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Avoided Emissions and Rebound Robustness in Data Center Heat Reuse

Anders S.G. Andrae
Chief Expert Environmental Protection Technology,
Huawei Technologies Sweden AB,
Skalholtsgatan 9, 16494 Kista, Sweden
anders.andrae@huawei.com

Correspondence: anders.andrae@huawei.com

Abstract – *Data centers are becoming increasingly important components of modern digital infrastructure, but their growing electricity demand has raised concerns regarding their environmental footprint. At the same time, data centers generate substantial quantities of low-grade waste heat that may be reused in nearby buildings or district heating systems. Such applications have attracted growing interest as examples of ICT-enabled heat-substitution solutions. However, methodologies for quantifying the associated avoided emissions remain under development, particularly in relation to emerging standards and guidance documents. This study applies internationally-aligned avoided-emissions frameworks to a published case study of direct waste heat reuse from a free-air-cooled data center. The engineering basis is derived from a previously published simulation of a 1 MW data center operating without heat pumps and reusing excess heat directly. The avoided-emissions calculation follows a standardized formulation including emissions from conventional heat production and emissions associated with the waste heat reuse solution. For the case with an Energy Reuse Factor (ERF) of 0.59 and a 40°C exhaust temperature, the avoided emissions are estimated to around 783 tCO_2e per year. Moreover, a new rebound robustness metric is proposed to quantify the magnitude of rebound effects required to overturn the avoided-emissions conclusion. The results indicate a break-even rebound of nearly 100% of the useful heat service, suggesting that the avoided-emissions claim is highly robust. The study reveals how ICT-enabled heat reuse can be assessed consistently using internationally standardized concepts and guidance while introducing a complementary break-even rebound and rebound robustness indicator for future research.*

Keywords: *avoided emissions; break-even rebound; data centers; waste heat recovery; rebound effects; rebound robustness*

I. INTRODUCTION

The rapid expansion of digitalization, cloud services, artificial intelligence, and connected devices has led to substantial growth in global data-center electricity consumption (Liu, et al., 2020; da Silva, et al. 2025; Mural, et al., 2026). Although improvements in hardware efficiency have mitigated some increases in energy demand, data centers remain major consumers of electricity (Jha, et al., 2025; Sheng, et al., 2026; Liao, et al., 2026). Consequently, considerable attention has been directed towards strategies that improve the environmental performance of data-center systems (Deng, 2025; Lei, et al., 2026; Wang, et al., 2026).
One strategy is the recovery and reuse of waste heat (Ao, et al., 2025; Zhang, et al. 2026; Ravi, et al., 2026; Liu, et al., 2026). Almost all electrical energy consumed by information technology equipment ultimately becomes heat. Rather than rejecting this heat to the environment, it may be reused to provide useful heating services in buildings, industrial processes, or district heating systems (Latif, et al., 2024). Such applications represent examples of ICT-enabled solutions in which digital infrastructure indirectly contributes to emission reductions outside its immediate operational boundary. An example is the direct free-air cooling in data centers enables the reuse of waste heat that substitutes conventional heat production in low-temperature cases such as greenhouses (Dimitropoulou, et al., 2025).

The quantification of these benefits requires robust avoided-emissions methodologies. The methodology has recently been investigated for liquid cooling of base stations (Andrae, 2025). Recent standardization efforts, including IEC 63372 (IEC, 2026) and related work in ETSI (ETSI, 2025), provide structured approaches for evaluating avoided emissions. Similarly, the WBCSD Guidance on Avoided Emissions (WBCSD, 2025) offers principles for assessing and communicating emission reductions resulting from products and

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services. Both approaches rely on a comparison between a reference scenario and an assessed solution.

Despite these developments, one issue remains largely unexplored. Existing methodologies typically quantify avoided emissions but provide limited insight into the robustness of the result. In particular, they do not explicitly address how large rebound effects would need to be before an avoided-emissions claim is invalidated.

The objective of this paper is therefore twofold. First, a published data-center waste heat reuse case (Ljungqvist, et al. 2023) is translated into an avoided-emissions assessment consistent with IEC 63372 (IEC, 2026) and WBCSD guidance (WBCSD, 2025). Second, a novel break-even rebound metric is proposed to evaluate the robustness of the resulting avoided-emissions claim.

