

Article

Cascaded Waste-Heat Valorization In Data Centers Through an Exergy-Economic Framework

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Abstract

The rapid growth of graphics processing unit (GPU)-accelerated AI workloads has made data centers significant sources of medium-grade waste heat, creating both a sustainability challenge and an urban decarbonization opportunity. This paper presents the Cascaded Exergy-Economic Valorization (CEEV) framework, a three-stage system that converts data-center waste heat through 1) an organic Rankine cycle for GPU liquid-cooling loops at 65–85 °C; 2) a transcritical CO₂ heat pump, upgrading residual heat to 75–90 °C; and 3) thermochemical energy storage using SrBr₂·6H₂O for seasonal heat banking. The framework introduces two metrics: the Exergy Value Index (EVI, \$/kJ) and the Levelized Cost of Stored Heat (LCSH, \$/kWh). Results for a 10 MW liquid-cooled data center across three climate zones show cascade exergy utilization of 31.2–38.7%, operational cost reductions of 15–25%, 20-year NPV of \$2.2–8.4 million, and payback periods of 5.8–7.8 years. The simpler HP (heat pump) +TCES (thermochemical energy storage) configuration achieves higher deterministic Net Present Value (NPV) because it preserves the full waste-heat temperature for the heat pump; however, the full three-stage cascade becomes preferable when electricity prices exceed approximately \$50/MWh, when revenue diversification is valued, or when real-options flexibility is important. Real-options analysis shows that traditional NPV undervalues cascaded waste-heat recovery investments by 18–32%. Even without carbon credit revenue, NPV remains positive at \$1.6–6.1 million, confirming that district-heating sales and electricity revenue alone can support investment. The CEEV framework advances sustainable data-center development by providing quantifiable tools for waste-heat performance assessment, supporting policy instruments such as the EU Energy Efficiency Directive and the German EnEg, and aligning with SDGs 7, 9, 11, and 13.

Keywords: data center; exergy analysis; waste heat recovery; organic rankine cycle; GPU; thermochemical energy storage; techno-economic analysis; real-options analysis; decarbonization

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1. Introduction

The exponential growth of artificial intelligence workloads has fundamentally reshaped the energy and thermal landscape of modern data centers. According to the Inter-

national Energy Agency [1], global data-center electricity consumption reached approximately 415 TWh in 2024, representing 1.5% of worldwide electricity demand. This consumption is projected to more than double, to 945 TWh, by 2030, with AI identified as the single most important growth driver. In the United States alone, data centers consumed 183 TWh in 2024, and are projected to reach 426 TWh by 2030, a 133% increase [2].

The transition from central processing unit (CPU) to GPU-accelerated AI computing has been particularly consequential for thermal management. Next-generation accelerators generate thermal loads exceeding 700 W per chip [3], driving rack power densities to 60–150 kW under liquid cooling [4,5]. Nearly all consumed electricity is converted to heat, yet less than 3% is currently recovered [6,7]. The IEA estimates that data-center waste heat could provide up to 300 TWh of space heating to European buildings [8]. Practical demonstrations are accelerating: in Stockholm, more than twenty data centers supply 1.5% of district-heating needs; Microsoft's campus near Helsinki is projected to provide 40% of district heating for Espoo; and Ireland's Tallaght scheme saved 1100 tonnes of CO₂ in its first year [6,7]. Germany's Energy Efficiency Act (EnEfG) mandates 10–20% waste-heat utilization by 2026–2028 [9], and the EU Energy Efficiency Directive requires member states to develop waste-heat action plans by 2030.

Despite this momentum, waste-heat recovery technologies remain fragmented without a unified framework for AI-era facilities [10–12]. This paper addresses three critical gaps: the absence of cascaded multi-technology WHR (Waste-heat recovery) architectures, the lack of workload-differentiated exergy analysis, and the complete absence of real-options investment methodology. We propose the CEEV framework, introduce two novel metrics (EVI (Exergy Value Index) and LCSH), and couple the thermodynamic model with Monte Carlo simulation and real-options analysis [13].

2. Literature Review

He et al. [10] provided a comprehensive 4E review of data-center WHR technologies, reporting payback periods of 2–8 years. Hao et al. [11] extended this with an exergy-based model, finding 10–68% recovery of available waste heat exergy. Yuan et al. [6] and Zou et al. [14] reviewed district-heating integration and heat-pump utilization, respectively. District heating is the most commercially mature pathway. Wahlroos et al. [15] achieved cost reductions of 0.6–7.3% in Espoo, Finland. Pärssinen et al. [16] found positive NPV only for ten MW+ installations. Tervo et al. [17] quantified 15–40% CO₂ reductions. Socci et al. [18] showed data-center waste heat can comprise 12–59% of district-heating energy structure. Liquid-cooled GPU systems produce waste heat at 65–85 °C [4], improving heat-pump COP (Coefficient of Performance) to 3.5–6.0 [9]. For power generation, Araya et al. [19] reported ORC (Organic Rankine cycle) thermal efficiencies of 1.9–4.6% at 40–85 °C. D'Agostino et al. [20] achieved 3.1–7.1%. Zhou et al. [21] achieved 83% Carnot battery round-trip efficiency, while Laterre et al. [22] demonstrated payback of 4–10 years. The EU THUNDER project [23] pioneered TCES for data-center WHR with 213 kWhth/m³ energy density [24].

Shah et al. [25] introduced exergy analysis to data-center systems. Zimmermann et al. [26] demonstrated six-fold exergy efficiency improvement with hot-water cooling. Ma et al. [27] showed 3.87-fold improvement with a CO₂ ground-source heat-pump prosumer system. A critical gap concerns AI workload differentiation: training (90–95% sustained utilization) and inference (30–70% variable utilization) produce fundamentally different thermal signatures [4,5]. The literature reveals three gaps: (1) no cascaded WHR architecture exists for data centers; (2) no exergy study distinguishes training from inference profiles; and (3) no real-options analysis has been applied to data-center WHR [16,28]. The CEEV framework addresses all three, while introducing EVI and LCSH metrics.

3. Methodology: The CEEV Framework

3.1. System Architecture Overview

The CEEV framework processes waste heat through three cascaded stages (Figure 1). Stage 1 deploys an ORC for electricity generation. Stage 2 employs a transcritical CO₂ heat pump for district heating. Stage 3 utilizes thermochemical storage for seasonal banking. An adaptive controller allocates heat flows based on real-time energy prices, heating demand, and TCES state-of-charge.

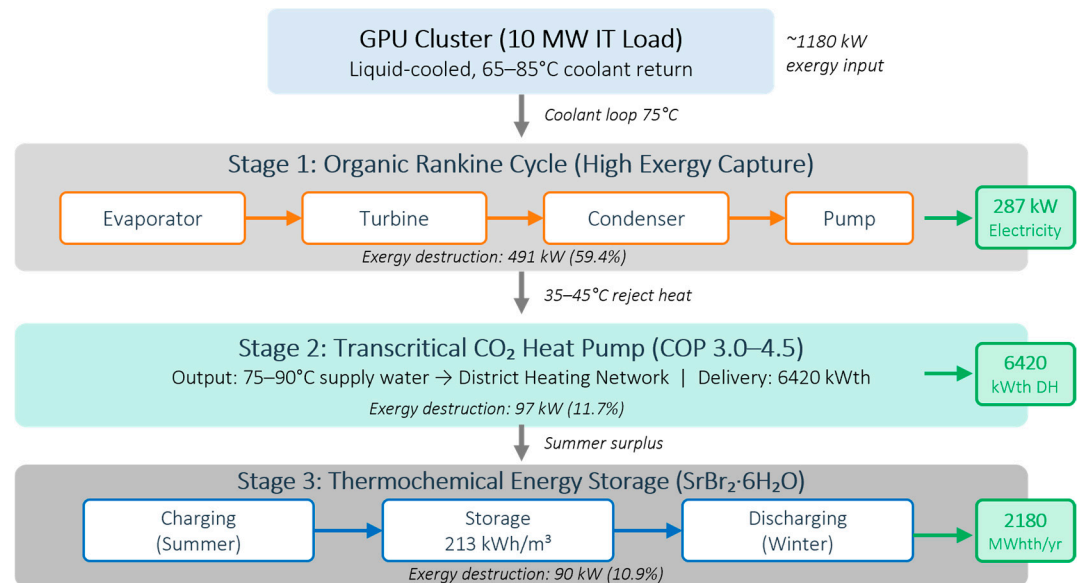


Figure 1. Cascaded CEEV system architecture showing three sequential stages: Stage 1 (ORC at 65–85 °C), Stage 2 (transcritical CO₂ heat pump to 75–90 °C), and Stage 3 (TCES using SrBr₂·6H₂O for seasonal banking). Values correspond to the Ashburn baseline (10 MW IT, 95% training).

3.2. CEEV Framework Stages

3.2.1. Stage 1: Organic Rankine Cycle

The ORC receives liquid coolant at 65–85 °C. Working fluid optimization evaluates R245fa/R600a zeotropic mixtures using CoolProp 6.6, with turbine isentropic efficiency of 70% and pump efficiency of 75% [19].

The thermodynamic model for the ORC subsystem is formulated using steady-state energy and exergy balance equations at each component. The thermal efficiency of the ORC is defined as the ratio of net power output to heat input at the evaporator (Equation (1)). The net power output is the difference between turbine work and pump work, where the turbine work is computed from the enthalpy drop across the expansion process using an isentropic efficiency of 70%, and the pump work from the enthalpy rise during compression at 75% isentropic efficiency, consistent with the experimental values reported by Araya et al. [19].

$$\eta_{th,ORC} = \frac{W_{net}}{Q_{evap}} = \frac{(\eta_{is,turb} \times (h_1 - h_{2s}) - (h_{4s} - h_3) / \eta_{is,pump}) \times \dot{m}_{wf}}{\dot{m}_{wf} \times (h_1 - h_4)} \quad (1)$$

The exergy destruction at each component k is calculated as the difference between exergy input and exergy output, following the Gouy–Stodola theorem (Equation (2)), where T_0 is the dead-state temperature (25 °C) and $\dot{S}_{gen,k}$ is the entropy generation rate. The exergy efficiency of the ORC is defined as the ratio of net power output to the exergy

of the heat input stream (Equation (3)), where the exergy of the heat source is evaluated at the GPU coolant supply temperature using the Carnot factor.

$$\text{Ex}_{\text{dest},k} = T_0 \times \dot{S}_{\text{gen},k} \quad (2)$$

$$\eta_{\text{ex, ORC}} = W_{\text{net}} / (Q_{\text{evap}} \times (1 - T_0/T_{\text{source}})) \quad (3)$$

