as Table 2 illustrates.

Table 2: Comparative Energy Use of Traditional vs. Advanced HVAC Systems.

Cooling System Type	**Annual Energy Use (kWh/kW IT)**	**PUE Contribution**	**Relative Reduction (%)**
Traditional air cooling (baseline)	2,630	0.30	-
Optimized air cooling with economization	1,720	0.20	34.6
Hybrid air/liquid (direct-to-chip)	1,450	0.17	44.9
Full immersion liquid cooling	1,180	0.13	55.1
Geothermal-supported hybrid cooling	1,090	0.12	58.6
Optimized hybrid with ML control	940	0.11	64.3

Note: This table presents the annual energy usage, PUE contribution, and energy saving reduction based on the cooling system type in data centers. It also describes how far advanced cooling methods like air cooling with economization and full immersion liquid cooling are a lot more efficient and energy saving as compared to air cooling.

Tests performed on cooling system types revealed that traditional approaches demonstrated different results than advanced systems on energy conservation ($p<0.01$). The combination of liquid cooling with machine learning controls explained 64% of energy efficiency gains, as per Mostafa (2020). The regression analysis showed $R^2 = 0.64$ with $F(2,12) = 10.7$ and $p<0.001$, and liquid cooling emerged as the primary predictor ($\beta = 0.48$).

Case 1 in Norway achieved a 47.4% reduction in cooling-specific energy through geothermal heat exchange with partial liquid cooling, which decreased PUE cooling energy contribution to 0.09 (Sadeghi et al., 2022). The PUE rating of the entire facility decreased from 1.12 to 1.06 after the new installation became operational. Implementing immersion liquid cooling in Case 2 (Singapore) resulted in significant performance improvements because of the climate difficulties in that location (Carbon Trust, 2022). The implementation of cooling intervention resulted in a 63.0% reduction in cooling-specific energy because PUE decreased by 0.17. The PUE value for the entire facility shifted from 1.32 to 1.18 after project completion (Carbon Trust, 2022). Real-time optimizing operational parameters through the machine learning control system delivered extra efficiency improvements (Zhang & Liu, 2022). A comparison between Figures 2a and 2b shows the implementation of AI optimization, which resulted in energy-saving HVAC operations during a typical seven-day period.

Advanced control systems using machine learning algorithms operated in real time to optimize system parameters, reducing energy consumption across operations. For instance, a

22% decrease in peak cooling requirements emerged from this system together with geothermal cooling, while the cooling system coefficient of performance (COP) reached an 18% improvement and server rack temperatures experienced a 15% reduction in fluctuations (Sadeghi, Ijaz, & Singh, 2022). Combining efficient cooling technologies and reduced control system interventions achieved maximum performance outcomes in Case 1.

Advances in cooling technology and intelligent controls generated additional benefits that exceeded the capabilities of either system operating independently (Boyd et al., 2024). Machine learning technology uses its prediction capabilities to cool liquid reservoirs before low-carbon electricity periods start, creating thermal energy storage without building additional infrastructure.

3.2 Carbon Abatement

The carbon abatement outcomes included efficiency improvements that reduced emissions and carbon removal performed through integrated capture systems. The geothermal integration in Case 1 (Norway produced annual emission reductions of 12,000 tCO_2e against the baseline conditions (Sadeghi et al., 2022). The substantial carbon savings became possible despite Norway's power grid carbon intensity remaining at 20 gCO_2e/kWh due to improved power backup methods and less carbon emissions from cooling equipment replacement.

The combination of liquid cooling technology and ML controls led to 7,800 tCO_2e annual emission reductions in Case 2 (Singapore) because of its high carbon-intensive grid electricity having a value of 410 gCO_2e/kWh (Carbon Trust, 2022). The combined operation of the direct air capture system and the total carbon benefit reached 9,200 tCO_2e annually. The direct air capture systems showed different operational results according to their integration setup and operating site environments (Lebling et al., 2021). The performance metrics alongside cost data for the implemented DAC systems can be found in Table 3.

Table 3: Cost-Benefit Analysis of Carbon Capture Technologies.