Research question: Can a published data-center waste heat reuse case be translated into an avoided-emissions assessment consistent with IEC 63372 and WBCSD guidance, and how robust are the resulting claims to potential rebound effects?

The present research is fully repeatable via a transparent, auditable and complete Python implementation available in the Appendix.

II. METHODS

2.1 Engineering Basis

The engineering basis of the study is derived from a published simulation of a direct free-air-cooled data center located in northern Sweden (Ljungqvist, et al., 2023). The facility operates at an IT load of 1 MW and does not employ heat pumps to upgrade waste heat. Instead, excess heat is reused directly whenever temperature conditions permit.

Three exhaust air temperatures were investigated: 30°C, 40°C, and 50°C. Corresponding ideal heat reuse temperatures were identified as 13°C, 17°C, and 18°C. The resulting Energy Reuse Factors (ERFs) were reported as 0.50, 0.59, and 0.66, respectively. These values indicate that higher exhaust temperatures increase the proportion of data-center energy that can be reused.

The analysis presented here focuses primarily on the central 40°C case with an ERF of 0.59, while the other cases are used to illustrate temperature sensitivity.

Table 1 shows where each parameter used in the avoided-emissions assessment comes from.

Table 1. Parameters used in the avoided-emissions assessment

Parameter	Value	Unit	Source	Remarks
IT load, P_{IT}	1	MW	Ljungqvist et al. (2023)	Engineering input
Operating time	8760	h/y	Assumed	Continuous operation
IT energy, E_{IT}	8760	MWh/y	Calculated	$P_{IT} \times t$
Exhaust temperature	30, 40, 50	°C	Ljungqvist et al. (2023)	Engineering input
ERF	0.50, 0.59, 0.66	–	Ljungqvist et al. (2023)	Reported values
Useful heat service, $Q_{service}$	5241	MWh/y	Calculated	Central 40°C case
PUE	1.014	–	Ljungqvist et al. (2023)	Represents highly efficient free-air cooling
Auxiliary electricity for heat-reuse, $E_{aux,proxy}$	122.64	MWh/y	Calculated	$(PUE - 1) \times E_{IT}$
Electricity emission factor, EF_{el}	20	kg CO_2e/MWh	Assumed	Low-carbon Nordic electricity
Reference heat emission factor, EF_{ref}	150	kg CO_2e/MWh	Assumed	Moderate conventional heat
Infrastructure emissions, E_{infra}	500	kg CO_2e/y	Engineering estimate	Sensitivity assumption
Rebound emission factor, EF_R	150	kg CO_2e/MWh	Assumed	Set equal to EF_{ref}
Avoided emissions, R	783	t CO_2e/y	Calculated	IEC 63372 model
Break-even rebound indicator, RR_{BE}	99.6	%	Calculated	Proposed metric

Parameters originating directly from (Ljungqvist, et al., 2023) are explicitly identified. Remaining parameters represent assumptions or calculations introduced in the present avoided-emissions assessment to operationalize the IEC 63372 framework.

2.2 Functional Unit

The functional unit is:

"Provision of one year of useful low-temperature heat service to a greenhouse in Luleå equivalent to 5241 MWh."

2.3 Avoided-Emissions Model

The avoided-emissions calculation follows the IEC 63372 formulation:

$$R = B - P \quad (1)$$

where:

- (R) is the avoided-emissions result,
- (B) is the reference scenario emissions,
- (P) is the assessed-system emissions.

All emissons are expressed in kg CO_2e/year or t CO_2e/year.

The reference scenario assumes that the useful heat service is supplied by a conventional heating system:

$$B = Q_{heat} \times EF_{ref} \quad (2)$$

where (Q_{heat}) is useful heat delivered (MWh/year) and (EF_{ref}) is the reference heat emission factor (kg CO_2e/MWh).

As shown in Eq. 3, the assessed system assumes direct waste heat reuse without heat pumps:

$$P = E_{aux,proxy} \times EF_{el} + E_{infra} \quad (3)$$

$$E_{aux,proxy} = (PUE - 1) \times E_{IT} \quad (4)$$

where $(E_{aux,proxy})$ is a conservative proxy for heat-reuse auxiliary electricity use (MWh/year), (EF_{el}) is the electricity emission factor (kg CO_2e/MWh), (E_{infra}) represents annualized embodied infrastructure emissions attributable to the heat-reuse solution (kg CO_2e/year), PUE is the Power Usage Effectiveness of the data center and E_{IT} is the IT equipment energy use (MWh/year).