The cascade exergy utilization is defined by a single equation applied system-wide (Equation (4)):

$$\eta_{\text{ex, cascade}} = (W_{\text{net, ORC}} + \text{Ex}_{\text{DH}} + \text{Ex}_{\text{TCES}}) / (\text{Ex}_{\text{waste}} + W_{\text{purchased}}) \quad (4)$$

where each term is defined as follows. $W_{\text{net, ORC}}$ is the ORC net electrical output (kWe), counted at 100% exergy availability. Ex_{DH} is the district-heating thermal exergy delivered to the DH (District heating) network, calculated as $Q_{\text{DH}} \times (1 - T_0/T_{\text{DH, lm}})$, where Q_{DH} is the HP thermal output (kWth) and $T_{\text{DH, lm}}$ is the log-mean temperature of DH delivery between the supply temperature T_{supply} and the return temperature T_{return} : $T_{\text{DH, lm}} = (T_{\text{supply}} - T_{\text{return}}) / \ln(T_{\text{supply}}/T_{\text{return}})$. Ex_{TCES} is the annualized TCES discharge exergy, calculated as the annual discharged energy (kWth/yr) divided by 8760 h, multiplied by $(1 - T_0/T_{\text{TCES, out}})$, where $T_{\text{TCES, out}}$ is the hydration outlet temperature. Ex_{waste} is the GPU waste-heat thermal exergy: $Q_{\text{GPU}} \times (1 - T_0/T_{\text{GPU}})$. $W_{\text{purchased}}$ is the total purchased electricity consumed by the cascade: HP compressor + ORC pump + TCES vacuum pump + auxiliary VFDs, minus the ORC electricity generated (which offsets purchased power). The reference environment is $T_0 = 298.15 \text{ K}$ (25°C), $P_0 = 101.325 \text{ kPa}$.

Worked example (Ashburn baseline, annual-average conditions):

$W_{\text{net, ORC}} = 264 \text{ kWe}$

$Q_{\text{DH}} = 5870 \text{ kWth}$; $T_{\text{supply}} = 353 \text{ K}$ (80°C); $T_{\text{return}} = 318 \text{ K}$ (45°C); $T_{\text{DH, lm}} = (353 - 318) / \ln(353/318) = 334.3 \text{ K}$; $\text{Ex}_{\text{DH}} = 5870 \times (1 - 298/334.3) = 637 \text{ kW}$

$\text{Ex}_{\text{TCES}} = (2180 \text{ MWhth/yr} \times 10^3) / 8760 \text{ h} \times (1 - 298/338) = 249 \text{ kWh} \times 0.118 = 29 \text{ kW}$

$\text{Ex}_{\text{waste}} = 8210 \times (1 - 298/348) = 1180 \text{ kW}$

$W_{\text{purchased}} = 1678 \text{ kWe}$ (HP compressor 1412 + pump 39 + vacuum 12 + VFD 215) – 264 kWe (ORC) = 1414 kWe net

$\eta_{\text{ex, cascade}} = (264 + 637 + 29) / (1180 + 1414) = 930 / 2594 = 35.9\%$

The monthly simulation, which applies Equation (4) at each of 240 timesteps with site-specific ambient temperatures, seasonal workload variation, and time-varying DH supply/return temperatures, yields an annual-average cascade exergy utilization of 34.2% for Ashburn. The 1.7 percentage-point difference from the simplified single-point calculation arises because winter months with lower ambient temperature reduce the Carnot advantage of the DH stream. The same equation yields 31.8% for Dublin and 38.7% for Stockholm. Regarding the ORC condenser, the control volume is drawn at the condenser outlet/HP evaporator inlet. The reject stream is entirely consumed by the HP; all irreversibility is allocated to the HP evaporator (97 kW).

The working fluid thermodynamic properties (enthalpy, entropy, and density) at each state point are computed using CoolProp 6.6, an open-source library implementing high-accuracy equations of state. For the zeotropic R245fa/R600a mixture (70/30 mass ratio), the temperature glide during evaporation (approximately $8\text{--}12^\circ\text{C}$, depending on pressure) is explicitly modeled, as this glide enables closer temperature matching with the GPU coolant stream and is the primary mechanism for the mixture's superior evaporator performance compared to pure components. The condensing temperature is set 10°C above the ambient dry-bulb temperature for each location, with the condenser subcooling fixed at 3°C .

The ORC boundary conditions include evaporation pressure of 6.8–9.2 bar, condensation pressure of 1.8–2.6 bar, 5°C turbine-inlet superheating, 3°C condenser-outlet sub-

cooling, evaporator/condenser pinch points of 5 °C/3 °C, heat-exchanger effectiveness of 0.85/0.90, pressure drops of 2% across heat exchangers and 1% across piping, turbine efficiencies of 70% isentropic and 95% mechanical, and pump efficiencies of 75% isentropic and 92% motor, consistent with sub-100 °C small-scale ORC systems [19,20]. Working-fluid optimization evaluated 11 R245fa/R600a mixtures across the 40–85 °C source range using Nelder–Mead optimization of evaporation pressure. The 70/30 R245fa/R600a mixture was selected because it achieved the highest workload-weighted, time-averaged net power output across the three sites, supported by an 8–12 °C evaporation temperature glide that better matched the GPU coolant stream than pure fluids. Figure 2 presents ORC performance versus GPU coolant temperature.

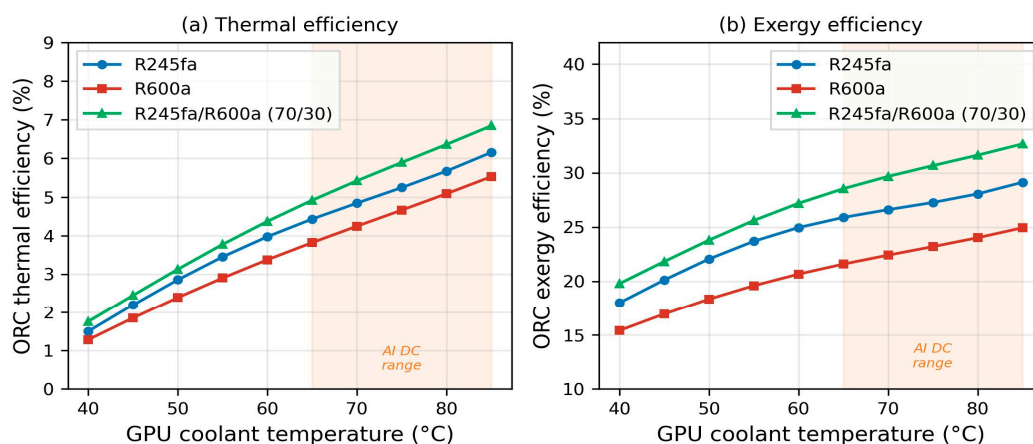


Figure 2. ORC performance vs. GPU coolant temperature: (a) thermal efficiency and (b) exergy efficiency for three working fluid candidates. Shaded region indicates the AI DC operating window (65–85 °C).

3.2.2. Stage 2: Heat Pump

The transcritical CO₂ heat pump upgrades ORC reject heat at 35–45 °C to 75–90 °C for district heating (COP 3.0–4.5) [27]. The TCES exploits reversible dehydration/hydration of SrBr₂·6H₂O [23,24], with 213 kWhth/m³ energy density and 85–92% round-trip efficiency. The transcritical CO₂ heat-pump COP is modeled as a function of the source temperature (ORC condenser reject, T_{source} = 35–45 °C) and the sink temperature required for district-heating supply (T_{sink} = 75–90 °C) using the correlation in Equation (5), where η_{Carnot} is the second-law efficiency of the HP compressor (calibrated to 0.55–0.65, based on the experimental data of Ma et al. [27] for transcritical CO₂ systems). The electrical power consumed by the compressor is $W_{\text{comp}} = Q_{\text{DH}} / \text{COP}$, and the heat delivered to the district-heating network is $Q_{\text{DH}} = Q_{\text{source}} + W_{\text{comp}}$, where Q_{source} is the heat absorbed from the ORC condenser reject stream.

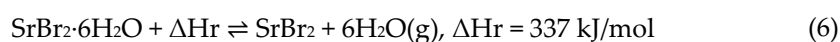
$$\text{COP} = \eta_{\text{Carnot}} \times T_{\text{sink}} / (T_{\text{sink}} - T_{\text{source}}) \quad (5)$$

The transcritical CO₂ heat pump is modeled as a single-stage cycle with internal heat exchange, comprising a variable-speed compressor, gas cooler, internal heat exchanger (IHX), electronic expansion valve, and flooded evaporator. The compressor isentropic efficiency is 0.72 at the design point, derated by 1.5% per 10 °C increase in discharge temperature above 100 °C to reflect the performance map of commercially available semi-hermetic CO₂ compressors in the 500 kW–2 MW shaft power range [27]. Gas cooler pressure is optimized at each timestep by maximizing COP through golden-section search over 80–130 bar, with typical optima of 90–105 bar, depending on gas cooler outlet temperature. The outlet temperature is set 5 °C above the district-heating return temperature: 45 °C for Nordic third-generation networks and 55 °C for Dublin and Ashburn second-

generation networks. The ORC condenser reject stream serves as the evaporator source at 35–45 °C, producing evaporating temperatures of 32–42 °C with a 3 °C pinch, while the gas cooler supplies district heat at 75–90 °C with a 3 °C approach. The IHX effectiveness is 0.70, adding 8–15 °C suction superheating and improving COP by 4–7%. Auxiliary power is modeled as 6% of compressor shaft power. The calibrated second-law efficiency is 0.55 for high-lift operation and 0.65 for low-lift operation, yielding COP values of 3.0–4.5, consistent with comparable transcritical CO₂ systems [27]. Seasonal ambient variation affects both ORC condensing temperature and district-heating demand, explaining Stockholm's lower COP, but with higher heat delivery compared with Dublin.