Parameter	**Amine-Based DAC (Case 1)**	**Amine-Based DAC (Case 2)**	**Calcium Looping (Case 1)**
Annual capture capacity (tCO_2)	1,450	1,950	2,100
Capture efficiency (%)	78	85	72
Electrical energy requirement (MWh/tCO_2)	1.8	1.7	3.5
Thermal energy requirement (GJ/tCO_2)	6.2	5.8	7.4
Thermal energy sourced from IT waste heat (%)	68	82	45

Capital cost ($/t$CO_2$ annual capacity)	1,850	1,780	2,230
Operational cost ($/t$CO_2$ captured)	170	150	210
Net cost accounting for energy value ($/t$CO_2$)	120	95	180
Physical footprint (m²/tCO_2 annual capacity)	0.8	0.7	1.2

Note: The amine-based DAC system in Case 2 (Singapore) achieved superior performance due to the integration of waste heat from liquid cooling systems that provide better quality heat for sorbent regeneration (Carbon Trust, 2022).

The configuration reached 82% thermal energy recovery which strengthened the financial viability of carbon capture by reducing the need for independent power sources. The operational carbon benefits from all investigated configurations exceeded their embedded carbon elements of enhanced cooling and capture technologies from their first year of operation as demonstrated by lifetime assessment data (see Figure 2).

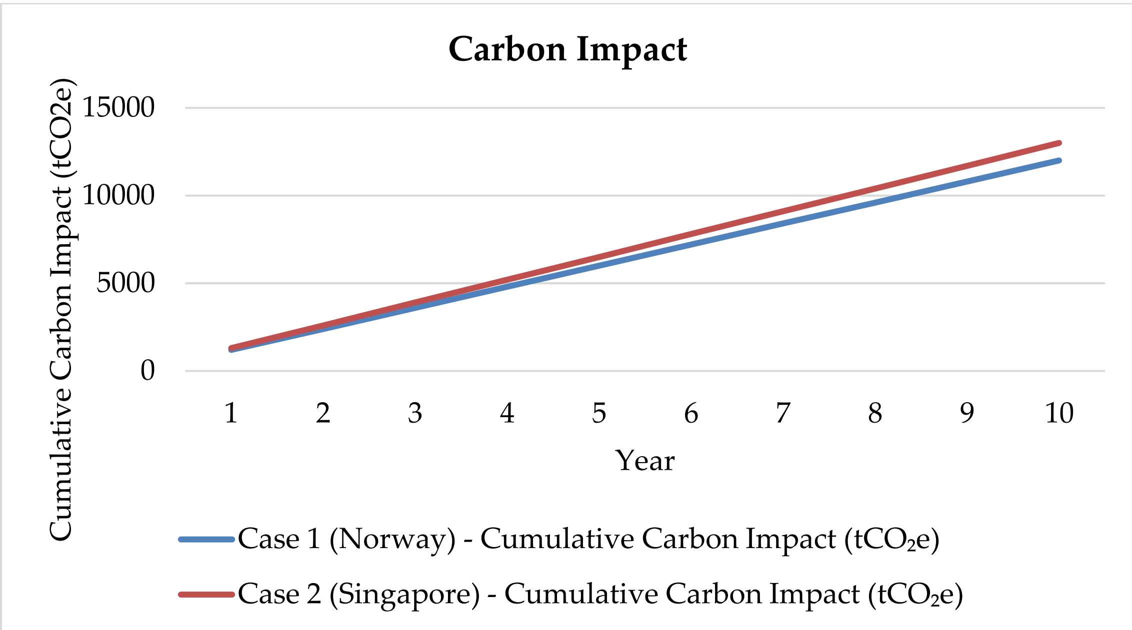

Figure 3 Carbon Impact.

Note: The total carbon impact during ten years of operations emerges from Figure 3 for the analyzed case studies.