Eq. 4 is a very rough estimation of specfic heat reuse electricity as it actually represents the enitire non-IT energy use of the data center.

2.4 WBCSD Alignment

The avoided-emissions assessment aligns naturally with WBCSD guidance (WBCSD, 2025).

The functional unit corresponds to the useful heat delivery. The baseline scenario is conventional heat production. The assessed solution is waste heat reuse from ICT infrastructure. The avoided-emissions result is obtained from comparison of these two scenarios.

The causal relationship between the solution and the avoided emissions is transparent because every unit of useful heat delivered by waste heat reuse directly displaces heat that would otherwise need to be generated conventionally.

2.5 Rebound Robustness Metric

A novel rebound robustness metric is proposed in Eq. 5 as an extension to existing avoided-emissions methodologies.

Rebound emissions are defined as:

$$RE = Q_R \times EF_R \quad (5)$$

where (Q_R) is rebound heat demand (MWh/year) and (EF_R) is the associated rebound emission factor (kg CO_2e/MWh).

At what level do rebound emissions exactly offset the avoided-emissions benefit?

The break-even condition occurs when rebound emissions exactly cancel the avoided-emissions benefit:

$$R - RE = 0 \quad (6)$$

where (R) is avoided emissions (kg CO_2e/year) and (RE) is rebound emissions (kg CO_2e/year).

This gives Eq. 7:

$$Q_{R,BE} = \frac{R}{EF_R} \quad (7)$$

where $(Q_{R,BE})$ is the break-even rebound demand (MWh/year) and (EF_R) is the emission factor associated with the rebound activity (kg CO_2e/MWh).

The result is expressed relative to useful heat service according to Eq. 8 as the novel (RR_{BE}) break-even rebound robustness indicator (%):

$$RR_{BE} = \frac{Q_{R,BE}}{Q_{service}} \times 100 \quad (8)$$

$(Q_{service})$ refers to the useful heat service delivered by the solution (MWh/year).

Higher values of RR_{BE} indicate a more robust avoided-emissions claim. Lower values indicate that relatively small rebound effects could overturn the avoided-emissions benefit.

A value of $RR_{BE} = 100\%$ means that the rebound would need to be equal to the entire useful heat service before the avoided-emissions result becomes zero.

III. RESULTS AND DISCUSSION

3.1 Engineering Performance

Table 2 summarizes the engineering performance reported for the three exhaust temperature cases.

Table 2. Engineering performance

Exhaust Temperature	ERF (Ljungqvist, et al. 2023)
30°C	0.50
40°C	0.59
50°C	0.66

The results indicate a clear increase in heat reuse potential with increasing exhaust temperatures.

3.2 Avoided Emissions

For the central 40°C case:

- E_{IT}(IT energy) = 1 MW × 8760 hours/y = 8760 MWh/y (Ljungqvist, et al. 2023)

- PUE = 1.014
- E_{DC}(Data center energy) = 8760 × 1.014 = 8883 MWh/y
- Q_{reuse}(Reused heat) = 8883 × 0.59 = 5241 MWh/y

Assuming a conventional heat emission factor EF_{ref} of 150 kg CO_2e/MWh, the reference scenario emissions are:

B = 150 × 5241 = 786150 kgCO_2e/y ≈ 786 t CO_2e/y

The assessed system requires only minor auxiliary electricity and infrastructure emissions:

$E_{aux} = (PUE - 1) \times E_{IT} = (PUE - 1) \times 1MW \times \frac{8760h}{year} = 123\ MWh$

$P = E_{aux} \times EF_{el} + EF_{infra} = 123 \times 20 + 500$ = 2952.8 kgCO_2e/y ≈ 3 t CO_2e/y

E_{aux} is assumed to be 1.4% of E_{IT} according to the reported PUE .

E_{aux} is a conservative proxy for heat recovery electricity based on the data center's non-IT electricity implied by PUE.

An engineering estimate for E_{infra} is 500 kgCO_2e/year if heat exchanger, circulation pumps, piping, controls each has some tonnes of embodied emissions and a lifetime of around 10 years. Annualized embodied emissions of the additional heat-recovery infrastructure are assumed to be 500 kg CO_2e/year. This magnitude is checked against recent heat-exchanger LCA literature (Boix Rodríguez, et al., 2024)

A sensitivity analysis shows negligible influence of adding E_{infra}.