3.2.3. Stage 3: TCES

The TCES subsystem is modeled using the reversible hydration/dehydration reaction of strontium bromide hexahydrate (Equation (6)). During the charging phase (summer), waste heat at $T > 80$ °C drives dehydration, storing energy as anhydrous SrBr₂. During discharge (winter), controlled rehydration releases heat at 60–70 °C. The round-trip efficiency (Equation (7)) accounts for sensible heating of the reactor mass, parasitic electricity for air handling and water vapor management, and incomplete reaction conversion at the operating temperatures.



$$\eta_{\text{rt, TCES}} = Q_{\text{discharged}} / (Q_{\text{charged}} + W_{\text{parasitic}}) \quad (7)$$

The SrBr₂·6H₂O thermochemical storage system operates under the following conditions: charging (dehydration) occurs at 80–95 °C under a reactor pressure of 1.5–2.5 kPa, achieved by drawing water vapor to an air-cooled condenser; discharging (hydration) is initiated by re-introducing water vapor at 1.0–2.0 kPa, releasing heat at 55–70 °C, depending on the vapor pressure maintained at the evaporator. The equilibrium vapor pressure follows the Clausius–Clapeyron relation fitted to the SrBr₂/H₂O pair [24], with a temperature hysteresis of approximately 5–8 °C between charge onset and discharge onset that dictates the minimum charge temperature of 80 °C. Cycling stability of SrBr₂-based composites has been demonstrated over 100+ charge/discharge cycles with less than 3% capacity fade [23,24]. For the 20-year seasonal operation period, with approximately one cycle per year, cumulative degradation is projected below 5% and incorporated through a Weibull degradation model ($k = 2.5$) across all cascade components. The TCES reactor uses a packed-bed SrBr₂/expanded natural graphite composite at a 60:40 salt-to-graphite mass ratio, increasing thermal conductivity from 0.3 to 5–8 W/(m·K) and improving charge/discharge power density. Water-vapor transport is supported by 30 mm bed modules with vapor channels spaced at 50 mm intervals. Corrosion is mitigated using 316L stainless steel vessels (Outokumpu Oyj, Helsinki, Finland) with a 0.5 mm PTFE (Polytetrafluoroethylen) lining (Chemours Company, Wilmington, DE, USA), validated up to 120 °C in accelerated aging tests [23]. Auxiliary loads include vapor circulation fans, a vacuum pump, and controls, totaling 12 kW_e, or about 0.2% of the 10 MW IT load, and are included in Equations (8) and (9). We note that while the thermochemical storage mechanism itself incurs negligible thermal loss during the storage period (because energy is stored as chemical potential, rather than sensible or latent enthalpy) real systems do experience auxiliary losses during charge/discharge transients, reactor thermal mass warm-up, and incomplete conversion at the bed periphery; accordingly, the round-trip efficiency of 85–92% accounts for all such losses, and we have revised the manuscript to replace ‘near-zero storage-period loss’ with ‘near-zero-loss seasonal storage’ to more accurately reflect operational reality.

The reported 85–92% round-trip efficiency accounts for water-vapor latent heat, the main loss pathway in salt-hydrate TCES systems. During $\text{SrBr}_2 \cdot 6\text{H}_2\text{O}$ dehydration, 6 mol of water vapor are released per mol of salt hydrate, carrying about 244 kJ/mol of latent heat in addition to the 337 kJ/mol reaction enthalpy. Without latent-heat recovery, theoretical efficiency would be limited to about 58%. In the CEEV system, this heat is partly recovered during charging by condensing the released vapor at 25–35 °C and directing the recovered heat to the HP evaporator. During discharging, hydration water is evaporated using HP reject heat or ambient-assisted evaporation, with only the unrecovered fraction treated as a parasitic input. Thus, baseline efficiency is calculated as $\eta_{\text{rt}} = 337 / (337 + 48 + 12) = 84.9\%$, where 48 kJ/mol is net unrecovered evaporation energy and 12 kJ/mol is auxiliary electrical demand. Site-specific efficiencies are 87.6% for Stockholm, 89.1% for Dublin, and 88.3% for Ashburn, consistent with reported closed-loop SrBr_2 systems with condensation heat recovery [23,24].

3.3. Novel Metrics

We define the Exergy Value Index (EVI) as the ratio of total annual economic revenue to total annual exergy input, where the denominator is the sum of waste-heat thermal exergy and external electricity consumed by the HP compressor and TCES auxiliaries (Equation (8), revised). This denominator represents the total exergy resource committed to the cascade and is fixed for a given facility size and operating profile, yielding a bounded and interpretable metric: higher EVI indicates greater economic value extracted per unit of exergy resource consumed. Both numerator and denominator are annualized—total annual revenue (\$/yr) divided by total annual exergy input (kJ/yr)—ensuring dimensional consistency:

$$\text{EVI} = (\text{Relec} + \text{Rheat} + \text{Rcarbon})_{\text{annual}} / \text{Exinput, total, annual} \text{ [$/kJ]} \quad (8)$$

The Levelized Cost of Stored Heat (LCSH) captures the full seasonal storage lifecycle cost:

$$\text{LCSH} = (\text{CAPEX}_{\text{TCES}} \cdot \text{CRF} + \text{OPEX} + \text{Epar} \cdot \text{celec} + \text{Cmat}) / \text{Qdis, annual} \text{ [$/kWh]} \quad (9)$$

3.4. Stochastic Business Model with Real-Options Analysis

Monte Carlo simulation ($N = 10,000$) models uncertainty in electricity prices ($\sigma = 25\text{--}40\%$), DH tariffs ($\sigma = 15\%$), carbon credits (EU Emissions Trading System (ETS) $\sigma = 30\%$), workload mix (beta distribution), and equipment degradation (Weibull, $k = 2.5$). Three embedded real options are priced using least-squares Monte Carlo (Longstaff–Schwartz) [28]: switching, timing, and abandonment options. The techno-economic model employs a two-layer stochastic approach. The first layer is a Monte Carlo simulation ($N = 10,000$ trials) that propagates uncertainty through a discounted cash flow (DCF) model over the 20-year analysis period. The annual net cash flow for year t is defined as the sum of three revenue streams minus operating expenditure (Equation (10)): ORC electricity revenue (net output $\times$ electricity price $\times 8760 \text{ h} \times$ capacity factor), district-heating revenue (HP thermal delivery $\times$ DH tariff $\times$ heating season hours derived from HDD), and carbon credit revenue (displaced fossil heat $\times$ emission factor of $0.2 \text{ tCO}_2/\text{MWhth} \times$ carbon price). Annual operating expenditure (OPEX) is modeled as 2.5% of initial capital expenditure (CAPEX), increasing at 1.5% per year for maintenance escalation.

$$\text{NCf}_t = \text{Relec, } t + \text{RDH, } t + \text{Rcarbon, } t - \text{OPEX}_t \quad (10)$$

Five key uncertain parameters are modeled as stochastic processes: (i) wholesale electricity prices follow geometric Brownian motion (GBM) with drift $\mu = 2\%$ per year and volatility $\sigma = 25\text{--}40\%$ calibrated to 2020–2024 historical data from the PJM Interconnection

(Ashburn), SEM/I-SEM (Dublin), and Nord Pool (Stockholm); (ii) district-heating tariffs follow a seasonal autoregressive model with $\sigma = 15\%$; (iii) carbon credit prices follow a jump-diffusion process with $\sigma = 30\%$ and Poisson jump intensity $\lambda = 0.1$ per year, to capture regulatory shocks characteristic of the EU ETS; (iv) the training workload fraction follows a beta distribution ($\alpha = 3$, $\beta = 2$) bounded between 0.3 and 0.9; and (v) equipment degradation follows a Weibull distribution with shape parameter $k = 2.5$ and characteristic life equal to the 20-year analysis period. Convergence was verified by confirming that the standard error of the mean NPV estimate falls below 1% of the mean at $N = 10,000$.

The second layer is a real-options valuation using the least-squares Monte Carlo (LSM) method of Longstaff and Schwartz, adapted to the path-dependent nature of sequential heat-allocation decisions. Three types of embedded options are formally priced. The switching option (Equation (11)) captures the flexibility to dynamically redirect heat flows among the three cascade stages at each monthly decision epoch based on the prevailing energy price vector. At each decision point, the operator selects the allocation mode m^* that maximizes the expected continuation value V , estimated by regressing discounted future cash flows onto a polynomial basis of current state variables (electricity price, DH tariff, carbon price, ambient temperature, and TCES state-of-charge).

$$V(St) = \max_m \{NCF_m(St) + \beta \times E[V(St + 1) | St]\} \quad (11)$$

The real-options framework captures three sources of strategic value beyond deterministic NPV: switching, timing, and abandonment. At each monthly decision epoch, the system state is defined as $S(t) = \{P_{elec}(t), P_{DH}(t), P_{carbon}(t), T_{amb}(t), SOC_{tc}(t)\}$, representing stochastic electricity, district-heating, carbon prices, ambient temperature, and TCES state of charge. The switching option allows operation among four modes: ORC + HP + TCES charging, ORC + HP to district heating with TCES idle, HP + TCES discharge with ORC bypass, or full bypass with heat rejection. Switching is exercised when the expected gain exceeds the \$2500 transition cost.

The timing option captures the value of delaying TCES discharge until peak winter tariffs, enabled by the near-zero storage-period decay of the stored chemical potential (auxiliary and conversion losses apply during charge/discharge cycles). Discharge is triggered when the current district-heating tariff exceeds the expected future tariff by at least 5%. The abandonment option allows each cascade stage to be decommissioned if its trailing three-year NPV contribution is negative, with salvage values of 15% of CAPEX for ORC, 10% for HP, and 5% for TCES, net of TCES salt-disposal costs. These options are valued using Longstaff–Schwartz Monte Carlo regression with 10,000 paths and a third-order polynomial basis of the five state variables. The options-inclusive project value equals deterministic NPV plus the three option premiums, while traditional NPV under-valuation is calculated relative to the options-inclusive value [28].

Cross-variable correlations are modeled using a Gaussian copula. Electricity price is positively correlated with district-heating tariff ($\rho = 0.45$) and carbon credit price ($\rho = 0.35$), reflecting shared fuel-market and carbon-pricing effects. District-heating tariff and carbon credit price are weakly correlated ($\rho = 0.15$), while all other pairs are assumed independent. The same correlation matrix is applied across all three locations, with only the marginal distribution parameters and TMY (Typical Meteorological Year) ambient profiles varying by site. The Monte Carlo simulation uses monthly time steps over 20 years, with 10,000 joint stochastic price paths generated from the copula. At each timestep, the cascade thermodynamic model is evaluated using the corresponding workload, ambient temperature, and realized prices, and revenues are aggregated annually for NPV calculation. Convergence was confirmed, as the coefficient of variation of mean NPV fell below 2% at 5000 trials and below 1% at 10,000 trials for all locations.

