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Beyond Energy Savings: How Grid Decarbonization and Service Life Redefine Building Technology Climate Impact[#]

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ABSTRACT

This study compares the embodied carbon and operational savings of BEMS, IoT sensor networks, digital twins and cloud-based AI over 20 years in an illustrative office scenario using Swedish electricity carbon intensity. Published data and stated assumptions are combined with proportional service-life allocation. Estimated net benefits are 2.1, 32.2, 12.6 and 16.5 kg CO_2e/m^2, respectively. The corresponding carbon recovery indicators are 18.1, 0.2, 3.4 and 4.8 years; these express allocated embodied carbon relative to annual net savings, rather than chronological break-even. For BEMS, counting full installations within the period instead changes the net balance to −4.9 kg CO_2e/m^2, demonstrating sensitivity to replacement accounting. Lower grid carbon intensity reduces avoided operational emissions and increases the relative importance of embodied carbon. The findings support context-specific assessment, with technology rankings conditional on savings, system boundaries and allocation assumptions.

Keywords: lifecycle carbon assessment, building automation systems, service life analysis, embodied carbon, grid carbon intensity, building energy efficiency

NOMENCLATURE

Abbreviations	
AI	Artificial intelligence
BEMS	Building energy management system
EPBD	Energy Performance of Buildings Directive
EPD	Environmental product declaration
IoT	Internet of Things
MEP	Mechanical, electrical and plumbing
MEPS	Minimum Energy Performance Standards
PUE	Power usage effectiveness
Symbols	
B_{20}	Net 20-year carbon balance [kg CO_2e/m^2]
C, S	Annual operational carbon cost / savings [kg CO_2e/(m^2 yr)]
E_b, E_t	Baseline / technology electricity use [kWh/(m^2 yr)]
EC_u, EC_{tot}	Unit / allocated embodied carbon [kg CO_2e/m^2]
g	Grid carbon intensity [kg CO_2e/kWh]
L, T	Service life / analysis period [yr]
N	Net annual operational benefit [kg CO_2e/(m^2 yr)]
n_r	Service-life equivalents [–]
s	Savings fraction [–]
PB	Carbon recovery indicator [yr]

1. INTRODUCTION

In the EU, buildings account for 40% of energy consumption and 36% of energy-related greenhouse gas emissions [1, 2]. Digitalization is increasingly promoted as a climate solution [3]. However, its net climate benefit depends on whether operational carbon savings exceed emissions associated with equipment production, installation, operation and replacement.

Sweden provides an important context for this comparison. The electricity carbon intensity adopted here is 41 g CO_2e/kWh [4]. Sweden has introduced climate declarations for new buildings [5]. Under the revised Energy Performance of Buildings Directive (EPBD), non-residential minimum energy performance standards (MEPS) target the worst-performing 16% of buildings by 2030 and 26% by 2033 [2, 6]. Boverket's preliminary calculations identified a potential 2033 office threshold of 174 kWh/(m^2 yr), expressed as a primary energy number [7]. This policy context motivates consideration of carbon outcomes alongside energy performance; the present analysis does not establish regulatory compliance.

While system-level estimates exist for MEP services, embodied carbon data for building automation equipment appear limited on a building-area basis (kg CO_2e/m^2). Methods exist for estimating embodied carbon from equipment mass (e.g., CIBSE TM65.1 reports an average of 9 kg CO_2e per kg of product for residential heating and hot-water equipment [8]), but conversion to building-area metrics requires equipment density data that may not be readily available. The Center for the Built Environment at UC Berkeley also identifies limited embodied carbon information for MEP systems compared with building structures and enclosures [9].

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Table 1 System boundaries and lifecycle stages included

Stage / category	Processes included
Analysis period	20 years
Embodied carbon (A1–A5)	Raw material extraction, manufacturing, transport and installation, as covered by the adopted estimates
Replacement (B4)	Replacement burdens represented through proportional service-life allocation
Operational carbon (B6)	Equipment electricity consumption and allocated cloud computing resources
Avoided emissions	Scenario electricity savings at the selected grid intensity

Industry sources provide useful estimates, although their boundaries and transparency vary. In the EGDC c-BEMS case study, device manufacturing and transport emissions were excluded because of limited data and treated as a minor contribution [10]. Such exclusions can affect comparisons between operational savings and embodied carbon.

Reviews identify data quality and methodological inconsistencies in embodied carbon assessment [11]. Environmental Product Declarations also differ in specificity and data quality [12], while estimating MEP impacts requires attention to material quantities and replacement over time [13]. This study compares four digital building technology scenarios using published data and stated assumptions. It examines how service-life allocation and electricity carbon intensity influence the balance between embodied carbon and operational savings.