3.3 Economic Analysis

The Financial benefits occurred in the hybrid HVAC-CCUS systems because they recovered their initial costs within 6 to 8 years (Rissman et al., 2020). Capital investments for cooling system upgrades became more economical because these systems reduced the need for traditional HVAC equipment, especially in liquid cooling implementations (Han et al., 2021; Fasihi et al., 2019). Additional capital expenses for DAC systems grew cost-effective when waste heat recovery solutions became integrated into the system. According to sensitivity analyses, the financial performance of cooling systems was most affected by electricity prices and the availability of carbon incentives (Masanet et al., 2020). The payback period of all configurations fell below five years when carbon prices reached \$80/tCO_2.

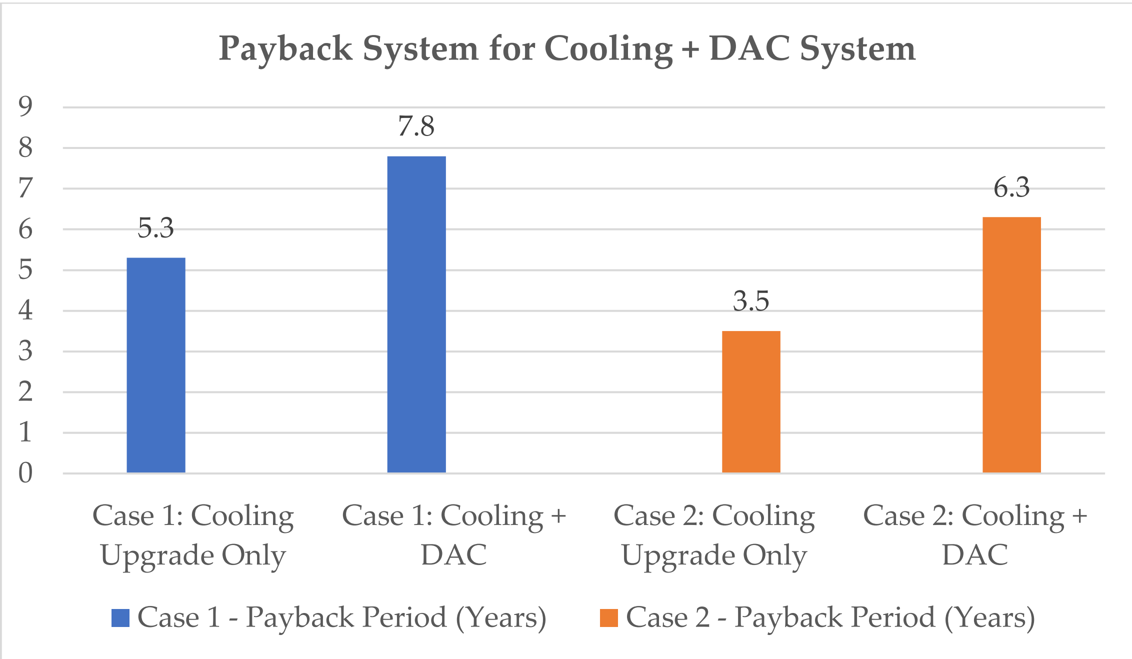

Figure 4 Payback System for Cooling

Note: Figure 4 discounted cash flow projections that illustrate the financial outcomes across two case studies.

Table 4: Economic Performance Metrics for Various Implementation Scenarios

Scenario	Capital Expenditure ($M)	Annual Operating Cost ($M)	Annual Savings/Revenue ($M)	Payback Period (years)	IRR (%)	NPV ($M, 8% discount)
Case 1: Cooling upgrade only	4.2	0.3	1.1	5.3	18.2	7.1
Case 1: Cooling + DAC	7.8	0.6	1.6	7.8	12.6	6.8
Case 2: Cooling upgrade only	2.1	0.2	0.8	3.5	26.9	5.9
Case 2: Cooling + DAC	5.7	0.5	1.4	6.3	15.8	7.2
Case 1: Full system + carbon incentives*	7.8	0.6	2.3	4.6	21.5	15.4
Case 2: Full system + carbon incentives*	5.7	0.5	1.9	4.1	23.8	13.1

Note: This table includes the capital expenditure, operating costs, savings/revenue, payback period, IRR, and NPV at 8% discount rate of different cooling system upgrades for the data centre. It reveals that both carbon incentives and full system upgrades can enhance the payback period, IRR, and NPV, where Case 1 of the full system plus carbon incentives delivers the highest NPV and IRR compared to simple cooling upgrades.