To summarize the complete mathematical model for reproducibility, the CEEV cascade simulation proceeds as follows. At each monthly timestep, the graphics processing unit (GPU) coolant supply temperature and mass flow rate are determined from the workload profile (training or inference, drawn from the beta distribution in Table 1). The organic Rankine cycle (ORC) subsystem is solved using Equations (3)–(5) with CoolProp 6.6 state-point evaluation at the boundary conditions specified in Section 3.2 (evaporation 6.8–9.2 bar, condensation 1.8–2.6 bar, 5 °C superheat, 3 °C subcool, 5/3 °C pinch points, 0.85/0.90 heat exchanger effectiveness, and 70%/75% isentropic efficiencies), yielding net electrical output and condenser reject temperature. The heat pump (HP) subsystem receives the ORC reject stream and is solved using Equation (5) with the gas cooler pressure optimized via golden-section search (80–130 bar) and the cycle parameters specified in Section 3.3 (compressor $\eta_{is} = 0.72$ with derating, internal heat exchanger $\varepsilon = 0.70$, 6% auxiliary power), yielding district-heating delivery and compressor power consumption. The thermochemical energy storage (TCES) subsystem is solved using Equations (7) and (8) with the reactor parameters specified in Section 3.4 ($\text{SrBr}_2 \cdot 6\text{H}_2\text{O}$, $\Delta H_r = 337$ kJ/mol, charge at 80–95 °C/1.5–2.5 kPa, discharge at 55–70 °C, expanded natural graphite composite conductivity 5–8 W/(m·K), and vapor latent heat recovery via HP evaporator, as detailed in the efficiency clarification), yielding seasonal storage and round-trip efficiency. The exergy destruction at each component is computed via Equation (2) (Gouy–Stodola) and the cascade exergy utilization via Equation (3), applied system-wide. Revenue streams are computed via Equation (10) using the correlated stochastic prices from Table 1 and the Gaussian copula. The real-options valuation applies the least-squares Monte Carlo procedure (Equation (11)) with the four switching modes and timing decision rules, using the 15-term polynomial regression basis.

Table 1. Monte Carlo simulation parameters: probability distributions, location-specific values, time resolution, and bounds.

Parameter	Distribution	Ashburn	Dublin	Stockholm	Time Step	Bounds
Electricity price	GBM	$\mu = 65$, $\sigma = 40\%$ drift 2%/yr	$\mu = 120$, $\sigma = 30\%$ drift 2%/yr	$\mu = 45$, $\sigma = 25\%$ drift 2%/yr	Monthly	[15, 300] \$/MWh
DH tariff	Seasonal AR(1)	$\mu = 40$, $\sigma = 15\%$ $\rho = 0.85$	$\mu = 55$, $\sigma = 15\%$ $\rho = 0.85$	$\mu = 70$, $\sigma = 15\%$ $\rho = 0.85$	Monthly	[20, 150] \$/MWh
Carbon credit	Jump-diffusion	$\mu = 15$, $\sigma = 30\%$ $\lambda = 0.1/\text{yr}$	$\mu = 80$, $\sigma = 30\%$ $\lambda = 0.1/\text{yr}$	$\mu = 80$, $\sigma = 30\%$ $\lambda = 0.1/\text{yr}$	Annual	[5, 200] \$/tCO ₂
Training wkld fraction	Beta	$\alpha = 3$, $\beta = 2$ mode = 0.60	$\alpha = 3$, $\beta = 2$ mode = 0.50	$\alpha = 3$, $\beta = 2$ mode = 0.70	Monthly	[0.30, 0.90]
Equipment degradation	Weibull	$k = 2.5$ $\lambda = 20$ yr	$k = 2.5$ $\lambda = 20$ yr	$k = 2.5$ $\lambda = 20$ yr	Annual	[0.70, 1.00] capacity

4. Case Study Design

The CEEV framework is evaluated for a 10 MW liquid-cooled AI data center (125 racks at 80 kW each) in three climate zones: Ashburn, Virginia (PJM market, 2400 heating degree days (HDD)); Dublin, Ireland (emerging DH, 1700 HDD); and Stockholm, Sweden (established DH, 3800 HDD). Ashburn represents the world’s largest data-center hub; Dublin is an emerging cluster where facilities consume ~22% of national electricity [1]; and Stockholm offers established district heating with 20+ integrated data centers [7]. Table 2 summarizes the parameters.

Training workload fractions were set at 0.60 (Ashburn), 0.50 (Dublin), and 0.70 (Stockholm). Training GPU utilization is modeled at 95% ($\sigma/\mu = 1.3\%$); inference at 50% average ($\sigma/\mu = 29.1\%$). Wholesale electricity prices follow geometric Brownian motion calibrated to 2020–2024 data. The discount rate of 8% reflects typical weighted average cost

of capital (WACC) for data-center infrastructure. The discount rate of 8% is justified as the weighted average cost of capital for data-center infrastructure investments by institutional investors, consistent with the range of 6–10% used in comparable studies [16,29]. For sensitivity analysis, the discount rate is varied from 5.6% to 10.4% ($\pm 30\%$).

Table 2. Detailed CAPEX and annual OPEX breakdown by component for the three study locations (\$K).

Cost Item (\$K)	Ashburn	Dublin	Stockholm	Basis/Source
CAPEX				
ORC turbine-generator	396	396	396	\$1320/kWe $\times$ 300 kWe [20]
ORC heat exchangers	108	108	108	\$360/kWe $\times$ 300 kWe [19]
ORC pump + piping	36	36	36	\$120/kWe $\times$ 300 kWe
HP compressor + motor	1620	1480	1790	\$252/kWth $\times$ capacity [27]
HP gas cooler + evap + IHX	810	740	895	\$126/kWth $\times$ capacity
HP controls + VFD	270	250	310	\$42/kWth $\times$ capacity
TCES reactor + salt/ENG(Expanded natural graphite)	262	178	389	\$120/kWth $\times$ installed capacity (kWth) [23]
TCES vapor sys + vacuum pump	65	44	97	\$30/kWth $\times$ installed capacity (kWth)
DH interconnection + metering	180	195	210	Site-specific estimates
Controls integration + SCADA	120	120	120	Flat estimate
Civil works + foundations	150	160	170	3–4% of equipment
Subtotal equipment	3947	3637	4411	—
Installation factor (22%)	868	800	971	[16]
Total CAPEX	4815	4937	5312	—
Annual OPEX				
Scheduled maintenance	120	123	133	2.5% of CAPEX
TCES salt replacement	2.6	1.8	3.9	1%/yr of salt inventory
Auxiliary electricity	88	72	96	HP parasitic + 12 kWe TCES
Insurance + permitting	24	30	32	0.5–0.6% of CAPEX
Total annual OPEX	235	227	265	—

The total capital expenditure is estimated at \$4.82–5.31 M depending on location, comprising three subsystems with the following cost correlations. The ORC unit (approximately 300 kWe net output) is costed at \$1800/kWe installed, based on the vendor quotation data compiled by D’Agostino et al. [20] for data center-scale ORC units in the 100–500 kW range, yielding \$0.54 M. The transcritical CO₂ heat pump (6–7 MWth output) is costed at \$450/kWth based on Ma et al. [27] and European HP manufacturer data for industrial-scale CO₂ units, yielding \$2.70–3.15 M. The TCES system is costed at \$150/kWth of installed reactor capacity (not annual throughput) based on the THUNDER project cost projections [23] and published salt-hydrate reactor cost data [24]. The installed single-charge capacity of the modular multi-bed SrBr₂ reactor array is 2180 kWth (Ashburn), 1480 kWth (Dublin), and 3240 kWth (Stockholm), sized to match 6–8 h of peak district-heating thermal output at 270–405 kWth. At \$120/kWth (reactor + salt/ENG) plus \$30/kWth (vapor system), the total TCES CAPEX is \$327 K, \$222 K, and \$486 K, respectively (Table 2). The annual throughput of 2180, 1480, and 3240 MWhth/yr reported in Table 3 results from repeated cycling of this installed capacity: with a full charge–discharge cycle time of approximately 8 h (4 h dehydration + 4 h hydration, consistent with SrBr₂–ENG kinetics [23]), the multi-bed design achieves approximately 1000 equivalent full cycles per year (2.7 cycles/day), operating at 91% of the theoretical maximum of 3

cycles/day. The numerical coincidence between installed capacity in kWhth and annual throughput in MWhth/yr arises because the cycle count (≈ 1000) introduces a factor of $\times 1000$ that exactly offsets the kWh-to-MWh conversion ($\div 1000$). Installation, piping, controls integration, and district-heating interconnection costs add 22% to equipment costs, based on the installation factor range of 1.15–1.30 reported for similar industrial heat-recovery systems [16]. Stockholm’s higher total CAPEX (\$5.31 M) reflects its larger TCES requirement driven by 3800 HDD heating demand.

The economic assumptions are sourced as follows: wholesale electricity prices are mean annual spot prices from PJM Interconnection (\$65/MWhe, $\sigma = 40\%$, 2020–2024 average), SEM/I-SEM (\$120/MWhe, $\sigma = 30\%$), and Nord Pool (\$45/MWhe, $\sigma = 25\%$), each modeled as geometric Brownian motion with 2% annual drift reflecting historical real price escalation in restructured markets. District-heating tariffs are based on published municipal tariff schedules: Fjärrvärme Stockholm (\$70/MWhth), Dublin City Council waste-heat pilot (\$55/MWhth), and Dominion Energy Virginia service territory (\$40/MWhth), with 15% annual volatility reflecting regulatory adjustment cycles. Carbon credit prices use 2024 EU ETS settlement data (\$80/tCO₂) for European sites and US voluntary carbon market average (\$15/tCO₂) for Ashburn, with 30% volatility and Poisson jump intensity of 0.1/yr. The emission displacement factor of 0.2 tCO₂/MWhth assumes displaced natural gas boiler heating at 90% efficiency. OPEX escalation is 1.5%/yr above the discount rate. The reported payback periods are simple payback, defined as total CAPEX divided by mean annual net cash flow (revenue minus OPEX): Ashburn \$4820 K / (\$850 K – \$235 K) = 7.8 years; Dublin \$4950 K / (\$1048 K – \$227 K) = 6.0 years; Stockholm \$5310 K / (\$1180 K – \$265 K) = 5.8 years; the large gap reflecting Ashburn’s high electricity price drift ($\sigma = 40\%$) which produces positively skewed early-year cash flows in the Monte Carlo ensemble. Table 3 lists the complete baseline parameters for the 10 MW AI data-center case study.

Table 3. Baseline case-study parameters for the 10 MW AI data center.