2. METHODOLOGY

2.1 System boundary and functional unit

The functional unit is one square meter of conditioned office floor area (m^2 A_{temp}) over 20 years. Table 1 summarizes the assessment boundary. End-of-life (Stage C) is excluded because of limited data. ICT studies highlight the importance of production emissions, although their shares vary by device and use pattern [14, 15]. This does not establish that disposal impacts are negligible for building automation equipment. The exclusion is therefore treated as a limitation of this simplified assessment, rather than evidence of a complete lifecycle inventory.

2.2 Baseline assumptions

Table 2 defines an illustrative office scenario and three electricity-grid contexts. The baseline and savings are treated as electricity use for this calculation. Results therefore do not represent a carrier-resolved assessment of a typical Swedish office or a calculation of its primary energy number.

Table 2 Baseline building and grid assumptions

Category	Details
Office scenario	Baseline 200 kWh/(m^2 yr)[a]; weekday occupancy with partial weekends; added digital equipment assumed available continuously
Grid carbon intensity	Sweden: 41 g CO_2e/kWh[b] [4] EU average: 242 g CO_2e/kWh [16] Poland: 662 g CO_2e/kWh [16]

[a] Scenario assumption informed by the Swedish building-energy context [17]; treated as electricity, not a measured office electricity benchmark. Added digital equipment loads are excluded from the baseline and included separately. [b] The adopted Swedish factor is a lifecycle value [4]; the EU and Poland factors are direct-combustion values [16]. These comparisons are illustrative because the accounting boundaries differ.

2.3 Technology data and assumptions

Table 3 combines research and industry sources with explicit scenario assumptions. Citations beside assumed allocations provide context; they do not establish the exact building-area values. BEMS, IoT, digital twins and cloud AI are assessed separately to show their assumed individual balances. In practice, these technologies can share sensing, control and computing infrastructure. Their separation does not establish equivalent service provision or demonstrate that supporting infrastructure can be omitted. The comparison is therefore conditional on the adopted boundaries. Software-support periods are proxies for allocation intervals, not measured hardware replacement lives, and cost savings do not directly establish energy savings.

2.4 Calculation methodology

Annual operational carbon savings S and operational carbon costs C are

$$S = E_b \cdot s \cdot g \tag{1}$$

$$C = E_t \cdot \mathrm{PUE} \cdot g \tag{2}$$

PUE is the ratio of total data-center energy to IT equipment energy [33]. Reported 2024 fleet values include 1.09 for Google [34] and 1.15 for AWS [28]. Here, PUE = 1.0 is an idealized lower-bound assumption for cloud overhead, rather than a measured value. For on-site equipment, E_t denotes the assumed total equipment electricity use and no data-center overhead is applied. The same grid factor is used for savings and technology electricity, including cloud processing; actual cloud locations may differ.

The net annual benefit, allocated embodied carbon, carbon recovery indicator and 20-year balance (T = 20 yr)

Table 3 Technology parameters used in the scenarios; ranges and proxies are shown where available

Parameter	BEMS	IoT sensor networks	Digital twins	Cloud-based AI optimization
Energy savings, s	13.8% (11.39–16.22%) [18]	20% scenario assumption; review reports up to 30% [19]	10% scenario assumption (review range 1–40%) [1]	14% assumption; related MPC literature reports cost savings, not an equivalent energy-saving factor [20]
Service life, L	9 yr (8–10) [21]	6 yr, embedded-module proxy for sensors and gateway [22]	10 yr, software-support proxy [23, 24]	5 yr, assumed infrastructure allocation interval informed by lifecycle sources [25, 26]
Service-life equivalents in 20 yr, n_r	2.22	3.33	2.00	4.00
Operational electricity, E_t [kWh/(m^2 yr)]	0.7, scenario assumption	0.3, scenario assumption informed by sensor-network literature [27]	1.5, assumed cloud allocation; infrastructure context [28]	1.5, assumed cloud allocation; infrastructure context [28]
Unit embodied carbon, EC_u [kg CO_2e/m^2]	9 (8–10; reported 7.7–9.5 t CO_2e for a 945 m^2 office floor) [29]	0.1, assumed sensors/gateway allocation; device-level context [30]	1.3 (0.5–2.0), assumed cloud allocation[c] [31, 32]	1.3, assumed cloud allocation[c] [31, 32]

[c] Cloud values and the stated range are scenario allocations, not independently verified building-area measurements.