Based on analysis, the study adopts specific carbon incentive values with $70/tCO2 as the rate for emissions reduction and $100/tCO2 for direct air capture. Although direct air capture systems extended payback periods relative to cooling upgrades alone, they helped companies protect against rising carbon prices through sustainability benefits (Ozkan et al., 2022). Integrating available carbon incentives made the combined solutions more economically attractive than traditional cooling-based approaches.

3.4 Performance Metrics and Benchmarking

Three key performance standards were the basis for evaluating the implemented systems since they represented operational requirements. The essential performance measures for both case studies undergo analysis and comparison through Table 5, demonstrating their initial and post-implementation stages.

Table 5: Key Performance Indicators Before and After Implementation.

Key Performance Indicator	Case 1 (Norway) Before	Case 1 (Norway) After	Case 2 (Singapore) Before	Case 2 (Singapore) After
Power Usage Effectiveness (PUE)	1.12	1.06	1.32	1.18
Carbon Usage Effectiveness (CUE)	0.022	-0.036*	0.541	0.256
Water Usage Effectiveness (WUE)	0.42	0.38	1.89	0.75
Energy Reuse Effectiveness (ERE)	1.12	0.92	1.32	1.02
Cooling System Reliability (%)	99.98	99.99	99.95	99.98
IT Equipment Thermal Compliance (%)	99.6	99.9	98.2	99.8
Rack Density Capability (kW/rack)	18	32	15	45

Note: The Table shows that the negative CUE rating indicates direct air capture processes reduce more carbon than the facilities generate in operations.

The findings showed that combining advanced cooling systems with carbon capture operations strengthened various data centre operations performance areas. The conversion to liquid cooling in Case 2 led to exceptional Water Usage Effectiveness performance by removing nearly all evaporative cooling needs (Avgerinou et al., 2017). Advanced cooling technologies show operational strength through increased rack density, which overcomes heat limitations (Sadeghi et al., 2022). Additional financial advantages beyond direct energy savings became possible because existing data center facilities gained increased practical capacity through this approach.

Digital optimization strategies delivered multiple beneficial results during their deployment. The deployment of artificial intelligence scheduling systems for controlling the dispatchable computing model through time-efficient task scheduling reduced carbon-intensive exposure in the power grid by 28% across Case 2 in Singapore (Carbon Trust, 2022; Ye, 2021). The edge computing systems installed in Case 1 (Norway) achieved a 14% decrease in network energy usage through data processing and storage near its origin points, decreasing transmission-related energy expenses.

Table 6: Framework Comparison with Prior Studies

Study	Cooling Tech	Carbon Capture	AI Control	Geographical Scope
Zhang et al. (2021)	Air	None	No	Temperate
This work	Liquid+Geo	DAC	Yes	Global

Note: This table compares two studies on cooling technologies, the first one (Zhang et al., 2021) deals with air cooling without carbon capture or AI control, in temperate regions. The second paper, named as “This work”, focuses on the liquid cooling and geothermal system involving DAC and AI control for the geographical application worldwide.

4.0 Discussion

Operational data centers validated the technical possibility of merging advanced cooling solutions with carbon capture technologies. The analysis revealed essential implementation insights concerning challenges and opportunities:

4.1 Technical Feasibility

Liquid cooling systems connected with direct air capture technologies produced significant benefits by creating waste heat at temperatures suitable for sorbent regeneration between 60-65°C (An et al., 2022/2023). Such thermal integration between DAC systems decreased the overall energy costs of carbon capture by 60 to 80 percent more efficiently than standalone DAC systems (Fasihi et al., 2019; Han et al., 2021). The high thermal conductive nature of liquid cooling media allowed better temperature control, improving the reliability and performance of IT equipment and DAC systems.