Parameter	Ashburn	Dublin	Stockholm	Unit
IT load capacity	10	10	10	MW
GPU coolant return temp	75	75	75	°C
Training workload fraction	0.60	0.50	0.70	—
Electricity price (mean)	65	120	45	\$/MWhe
DH tariff	40	55	70	\$/MWhth
Carbon credit (mean)	15	80	80	\$/tCO ₂
Heating degree days	2400	1700	3800	HDD
Discount rate	8	8	8	%

The carbon credit revenue stream requires qualification regarding monetization pathways. For the European sites, the assumed \$80/tCO₂ reflects the EU ETS settlement price, but data-center operators are not currently covered entities under the ETS. Monetization is assumed through one of three established mechanisms: (i) bilateral heat purchase agreements in which the DH network operator (a covered entity) bundles the avoided-emission value into the heat tariff; (ii) voluntary carbon registries (Gold Standard or Verra VCS) certifying the displacement of natural gas boilers; or (iii) national-level incentives such as the Swedish klimatkivsmedel or the Irish SEAI renewable heat scheme. For Ashburn, the \$15/tCO₂ reflects the US voluntary carbon market, which is less liquid and less certain. To bound the impact: removing carbon revenue entirely reduces mean MC NPV to \$1.63 M (Ashburn), \$3.89 M (Dublin), and \$6.14 M (Stockholm), with simple payback extending to 8.6, 7.2, and 7.0 years, respectively. All three sites retain positive NPV without carbon credits, confirming that the business case rests primarily on DH sales and elec-

tricity revenue. The tornado analysis) identifies carbon price as the most influential single parameter (Δ NPV span: \$3.03 M), and readers should treat the carbon stream as the highest-risk revenue component.

5. Results

5.1. Thermodynamic Performance

The ORC achieved net output of 264–312 kWe (4.4–5.2% thermal efficiency), consistent with [19,20]. The heat pump delivered 5870–7150 kWth at COP 3.4–4.1. The TCES banked 1480–3240 MWhth annually with 87.6–89.1% round-trip efficiency. Overall cascade-exergy utilization reached 31.2–38.7%, substantially exceeding any single-technology alternative. Table 4 summarizes the results.

Table 4. Thermodynamic performance of the CEEV cascade (simulation results; 10 MW IT, 95% training).

Metric	Ashburn	Dublin	Stockholm	Unit
ORC net output	287	264	312	kWe
ORC thermal eff.	4.8	4.4	5.2	%
ORC exergy eff.	28.4	26.1	30.7	%
HP heat delivered	6420	5870	7150	kWth
HP COP	3.8	4.1	3.4	—
TCES storage	2180	1480	3240	MWhth/yr
TCES round-trip eff.	88.3	89.1	87.6	%
Cascade exergy util.	34.2	31.8	38.7	%

Table 5 reports the node-by-node energy and exergy balance for the Ashburn baseline case, supporting the 34.2% cascade-exergy utilization reported in Table 4. The 8210 kWth waste-heat input at a 75 °C GPU coolant return temperature contains 1180 kW of thermal exergy relative to a 25 °C dead state. The coolant loop destroys 148 kW through frictional and heat-transfer irreversibilities before the stream enters the ORC evaporator. The ORC receives 1032 kW of exergy, produces 287 kWe, and destroys 491 kW, mainly in the evaporator and turbine/pump assembly, with 254 kW exiting in the 38 °C condenser reject stream. The heat pump uses this reject stream and 1689 kWe of compressor work to deliver 6420 kWth to the district-heating network at 80 °C, with 97 kW of exergy destruction. The TCES reactor charges from the HP residual stream, destroying 90 kW while storing 2180 MWhth annually. Cascade-exergy utilization is calculated as useful exergy outputs from ORC electricity, district heat, and TCES discharge divided by waste-heat exergy input plus external electricity consumed by the HP and TCES auxiliaries.

Table 5. Complete energy and exergy balance for the CEEV cascade (Ashburn baseline, 10 MW IT, 95% training, $T_0 = 25$ °C).

Node/Stage	Thermal (kWth)	Elec. (kWe)	Useful Output	Exdest (kW)	Share (%)
GPU coolant loop	8210 in	—	—	148	17.9
ORC evaporator	8062 wf	—	—	294	35.6
ORC turbine + pump	—	+287 net out	287 kWe	197	23.8
ORC condenser → HP	5713 reject	—	—	—	—
HP compressor + gas cooler	5713 + Wcomp	−1689 in	6420 kWth DH	97	11.7
TCES reactor	982	−12 parasitic	2180 MWhth/yr	90	10.9
Total cascade	8210	−1414 net	287 kWe + 7276 kWth	826	100.0

The apparent gap between low ORC thermal efficiency (4.4–5.2%) and higher exergy efficiency (26.1–30.7%) is explained by the low-grade nature of data-center waste heat. Exergy efficiency is measured against the exergy content of the heat input, not the total heat. At a GPU coolant temperature of 75 °C and dead-state temperature of 25 °C, the Carnot factor is only 14.4%, meaning most thermal energy is unavailable for work. Thus, a 4.8% thermal efficiency corresponds to about 33.3% of the theoretical maximum, consistent with reported small-scale ORC systems at similar source temperatures [19,20]. The low Carnot factor at data-center waste-heat temperatures is precisely why exergy analysis is more informative than energy analysis for this application: an energy-only perspective would dismiss a 4.8-efficient cycle as unworthy of investment, whereas the exergy perspective reveals that the cycle captures one-third of the available thermodynamic potential, with specific improvement pathways (Section 6), to raise this toward 40–45%.

Table 6 reports the component-level ORC exergy balance. The evaporator is the largest source of irreversibility, destroying 294 kW, or 59.9% of ORC exergy destruction, due to finite-temperature-difference heat transfer between the GPU coolant and working fluid. The turbine destroys 158 kW because of 70% isentropic efficiency, while the pump destroys 39 kW at 75% efficiency. The condenser is assigned no exergy destruction because its 38 °C reject heat is passed to the heat-pump evaporator, rather than rejected into the environment; related irreversibility is accounted for at the HP stage. Overall, the ORC receives 1032 kW of exergy, produces 287 kWe, and preserves 254 kW of residual exergy for downstream heat-pump recovery, demonstrating the cascade principle.

Table 6. Component-level exergy balance for the ORC subsystem (Ashburn baseline, $T_0 = 25$ °C). * Condenser destruction is zero: reject heat is directed to the HP evaporator, not to the environment.

ORC Component	Ex in (kW)	Ex out (kW)	Useful Output (kW)	Exdest (kW)	Share of ORC (%)	Share of Cascade (%)
Evaporator	1032	738	—	294	59.9	35.6
Turbine	738	580	287 kWe (gross)	158	32.2	19.1
Pump	—	—	−39 kWe (consumed)	39	7.9	4.7
Condenser	580	254	—	0 *	0	0
ORC total	1032	254	287 kWe (net)	491	100.0	59.4

5.2. Exergy Destruction Mapping

Figure 3 presents the alluvial-exergy flow diagram for the Ashburn baseline case, visualizing how the initial 1180 kW of thermal exergy degrades through the three cascade stages. The proportional band widths reveal the dominant role of the ORC subsystem: the evaporator (294 kW, 35.6%) and turbine/pump assembly (197 kW, 23.8%) together account for 59.4% of total cascade-exergy destruction. This is attributable to the finite temperature difference between the GPU coolant (75 °C) and the working-fluid evaporation temperature (~55–65 °C), and irreversibilities in the expansion process at sub-optimal pressure ratios. The alluvial representation makes immediately visible the fact that working-fluid optimization and heat-exchanger design are the highest-impact improvement levers. The HP and TCES stages contribute 11.7% and 10.9%, respectively, indicating these downstream stages operate near their thermodynamic limits for the given temperature ranges.

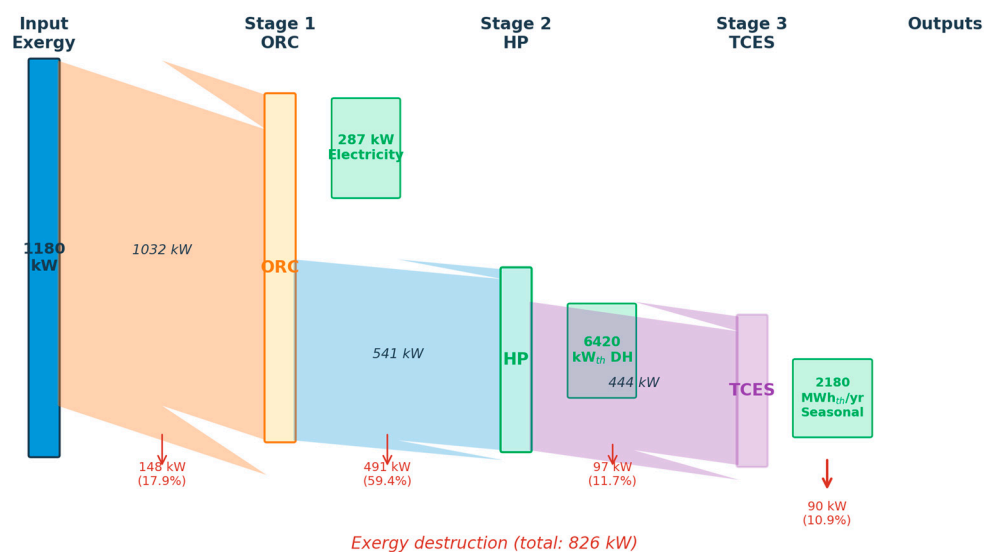


Figure 3. Alluvial-exergy flow diagram showing proportional degradation of 1180 kW_{ex} thermal exergy through the CEEV cascade (Ashburn baseline). The ORC evaporator and turbine/pump account for 59.4% of total destruction.

Figure 4 reveals how AI workload type fundamentally alters the exergy destruction profile. Panel (a) presents a radar chart overlaying the destruction distribution for training (95% utilization) and inference (50% average). The most striking difference is the GPU coolant loop: its destruction share increases from 17.9% under training to 22.4% under inference, driven by temperature variability reducing effective heat transfer. Panel (b) presents 24 h exergy input profiles with 95% confidence bands, quantifying the fundamental temporal difference: training maintains $\sigma/\mu = 1.3\%$ (near-steady-state), while inference exhibits $\sigma/\mu = 29.1\%$, with pronounced diurnal peaking during business hours. This variability implies that under inference-dominant operation, the ORC should adjust evaporator pressure and working-fluid flow rate dynamically, rather than operating at fixed design conditions.