Table 4 Scenario carbon performance under Swedish grid conditions (41 g CO_2e/kWh)

Technology	S (1)	C (2)	N (3)	EC_{tot} (4)	PB (6)	B_{20} (7)
BEMS	1.13	0.03	1.10	20.0	18.1	+2.1
IoT sensors	1.64	0.01	1.63	0.33	0.2	+32.2
Digital twins	0.82	0.06	0.76	2.6	3.4	+12.6
Cloud AI	1.15	0.06	1.09	5.2	4.8	+16.5

Units: S, C, N in kg CO_2e/(m^2 yr); EC_{tot} and B_{20} in kg CO_2e/m^2; PB in years. Numbers in parentheses refer to equations.

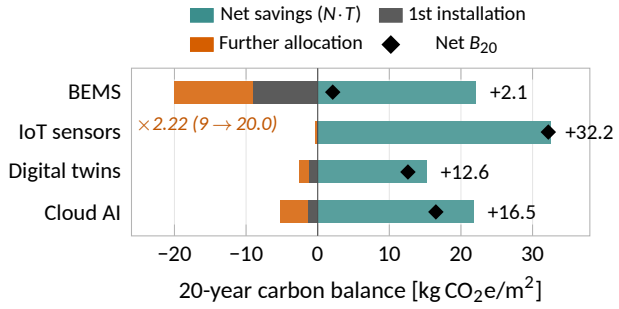

Fig. 1 Net operational savings and proportionally allocated embodied carbon over 20 years; diamonds mark B_{20}

follow as

$$N = S - C \tag{3}$$

$$EC_{tot} = EC_u \cdot n_r \tag{4}$$

$$n_r = T/L \tag{5}$$

$$PB = EC_{tot}/N \tag{6}$$

$$B_{20} = N \cdot T - EC_{tot} \tag{7}$$

Here, n_r represents service-life equivalents, including the initial installation, rather than discrete replacement events. Embodied carbon is allocated proportionally to the service life used within the analysis period. For $N > 0$, PB expresses this allocated burden relative to annual net savings; it does not identify chronological break-even when replacements occur. A positive B_{20} indicates a net benefit under these assumptions; a negative value indicates a net carbon cost. Grid intensity, annual savings and unit embodied carbon are held constant.

3. RESULTS

3.1 Annual operational carbon benefits

Table 4 summarizes the annual savings, technology emissions and net benefits calculated using Eqs. (1)–(3). Annual net operational benefits range from 0.76 kg CO_2e/(m^2 yr) for digital twins to 1.63 kg CO_2e/(m^2 yr) for the IoT scenario. Allocated embodied carbon varies more widely, from 0.33 kg CO_2e/m^2 for IoT to 20.0 kg CO_2e/m^2 for BEMS.

3.2 Carbon recovery indicators and 20-year balance

Under proportional allocation, all four scenarios have positive 20-year balances (Table 4). Fig. 1 separates the initial embodied burden from the additional service-life allocation and compares their sum with cumulative net operational savings. The PB indicator ranges from 0.2 years for IoT to 18.1 years for BEMS.

Table 5 Carbon recovery indicators (years) across grid carbon intensities

Technology	Sweden	EU average	Poland	Sweden/ Poland
BEMS	18.1	3.1	1.1	16.1×
IoT sensors	0.2	<0.1	<0.1	16.1×
Digital twins	3.4	0.6	0.2	16.1×
Cloud AI	4.8	0.8	0.3	16.1×

Ratios use unrounded indicators.

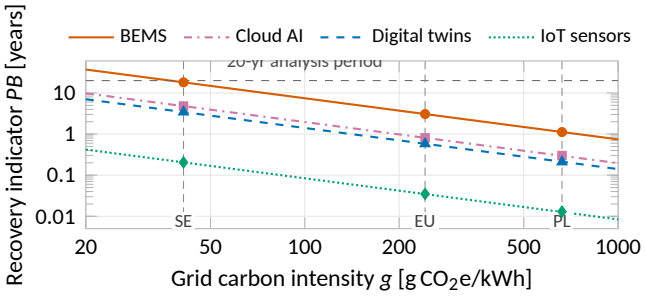

Fig. 2 Carbon recovery indicator versus grid intensity (Eq. 6); markers show the adopted Swedish, EU and Polish factors

3.3 Grid carbon intensity sensitivity

Table 5 compares *PB* across three adopted electricity factors. Fig. 2 extends the calculation continuously over grid intensity. Because the same factor scales both operational savings and technology emissions, *PB* is inversely proportional to g in this model. The common 16.1 ratio follows directly from 662/41, rather than providing independent evidence of differences between technologies. The mixed factor boundaries noted in Table 2 limit direct country comparisons.