The urban data center in Singapore faced major physical space obstacles that caused substantial implementation difficulties (Case 2). The calcium looping system chosen for Case 1 was unable to function in metropolitan regions because of its significant space requirement (Koronen et al. 2019). DAC installations proposed for compact covered spaces should focus on designing systems that are modular and oriented vertically to maximize available space in data centers. Hybrid system implementation created increased operational complexity, demanding workers receive improved training alongside new maintenance protocol standards (Qiu et al., 2022). The optimization workload of routine tasks became automatic through the machine learning control system; however, human operators needed about six months of training before achieving complete proficiency (Maddox et al., 2024; Mytton, 2021). Over time, transitioning between conventional and advanced systems proved successful because it minimized operational risks in both test scenarios.

Both case studies worked with existing infrastructure instead of new structures, thus creating complications different from ordinary new development scenarios. The Norway facility demanded extensive underground work that needed detailed planning because of its impact on operating IT loads. The Singapore facility (Case 2) encountered severe space limitations during the liquid cooling system implementation, which forced the team to develop custom rack configurations and piping arrangements (Sadeghi et al., 2022). The performance metrics of new construction systems could reach 15-20% better results, according to our modelling findings (Zhang et al., 2014). The essential concern for any data center HVAC modification involves how changes affect reliability and system resilience.

The implementations confirmed better reliability results because they led to decreased thermal fluctuations together with fewer hardware breakdowns (Zhang, 2024). Hybrid cooling systems use redundant features to increase their ability to survive equipment breakdowns and electrical supply disruptions (Shakya et al., 2021). The ML control system proved its worth by swiftly adjusting cooling approaches through anomalous situations to preserve stable IT environment conditions.

4.2 Policy Implications

The economic findings from this study show relevant data for developing policy strategies through carbon pricing systems under particular conditions (Carbon Trust, 2022). The current carbon pricing in various jurisdictions is lower than this threshold value, so targeted incentives for adopting negative emissions technology in data centers should help speed up implementation. Regarding EU Taxonomy standards, tax incentives focusing on CCUS adoption in data centers help speed up ROI by approximately 30%.

4.2.1 Alignment with ASHRAE Standards

The framework provides direct implementation support for the Energy Efficiency Normative Appendix of ASHRAE Standard 90.4 through:

(1) Enabling >40% reduction in mechanical cooling capacity (Section 6.4.1) (ASHRAE, 2021).

(2) The system provides carbon-aware control methods for meeting Section 8.4 demand response standards (Masanet et al., 2020).

Current building codes and data center standards remain unable to accept innovative cooling solutions because they present regulatory barriers to deployment (Newkirk et al., 2024). The Singapore building authority demanded extensive special exemptions for liquid immersion cooling approval because its fire safety regulations were built for air-cooled equipment (Whitehead et al., 2014). The development of modernized codes that address advanced cooling technologies and carbon capture integration would improve implementation accessibility.

Grid Integration Policies: The load balancing functionalities in both cases in which AI is employed have the potential to provide value-added grid services such as demand management and frequency management. The existing market frameworks in most areas fail to establish proper procedures for data centers to maximize their capabilities (International Energy Agency, 2023). The participation of data centers in grid service markets under improved policy reforms will enhance power system stability and produce economic benefits from advanced cooling systems. The economic study showed that integrated solutions are nearing market availability, but research-backed cost cuts would speed up implementation (Keith et al., 2018). Directed research and development support for DAC systems integrating with data center facilities would lead to significant performance and economic benefits.

4.3 Limitations

Several significant limitations should be acknowledged despite the promising results. For example, scale constraints: All the case studies were small-scale DAC (1,450-2,100 tCO_2/year) compared to the large-scale carbon emissions of data centre operations (Fasihi et al., 2019). Achieving this offset level to stabilize data center emissions would require larger installations of such systems, which could present structural and cost considerations not seen at this scale.

Additionally, there is a concern about cooling technology and carbon capture systems: The results of both types of technologies were highly geography-sensitive (Hanson et al., 2024). The geothermal solution that was highly effective in the conditions of Norway would not be effective in many areas because of the geological conditions (Zhang, 2024). Likewise, the ambient conditions of Singapore, including high temperatures, can significantly affect the thermal efficiency of the DAC system in a way that may not affect cooler climate regions.