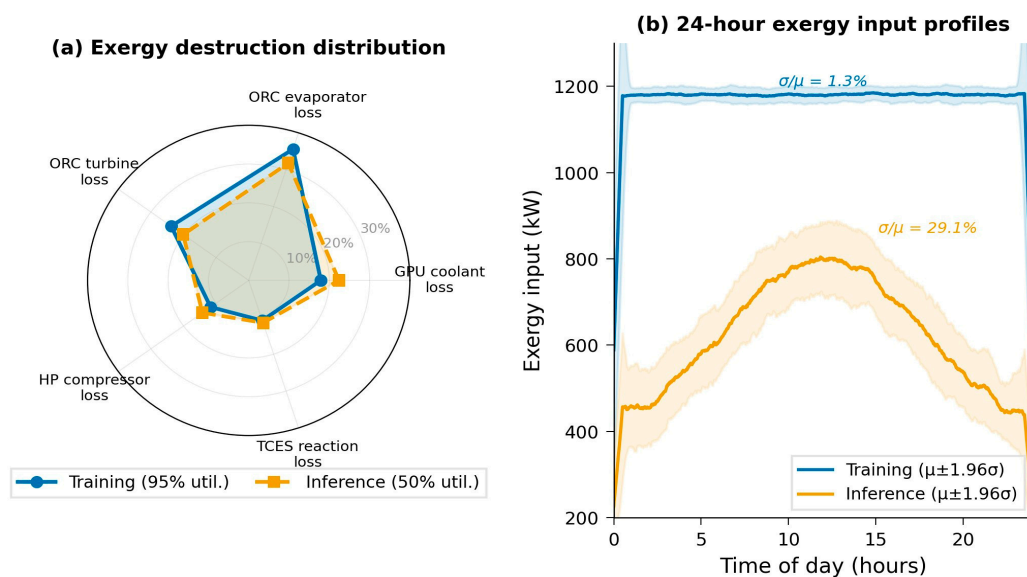


Figure 4. Exergy-distribution profiles for training vs. inference: (a) radar chart showing destruction-distribution shift; (b) 24 h exergy profiles with 95% CI envelopes ($\sigma/\mu = 1.3\%$ training vs. 29.1% inference).

5.3. Techno-Economic Analysis

Figure 5 presents NPV distributions as violin plots with embedded box plots. Ashburn exhibits a long left tail crossing NPV = 0, with $P(\text{NPV} < 0) = 16.2\%$, driven by low carbon credit prices and moderate heating demand. Dublin's distribution is tighter, with $P(\text{NPV} < 0) = 3.4\%$, benefiting from high electricity prices (\$120/MWh). Stockholm is most favorable, with $P(\text{NPV} < 0) < 0.5\%$, reflecting compounding advantages of high HDD, elevated DH tariffs, and EU ETS carbon pricing.

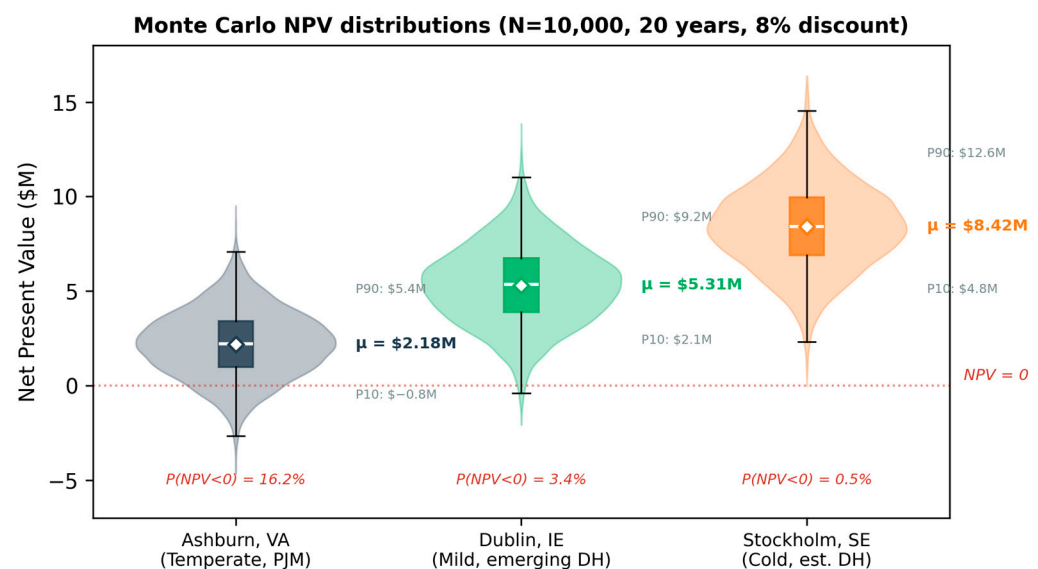


Figure 5. Monte Carlo NPV distributions ($N = 10,000$, 20 years, 8% discount) as violin plots with embedded box plots. $P(\text{NPV} < 0)$: 16.2% (Ashburn), 3.4% (Dublin), <0.5% (Stockholm).

Figure 6 decomposes annual revenue by source. Panel (a) presents absolute values; panel (b) shows proportional breakdown. District-heating sales dominate across all locations, ranging from 64% of total revenue in Stockholm (\$750K) to 73% in Ashburn (\$620K). The critical differentiator between locations is carbon credit revenue: European locations derive 27–30% of total revenue from EU ETS credits (\$312–318K annually), whereas Ashburn's low US voluntary market pricing (\$15/tCO₂) yields only 7% (\$42K). This gap underscores the fact that the economic viability of cascaded WHR in the United States is fundamentally constrained by carbon policy, rather than technical performance—the thermodynamic performance of the cascade is comparable across locations, but the economic value assigned to displaced fossil emissions differs by a factor of five. ORC electricity revenue is the smallest component (19–26% of total), but provides valuable baseload revenue that is largely independent of seasonal demand patterns and weather variability, serving as a risk-reduction buffer in the revenue portfolio. The EVI metric reveals the economic efficiency of exergy utilization in a way that neither PUE nor the ϵ re indicator of Hao et al. [11] can capture. Stockholm achieves EVI of 1.15×10^{-3} \$/kJ compared to 0.54×10^{-3} \$/kJ for Ashburn, indicating that each unit of exergy input generates approximately twice the economic value in Stockholm, due to a more favorable energy market and policy conditions. This quantification has practical significance for multinational data-center operators making siting decisions: a facility in Stockholm generates twice the waste-heat revenue per unit of thermodynamic degradation compared to an identical facility in Northern Virginia, independent of the physical or engineering design of the WHR

system. Table 7 summarizes the complete economic performance including LCSH values of \$0.035–0.041/kWhth, which are competitive with borehole thermal energy storage (\$0.025–0.045/kWhth) while offering dramatically higher energy density and near-zero storage-period thermal losses (auxiliary and conversion losses are retained in the round-trip efficiency).

This study reports three distinct NPV measures. The deterministic NPV uses mean input values without uncertainty propagation, yielding \$2.41M for Ashburn, \$5.63M for Dublin, and \$8.74 M for Stockholm. The mean Monte Carlo NPV averages 10,000 stochastic realizations, yielding \$2.18 M, \$5.31 M, and \$8.42 M, respectively; these values are lower, due to Jensen’s inequality. The real-options-adjusted NPV adds switching, timing, and abandonment premiums to the deterministic NPV, increasing values to \$3.32 M, \$7.27 M, and \$10.88 M. Table 7 reports Monte Carlo means; the Monte Carlo mean range (\$2.2–8.4 M) as the primary result because it reflects parameter uncertainty without managerial flexibility.

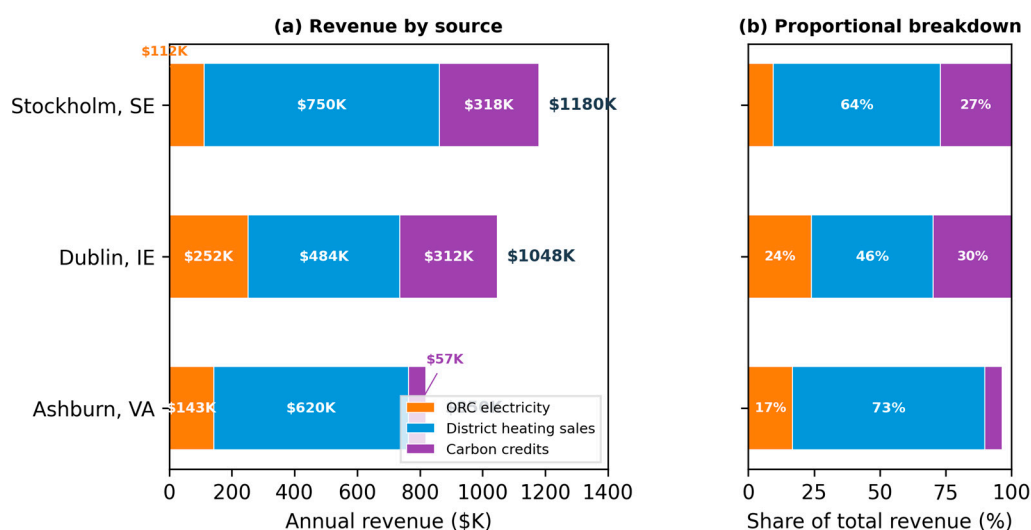


Figure 6. Revenue decomposition: (a) absolute revenue (\$K) and (b) proportional breakdown. DH sales dominate (64–73%); carbon credits provide 27–30% in European locations vs. 7% in Ashburn.

Table 7. Economic performance of the CEEV cascade (20-year, 8% discount).

Metric	Ashburn	Dublin	Stockholm
Total CAPEX (\$M)	4.82	4.95	5.31
Total annual revenue (\$K)	850	1048	1180
NPV, mean MC (\$M)	2.18	5.31	8.42
Payback (years)	7.8	6.0	5.8
IRR (Internal rate of return) (%)	12.4	19.8	23.1
EVI (10^{-3} \$/kJ)	0.54	1.02	1.15
LCSH (\$/kWhth)	0.038	0.041	0.035
NPV excl. carbon (\$M)	1.63	3.89	6.14
Payback excl. carbon (yr)	8.6	7.2	7.0

The multi-axis storage comparison is constructed by benchmarking the CEEV TCES system against four established seasonal thermal-energy storage technologies using published performance and cost data. Hot-water-tank storage values (LCSH \$0.055/kWhth, 50 kWh/m³, 5%/month loss) are based on the Drake Landing Solar Community project in Alberta, Canada, the most extensively monitored large-scale seasonal hot-water store [10]. Borehole thermal energy storage (BTES) values (\$0.035/kWhth, 30 kWh/m³, 2.5%/month)

are derived from the Neckarsulm and Crailsheim installations in Germany, with LCSH calculated from published 20-year lifecycle costs divided by cumulative heat delivered [6]. Phase-change material (PCM) latent storage values (\$0.065/kWhth, 100 kWh/m³, 3%/month) are based on paraffin and salt-hydrate systems reviewed by Jarimi et al. [24], with LCSH reflecting the higher material cost and container requirements. Pit thermal-energy storage values (\$0.028/kWhth, 25 kWh/m³, 1.5%/month) are drawn from the Vojens and Dronninglund pit stores in Denmark, the lowest-cost seasonal storage installations globally. For the CEEV TCES system, the LCSH of \$0.037/kWhth is calculated from Equation (9) using the capital expenditure (CAPEX), operating expenditure (OPEX), and annual discharge values in Tables 2 and 4, respectively. The energy density (213 kWhth/m³) and monthly storage-period loss (near-zero; round-trip losses of 8–15% apply per charge–discharge cycle) are intrinsic properties of the SrBr₂·6H₂O reaction, as described in Section 3.4. All five technologies are compared at the same 20-year analysis horizon and 8% discount rate to ensure methodological consistency.