Hence:

$R = 786150 - 2952.8$ = 783197.2 kg CO_2e/y ≈ 783 t CO_2e/y

This corresponds to approximately 783197.2/5241 ≈ 149 kg CO_2e/MWh of useful heat delivered.

The results indicate that nearly all emissions associated with conventional heat production can be avoided under the assumed conditions.

3.3 Temperature Sensitivity

Increasing exhaust temperature increases ERF and therefore increases useful heat delivery. Consequently, as shown in Figure 1, avoided emissions increase as exhaust temperature rises from 30°C to 50°C.

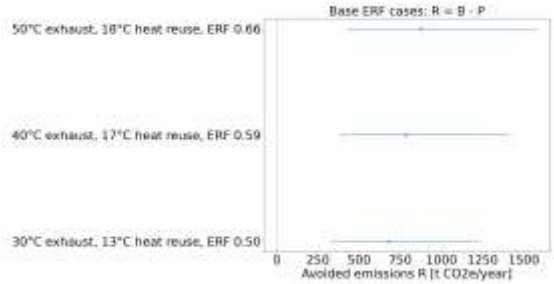

Figure 1. Avoided emissions relation to exhaust temperature

3.4 Uncertainty Analysis

Monte Carlo simulation is used to propagate uncertainty in key parameters (Table 3), including ERF, PUE, electricity emission factors, heat emission factors, and infrastructure emissions.

Table 3. Uncertainty factors used

Parameter	2σ factor
ERF	1.10
PUE	±2%
Electricity EF	1.70
Reference heat EF	1.90
Infrastructure emissions	2.00

Figure 2 shows that the resulting distribution of avoided emissions remains strongly positive across the simulated parameter space.

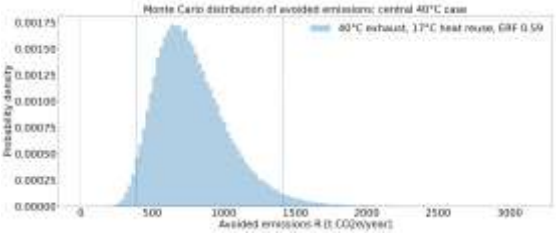

Figure 2. Monte Carlo distribution of avoided emissions for the central 40°C case

Mean and median values are close to the deterministic estimate, while the probability of positive avoided emissions approach 100%.

The uncertainty analysis therefore supports the conclusion that the avoided-emissions benefit is robust to parameter uncertainty.

3.5 Sensitivity analysis

Figure 3 shows that the model is driven by the reference heat emission factor. The uncertainty analysis indicates that the reference heat emission factor is the dominant driver of the avoided-emissions result. This reflects the fact that the environmental benefit of heat reuse primarily depends on the carbon intensity of the displaced heat source.

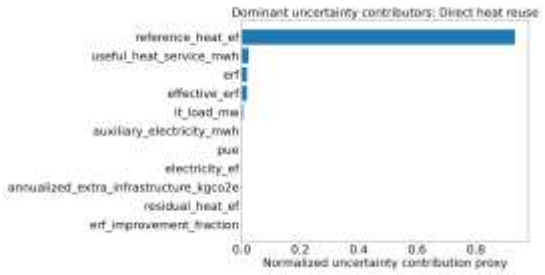

Figure 3. Tornado chart for uncertainty contributors dominated by reference heat emission factor

3.6 Alignment with IEC 63372

As the reference and assessed scenarios are clearly defined, and all calculations are based on a common functional unit, the case study maps directly onto the IEC 63372 (IEC, 2026) framework through Eq. 1.

3.7 Alignment with WBCSD

The assessment also satisfies the key principles of WBCSD avoided-emissions guidance.

The service is explicitly defined as useful heat delivery. Moreover, the baseline is conventional heat production, and the substitution mechanism is transparent and physically measurable.

Accordingly, the resulting avoided-emissions claim can be interpreted consistently under both IEC 63372 and WBCSD.

3.8 Rebound Robustness

The central case produces a rebound robustness break-even (RR_{BE}) value of approximately 99.6%:

$$Q_{R,BE} = \frac{783000}{150} \approx 5220$$

$$RR_{BE} = \frac{Q_{R,BE}}{Q_{service}} \times 100 = \frac{5220}{5241} \times 100 = 99.6\%$$

This means that rebound heat demand would need to approach the magnitude of the useful heat service itself before the avoided-emissions benefit vanishes.