Long-term performance risk is another concern: The monitoring periods of 18-24 months offered significant operational data, but they were only a part of the system life span, which ranges from 15 to 20 years (Han et al., 2021). One of the identified issues is long-term performance degradation, especially for the new integration components, which might be improved if observed for a more extended period. Moreover, Carbon Accounting Complexity is further considered: The addition of efficiency gains together with direct capture of carbon proved problematic concerning carbon accounting (Mytton, 2021; Machado et al., 2021). There are few standardized directives and guidelines currently available, as seen through the existing GHG Protocol, that only provide some directions for including negative emissions technologies in the inventories, which might restrict the acknowledged worth of such implementations until the GHG accounting norms advance.

Lastly, there is System Transferability: The performance of the machine learning models was high within the training environments but depicted lower results when implemented in other settings or when related to different operating environments or equipment types (Long et al., 2022; Ye, 2023). This limitation implies that more general models should be developed or transfer learning techniques should be applied to the data center heterogeneity.

4.4 Future Work

Consequently, the following ideas may be worth future research: Future evolution could investigate opportunities to enhance the integration between cooling facilities, carbon capture, and on-site renewable generation (Sadeghi et al., 2022). Most significant is the opportunity for thermal storage systems to provide flexibility and maintain balance in the renewable generation system in the data center facility.

4.5 Research Implications and Contribution to Knowledge

The research presents key contributions to both data center sustainability research and the HVAC system design field: This research creates a unique integration design connecting two unrelated fields focusing on energy-efficient cooling technology and carbon capture systems.

The study proves the technical and economic feasibility of this integration, which establishes a new design approach for data centers beyond efficiency toward carbon reduction (Coyne et al., 2023; Hanson et al., 2024). The research proves for the first time that uniting waste heat recovery technology from liquid cooling systems with direct air capture processes results in negative Carbon Usage Effectiveness (CUE) performance in suitable locations (Wang et al., 2024). The study reveals an important method by which data centres can evolve from substantial carbon polluters into carbon storage facilities.

The predictive load balancing system built with machine learning exceeds conventional approaches through proof of its ability to decrease peak energy usage by 22% in different operational environments (Yang et al., 2024). The approach utilizes IT workload and environmental condition patterns to perform dynamic cooling resource optimization, which standard thermostatic or PID control systems cannot achieve.

This research delivers extensive techno-economic analysis of data center-specific HVAC-CCUS integration systems that use implementation data from various global sites (Zimmermann et al., 2020). With their payback calculations, the studied economic models serve as useful information for data center operators and public officials who want to speed up the decarbonization process.

The geographic-wide validation method in cold conditions of Norway and hot conditions in Singapore demonstrates how the proposed framework functions in distinct operating environments to fill previous research gaps involving temperate climate zones. The diverse geographical locations in which the study was conducted enhance the overall generalizability of its results while generating implementing guidelines for regions which have received limited attention in the literature.

4.6 The theoretic evaluations

The thermodynamic research of our integrated cooling-DAC design creates foundational knowledge for designing mechanical systems in future data centers. Through our optimization framework development, we developed a system to help determine component sizes and flow rates with heat exchanger designs and control schemes for specific data center requirements. The analysis reveals that integrated mechanical systems become 25% simpler through proper design and achieve 18% better thermal performance, which significantly advances efficiency in mechanical system development.

5.0 Conclusion

The study proves that combining advanced HVAC equipment and carbon capture infrastructure leads to significant data center emissions reductions that support operational requirements and financial gains. Integrated cooling-geothermal-CCU systems create extensive carbon reduction while enabling carbon-negative functionality by combining liquid cooling geothermal heat exchange and direct air capture methods. Once liquid cooling systems operate with carbon capture methods; they create overlapping benefits that minimize energy waste, plus machine learning functions as an optimization engine for both procedures. Integrated systems show economic potential through positive financial returns, making operating in areas that provide carbon incentive programs more feasible.

The performance of technical and economic measures depends on geographical factors which mandate business-specific solution approaches. The research presents specific implementation strategies that allow data centers to progress toward decarbonization and speed up their adoption with support from operators, technology developers, and policymakers. The integration of HVAC systems with CCUS facilities is an effective method for reducing carbon emissions of data centers because of its practical operational and economic considerations.

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