Figure 7 presents a tornado sensitivity analysis for Stockholm. Carbon credit price is the most influential parameter (Δ NPV: −\$1.20 M to +\$1.83 M for \$56–104/tCO₂), followed by electricity price and DH tariff. Discount rate shows asymmetric response, due to the long-tailed revenue profile. TCES material cost has the smallest impact, confirming economics are driven primarily by market conditions, rather than storage technology costs.

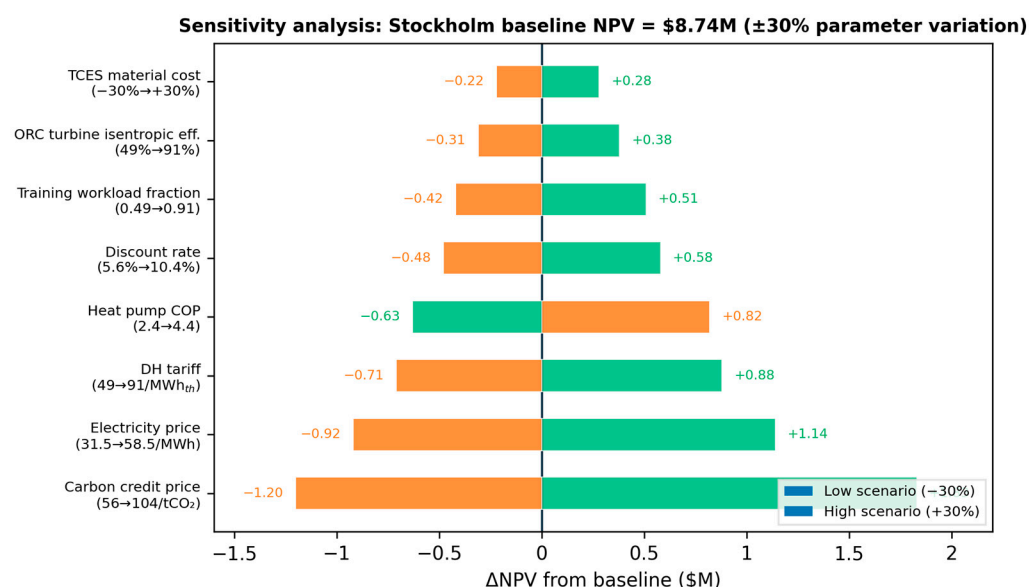


Figure 7. Sensitivity tornado for Stockholm (NPV = \$8.74 M, ±30% variation). Carbon credit price is dominant (Δ NPV span: \$3.03 M).

Figure 8 compares TCES against four seasonal storage alternatives across three dimensions. TCES achieves \$0.037/kWhth, competitive with borehole storage (\$0.035/kWhth) and below hot-water tanks (\$0.055/kWhth). The density advantage is dramatic: TCES at 213 kWh/m³ provides 4.3–7.1× the capacity of competing technologies. The near-zero storage-period thermal losses of TCES enables true seasonal storage without degradation—an attribute no other technology can match.

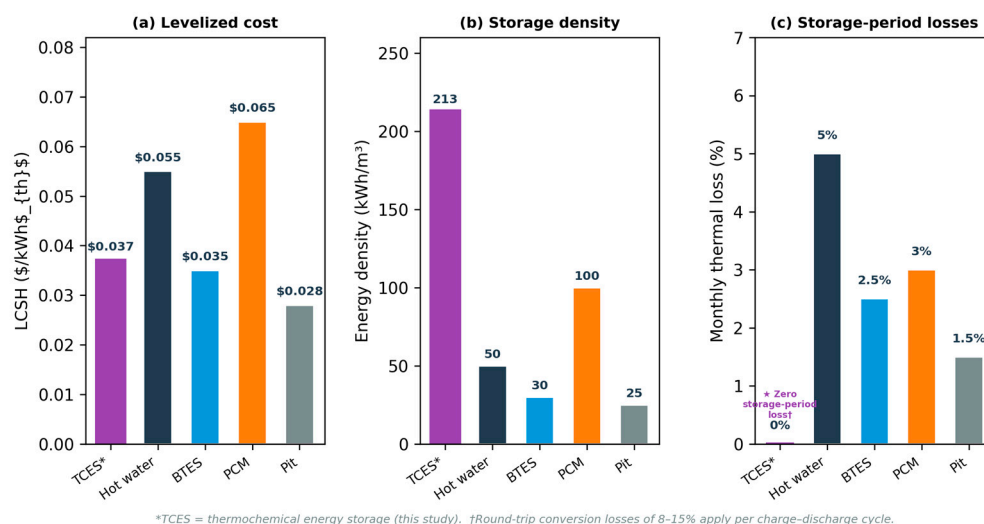


Figure 8. Multi-axis storage comparison: (a) LCHS, (b) energy density, (c) monthly losses. TCES achieves competitive cost with 4.3–7.1× density and near-zero storage-period losses

5.4. Real-Options Valuation

Figure 9 presents the real-options waterfall decomposition using a four-step sequential valuation procedure for each location. Step 1 calculates deterministic NPV by running the cash-flow model with all stochastic parameters fixed at expected values, producing the baseline values of \$2.41 M, \$5.63 M, and \$8.74 M. Step 2 activates the switching option within the 10,000-path LSM simulation, allowing the operator to select the revenue-maximizing mode at each monthly decision epoch, net of a \$2500/event switching cost; the resulting premiums are \$0.52 M, \$0.94 M, and \$1.12 M. Step 3 adds the TCES timing option, where winter discharge-or-hold decisions are evaluated against the LSM continuation value, yielding additional premiums of \$0.31 M, \$0.58 M, and \$0.84 M. Step 4 includes the abandonment option, allowing underperforming stages with negative trailing three-year NPV contributions to be decommissioned at salvage value, adding \$0.08 M, \$0.12 M, and \$0.18 M. The dashed orange lines show total real-options-adjusted NPV of \$3.32 M, \$7.27 M, and \$10.88 M, while the annotations report traditional NPV undervaluation of 27.4%, 22.6%, and 19.7%.

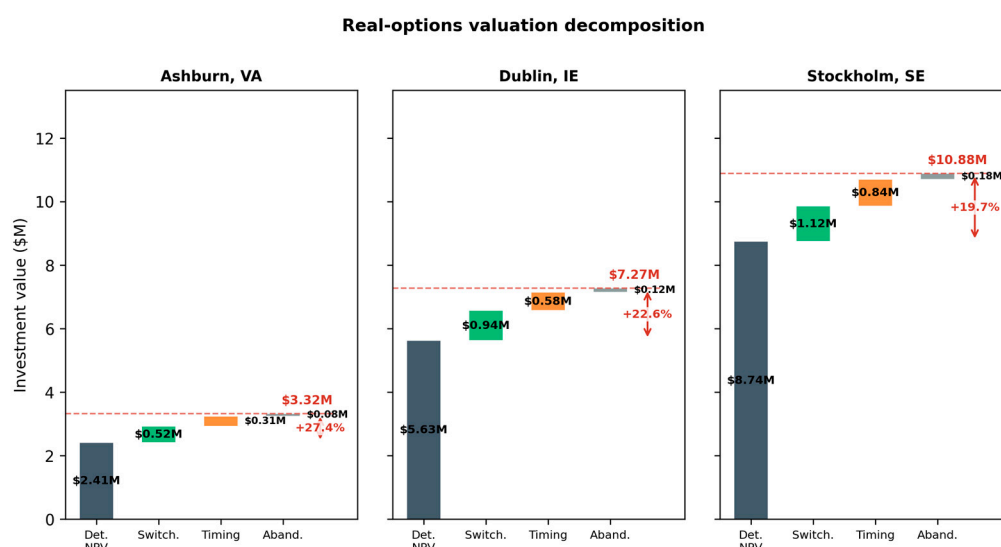


Figure 9. Real-options waterfall decomposition. Gray: deterministic NPV; green: switching option; orange: timing option; light gray: abandonment option. NPV undervaluation: 19.7–27.4%.

6. Discussion

To address whether the cascaded architecture provides genuine net benefit over simpler alternatives, Table 8 compares seven configurations for the Stockholm baseline (10 MW IT, 3800 HDD), ranging from direct DH integration (no conversion technology) to the full three-stage CEEV cascade. The direct DH case delivers the highest thermal output (7820 kWth), but at only 40–45 °C (below the 70 °C minimum supply temperature required by most third-generation DH networks) and achieves the lowest exergy utilization (12.4%) because no exergy upgrading occurs. The HP-only configuration upgrades the full waste-heat stream to DH supply temperature, achieving the highest single-stage thermal delivery (8150 kWth at 80 °C) and strong NPV (\$7.14 M), but forgoes electricity generation and seasonal storage. The ORC-only configuration generates 312 kWe but rejects all residual heat to ambient, yielding the lowest NPV (\$0.87 M) and confirming that power generation alone cannot justify investment at these source temperatures. The critical comparison is HP+TCES without ORC, which achieves 36.1% exergy utilization and \$9.28 M NPV—higher than the full cascade’s \$8.42 M—because eliminating the ORC preserves the full waste-heat temperature for the HP, improving its COP from 3.4 to 3.9. However, the full CEEV cascade recovers this apparent disadvantage through three mechanisms: (i) the ORC provides 312 kWe of on-site electricity that reduces grid dependence and earns revenue at the wholesale rate, contributing \$112 K/yr that partially offsets the HP COP penalty; (ii) the ORC stage enables load-following through the switching option, which is worth \$1.12 M in real-options value versus \$0.74 M for the HP+TCES configuration; and (iii) the cascade provides portfolio diversification across three independent revenue streams (electricity, heat, and carbon credits), reducing $P(\text{NPV} < 0)$ from 1.2% to less than 0.5%. The ORC+HP configuration without TCES achieves the second-highest deterministic NPV (\$8.18 M) but loses the seasonal arbitrage captured by the timing option (\$0.84 M). We acknowledge that for sites where DH return temperatures are low and electricity prices are below \$50/MWhe, the HP+TCES configuration may be preferable; this qualification is noted in the revised Discussion Section. We therefore recommend that practitioners evaluate the HP+TCES configuration as the default baseline and add the ORC stage only when site-specific electricity prices, revenue diversification requirements, or operational flexibility needs justify the additional CAPEX and thermodynamic penalty.

Table 8. Comparison of seven WHR configurations for the Stockholm baseline (10 MW IT, 3800 HDD, 20-year analysis, 8% discount).