The result therefore indicates a highly robust avoided-emissions claim.

Table 4 is outlined to help interpretation of RR_{BE}.

Table 4. Classification for RR_{BE}

Break-even rebound robustness indicator	Interpretation
<10%	Fragile
10–25%	Moderately robust
25–50%	Robust
50–100%	Very robust
>100%	Extremely robust

These categories are proposed here and are not part of IEC 63372 or WBCSD guidance. The proposed classification thresholds should be regarded as exploratory.

3.9 Implications for ICT-Enabled Climate Solutions

The present case displays an important feature of many ICT-enabled avoided emissions scenarios. The benefit does not arise because the data center consumes less electricity. Rather, it arises because waste heat generated by ICT infrastructure substitutes conventional heat production elsewhere in the economy.

This represents a typical enabling effect and demonstrates how digital infrastructure can contribute to emission reductions beyond its direct operational boundary.

3.10 Limitations

Several assumptions are introduced to make the avoided-emissions framework workable. The reference heat emission factor, electricity emission factor, and annualized infrastructure emissions do not originate directly from (Ljungqvist, et al., 2023) but are selected to represent plausible operating conditions. The resulting avoided-emissions estimates are therefore sensitive to the assumed characteristics of the displaced heat source.

The study further assumes that the data center exists independently of the heat-recovery application. This is in line with consequential LCA approaches. As a result, embodied emissions associated with servers, buildings, and ICT equipment are excluded from the assessed solution, whereas only additional heat-recovery infrastructure is represented by E_{infra}.

The proposed break-even rebound classification thresholds should be regarded as exploratory and require validation in future case studies. Furthermore, the uncertainty analysis relies on assumed probability distributions that are not derived from empirical measurements.

Despite these limitations, the analysis demonstrates how an existing engineering heat-reuse study can be translated into an avoided-emissions assessment consistent with IEC 63372 principles and compatible with WBCSD guidance.

IV. CONCLUSION

This study translated a published data-center heat reuse case into an avoided-emissions assessment consistent with IEC 63372 principles and compatible with WBCSD avoided-emissions guidance.

The central result of approximately 783 tCO_2e/year depends principally on the assumed reference-heat emission factor, electricity emission factor, useful heat recovery and additional

infrastructure emissions. In practical terms, the result demonstrates that direct reuse of low-temperature waste heat from a 1 MW data center can provide substantial avoided emissions where a compatible heat demand exists and conventional heat production is displaced. The result is supported by uncertainty analysis.

A break-even rebound robustness metric is proposed as an extension to existing methodologies. The break-even rebound indicator is proposed as a supplementary robustness metric and is not part of IEC 63372 or WBCSD guidance. The indicator expresses in this case how large an induced heat demand would have to become before the estimated avoided-emissions benefit is eliminated.

The resulting metric value of approximately 99.6% indicates that substantial rebound would be required before the avoided-emissions benefit is eliminated. The quantitative result remains case-specific, however, because the emission factors are assumed and the probability distributions used in the uncertainty analysis are not empirically established. The present case for amount and temperature of heat does not practically involve a greenhouse application, but it is a technically plausible application (Dimitropoulou, et al., 2023; Latif, et al., 2025).

Future work should investigate the applicability of the proposed metric to other ICT-enabled climate solutions, including teleworking, videoconferencing, artificial intelligence services, smart-energy systems, and digital optimization technologies.

AUTHOR'S CONTRIBUTION

Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing: Author. Software: Python implementation. To maximize transparency and reproducibility, the author used ChatGPT as an interactive scientific research assistant supporting software development, manuscript editing and methodological discussions throughout the development of the study. The AI contributed to software development, code debugging, figure optimization, language editing, and critical discussion of methodological alternatives. All generated content was independently reviewed, modified where necessary, verified against the cited literature, and approved by the author before inclusion in the final manuscript.

AVAILABILITY DATA AND MATERIALS

All data needed to reproduce the research are available in the article. Appendix - Python code for repeatability of the research: *https://colab.research.google.com/drive/1zjFNlGnpxyZoq785s7d2f_WK0QihjrpU?usp=sharing*.

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