4. DISCUSSION

4.1 The service life multiplier effect

Under proportional service-life allocation, BEMS embodied carbon increases from 9 to 20 kg CO_2e/m^2 over 20 years (Table 4, Fig. 1). The corresponding recovery indicator increases from 8.2 to 18.1 years. This illustrates the importance of service life, although the result depends on the allocation convention.

The IoT scenario represents 3.33 service-life equivalents, but its allocated embodied carbon remains small (0.33 kg CO_2e/m^2) because of the low assumed unit burden. Thus, service life and unit embodied carbon jointly influence the balance. This is consistent with the broader importance of embodied carbon and temporal boundaries in lifecycle assessment [35, 36].

4.2 Grid carbon intensity

The BEMS recovery indicator is 18.1 years at the adopted Swedish factor, compared with 3.1 years at the EU-average factor. Under otherwise unchanged assumptions, cleaner electricity reduces the avoided emissions associated with each unit of electricity saved, while embodied burdens remain constant. As electricity systems decarbonize [37], service life and manufacturing emissions may become more important to the net balance. This concerns carbon performance and does not remove other benefits of energy efficiency, such as lower demand or operating costs.

4.3 Technology-specific performance

IoT sensor networks have the largest calculated net benefit, +32.2 kg CO_2e/m^2, under the assumed 20% savings and low embodied burden. This conditional result does not demonstrate that sensors alone deliver these savings or that they provide the same functions as a BEMS.

BEMS have a small positive balance of +2.1 kg CO_2e/m^2 under proportional allocation. Their allocated embodied burden uses approximately 91% of cumulative net operational savings. As the replacement sensitivity below shows, this benefit is not robust to the allocation convention.

Digital twins and cloud AI produce estimated balances of +12.6 and +16.5 kg CO_2e/m^2, respectively. These depend on assumed cloud allocations, service intervals and energy savings. Increased computing demand may also introduce rebound effects [38]. The ranking should therefore be interpreted as a comparison of scenarios, not a universal ranking of technology types.

4.4 Implications for building policy

The findings support considering lifecycle carbon alongside energy performance. Technologies pursuing similar energy-saving objectives can produce different carbon balances. However, the present electricity-based scenario does not establish MEPS compliance: delivered electricity and a regulatory primary energy number cannot be compared directly. Policy interpretation requires consistent energy metrics and comparable system boundaries.

4.5 Data quality and epistemic uncertainty

Building-area embodied carbon estimates depend on equipment density and infrastructure allocation. The assumed IoT and cloud values need validation against explicit equipment inventories or documented allocation calculations. Industry estimates and lifecycle proxies are useful for exploratory comparison but do not establish

verified performance. Excluding manufacturing emissions, as in the cited case study [10], can further affect the balance between reported savings and equipment burdens.

4.6 Limitations and future research

The main limitations are:

- *Replacement allocation:* counting full BEMS installations at years 0, 9 and 18, without residual-life credit, increases embodied carbon to 27 kg CO_2e/m^2 and changes the 20-year balance from +2.1 to −4.9 kg CO_2e/m^2. This alternative exposes the sensitivity of the BEMS conclusion.
- *Input uncertainty:* savings, service-life proxies and per-area allocations are not probabilistically assessed. Additional infrastructure needed to realize the assumed savings may alter the technology ranking.
- *Operational conditions:* commissioning and occupant behavior affect realized savings [39, 40]. PUE = 1.0 omits cloud overhead, and processing may use a different electricity mix.
- *Temporal and inventory boundaries:* grid factors are static and not fully harmonized; end-of-life is excluded. Refurbishment and component reuse could reduce future replacement burdens.

Future work should validate equipment inventories and measured savings, separate energy carriers, and examine discrete replacements and changing grid intensity.

5. CONCLUSIONS

This scenario assessment illustrates how embodied carbon, service life and electricity carbon intensity shape the climate balance of digital building technologies. Under proportional allocation, estimated 20-year benefits range from 2.1 kg CO_2e/m^2 for BEMS to 32.2 kg CO_2e/m^2 for IoT. Counting full BEMS installations instead changes its balance to −4.9 kg CO_2e/m^2, showing that replacement accounting can reverse the result.

Lower electricity carbon intensity increases the relative importance of embodied burdens. The findings support transparent, context-specific assessment alongside energy performance evaluation. Technology rankings remain conditional on savings, infrastructure boundaries and allocation assumptions; they do not establish equivalent services or regulatory compliance.

DECLARATION OF GENERATIVE AI USE

The authors used AI tools for language editing and manuscript revision, reviewed the output, and take full responsibility for the paper.

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