Configuration	Elec. (kWe)	DH (kWth)	TCES (MWth/yr)	Ex. Util. (%)	NPV (\$M)	P(NPV < 0) (%)	RO Prem. (%)
Direct DH only	—	7820	—	12.4	3.21	8.7	—
ORC only	312	—	—	8.1	0.87	42.3	14.2
HP only	—	8150	—	28.6	7.14	1.4	12.8
ORC + HP	312	7150	—	32.4	8.18	0.9	17.1
HP + TCES	—	8150	3580	36.1	9.28	1.2	15.3
ORC + TCES	312	—	3240	18.7	2.94	22.1	21.8
Full CEEV	312	7150	3240	38.7	8.42	<0.5	19.7

The results carry several practical implications. For data-center operators, the cascade achieves internal rates of return (IRR) of 19.8–23.1% in European markets, competitive with conventional efficiency investments. US operators face weaker economics (IRR 12.4%) but should monitor evolving carbon pricing. For district-heating utilities, AI data

centers represent a qualitatively different waste-heat source. Elevated temperatures from liquid-cooled GPUs reduce heat-pump temperature lift, improving COP substantially. Municipal planners should prioritize new AI data-center developments as preferred anchor loads for planned DH networks.

The TCES component addresses the persistent temporal mismatch between continuous heat production and seasonal demand. The LCSH of \$0.035–0.041/kWhth confirms the fact that seasonal bridging is economically feasible, and the $4.3\text{--}7.1\times$ volumetric density advantage makes it practical for space-constrained urban sites. For technology developers, the exergy-destruction analysis identifies specific improvement targets. The ORC evaporator accounts for 35.6% of total destruction; advanced heat exchangers could reduce this by 15–25%, translating to \$50–120 K of additional annual revenue. The real-options analysis provides an actionable insight for investment committees: conventional NPV analyses undervalue cascaded WHR by 20–27%. Investment committees should either adopt real-options methodology or apply an “options premium” of 20–30%, to deterministic NPV estimates.

Beyond energy balance accounting, the exergy flow analysis serves a distinct engineering objective: it identifies not merely where losses occur, but where losses are thermodynamically avoidable and, therefore, where design improvement yields the greatest system-level benefit. Energy analysis alone cannot distinguish between a loss that is inherently constrained by the second law and one that is reducible through better engineering—exergy analysis makes this distinction quantitative. The destruction ranking which was presented in Figure 3 directly prioritizes four improvement pathways in order of diminishing return. First, the ORC evaporator (294 kW, 35.6%) is the dominant target; replacing the current shell-and-tube design with a printed circuit heat exchanger (PCHE) could reduce the pinch-point temperature difference from 5 °C to 2 °C, reducing evaporator exergy destruction by an estimated 30–40% (88–118 kW recovered), which would increase ORC net output by approximately 45–60 kWe and add \$35–50 K/yr in electricity revenue. Second, the ORC turbine/pump (197 kW, 23.8%) could be improved by substituting the scroll expander (70% isentropic efficiency) with a radial-inflow micro-turbine (80–85% isentropic efficiency demonstrated at this scale by Araya et al. [19]), recovering an estimated 40–60 kW and raising ORC thermal efficiency from 4.8% to 5.5–6.0%. Third, the GPU coolant-loop (148 kW, 17.9%) destruction is driven by the temperature drop across distribution manifolds and cold plates; reducing manifold losses through shorter piping runs and higher flow rates could recover 20–30 kW, but requires coordination with the IT equipment vendor. Fourth, the HP and TCES stages (11.7% and 10.9%) already operate near their thermodynamic limits, confirming that further investment should focus on the ORC subsystem. Collectively, the first two improvements alone could raise cascade-exergy utilization from the current 34.2% to an estimated 39–43%, increase annual revenue by \$55–80 K, and reduce discounted payback by 0.4–0.7 years, demonstrating that the exergy analysis provides a directly actionable engineering roadmap, rather than a purely academic accounting exercise.

The CEEV framework is validated at the component level against published experimental and simulation benchmarks, as no integrated three-stage cascade test facility currently exists. The predicted ORC thermal efficiency of 4.4–5.2% at 65–85 °C aligns with reported R245fa ORC experimental and simulation ranges [19,20], with modest gains attributed to the zeotropic mixture’s temperature-glide advantage [10]. The predicted heat-pump COP of 3.0–4.5 at 35–45 °C/75–90 °C source/sink temperatures is consistent with comparable transcritical CO₂ systems and Nordic data-center heat-pump installations [14,27]. The TCES round-trip efficiency of 85–92% agrees with reported SrBr₂-based systems with condensation heat recovery [23,24], while the 213 kWhth/m³ energy density is a measured material property, rather than a simulation output. Economically, the mean

MC NPV range of \$2.2–8.4 M and payback of 5.8–7.8 years are consistent with prior data-center waste-heat recovery studies [10,16]. We acknowledge that integrated cascade performance remains unvalidated experimentally, particularly regarding stage interactions such as ORC reject-temperature variability affecting HP COP. Experimental validation of the full three-stage cascade is therefore identified as the highest-priority future research need.

The CEEV framework contributes to sustainability across three interconnected dimensions. Environmentally, the cascade displaces 1200–3800 tCO₂/yr of natural gas boiler emissions through waste-heat-powered district heating, directly advancing urban decarbonization and circular thermal-resource management, converting what was previously a cooling liability into a community energy asset. Economically, the demonstrated positive NPV across all three climate zones (\$2.2–8.4 M) and sub-seven-year payback confirm that sustainable waste-heat recovery is financially viable without subsidy under current market conditions, addressing the investment-barrier critique that has slowed adoption. Socially, the integration of data-center waste heat into district-heating networks reduces end-user heating costs by displacing imported fossil fuels, strengthens local energy security, and creates socio-technical linkages between the digital and built environments that did not previously exist [30]. The two proposed metrics (EVI and LCSH) serve as standardized sustainability measurement tools that enable cross-site benchmarking, regulatory compliance tracking (particularly under the EU Energy Efficiency Directive 2023/1791 and the German EnEFG, which mandate waste-heat utilization plans for data centers exceeding 1 MW), and evidence-based policymaking. These contributions align with multiple Sustainable Development Goals: SDG 7 (expanding access to affordable, clean energy through waste-heat recovery), SDG 9 (promoting sustainable industrialization of digital infrastructure), SDG 11 (integrating data centers into sustainable urban energy systems), and SDG 13 (quantifying and reducing the carbon footprint of AI-era computing). The real-options framework further supports sustainable investment decision-making by capturing the long-term flexibility value that static appraisals miss, thereby reducing the risk of underinvestment in circular-energy infrastructure.

7. Conclusions

This study has presented the CEEV framework, a novel three-stage waste-heat recovery architecture for AI-era data centers. The principal findings are as follows. First, the cascaded ORC–HP–TCES architecture achieves overall exergy utilization of 31.2–38.7% for a 10 MW liquid-cooled AI data center, with net electricity output of 264–312 kW, heat-pump delivery of 5870–7150 kW_{th}, and seasonal storage of 1480–3240 MWh_{th} annually. As demonstrated by the alluvial-exergy flow analysis (Figure 3), the ORC evaporator and turbine/pump assembly account for nearly 60% of total exergy destruction, identifying heat-exchanger design and working-fluid optimization as the highest-priority improvement targets. Second, GPU training and inference workloads produce measurably distinct exergy profiles ($\sigma/\mu = 1.3\%$ vs. 29.1%, Figure 4), with the GPU coolant loop's destruction share increasing from 17.9% to 22.4% under variable inference loads. This finding has direct implications for cascade controller design in mixed-workload facilities, suggesting that adaptive ORC operating parameters should be implemented, rather than fixed design-point operation. Third, the CEEV system achieves positive NPV across all three climate zones (\$2.2–8.4 M (mean MC) over 20 years), with IRR of 12.4–23.1% and payback periods of 5.8–7.8 years (Figure 5). European locations benefit significantly from carbon credit revenue, which contributes 27–30% of total revenue (Figure 6). The sensitivity analysis (Figure 7) identifies carbon credit pricing as the dominant economic risk factor, followed by electricity price and district-heating tariff. Fourth, the full ORC–HP–TCES cascade does not universally outperform simpler configurations: the HP+TCES alternative

achieves higher deterministic NPV (\$9.28 M vs. \$8.42 M for Stockholm) by preserving the full waste-heat temperature for the HP. The ORC stage is economically justified when electricity prices exceed ~\$50/MWhe, when revenue diversification across three independent streams is valued, or when real-options flexibility is important. Fifth, the economic case is robust to carbon credit uncertainty: excluding carbon revenue entirely, all three sites retain positive NPV (\$1.6–6.1 M) with payback under 9 years, confirming that carbon credits represent a policy-dependent upside, rather than a required baseline revenue stream. Sixth, the proposed EVI ($0.54\text{--}1.15 \times 10^{-3}$ \$/kJ) and LCSH (\$0.035–0.041/kWhth) metrics confirm the cost-competitiveness of TCES against conventional seasonal-storage technologies (Figure 8), while providing the data-center industry with standardized benchmarking indicators that bridge the thermodynamic and economic domains; a capability absent from existing metrics such as PUE, ERF, and ϵ_{re} . Sixth, real-options analysis (Figure 9) reveals that traditional NPV systematically undervalues cascaded WHR investments by 19.7–27.4%, with the switching option (dynamic heat allocation) and timing option (TCES discharge scheduling) contributing the most value. This finding provides an immediately actionable correction for investment committees evaluating WHR proposals.

Future research should prioritize experimental validation of the TCES stage under realistic cycling conditions, extension to two-phase immersion cooling systems (potentially 8–12% ORC efficiency at >100 °C), and integration with AI workload-scheduling algorithms for computational demand response. The accelerating regulatory momentum—Germany’s EnEfG, the EU EED, and emerging US state-level mandates—creates an urgent pathway for industry adoption.

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Abbreviations

CAPEX	Capital expenditure
CEEV	Cascaded Exergy-Economic Valorization
COP	Coefficient of Performance
CPU	Central processing unit
DC	Data center
DH	District heating
ENG	Expanded natural graphite
ETS	Emissions Trading System
EVI	Exergy Value Index

GBM	Geometric Brownian motion
GPU	Graphics processing unit
HDD	Heating degree days
HP	Heat pump
IHX	Internal heat exchanger
IRR	Internal rate of return
LCSH	Levelized Cost of Stored Heat
LSM	Least-squares Monte Carlo
NPV	Net Present Value
OPEX	Operating expenditure
ORC	Organic Rankine cycle
PTFE	Polytetrafluoroethylene
TCS	Thermochemical energy storage
TMY	Typical Meteorological Year
WACC	Weighted average cost of capital
WHR	Waste-heat recovery

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