ECOS 2026: Dynamic Life Cycle Analysis of Energy Storage Systems: A Scalable Framework for Real-World Demonstrations from the 'SINNOGENES' EU Research Project

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Abstract:

The increasing integration of renewable energy sources and energy storage technologies in multi-vector energy systems introduces significant challenges for conventional sustainability assessment methods. In particular, standard Life Cycle Assessment (LCA) and Life Cycle Costing (LCC) approaches, typically based on static inventories and annual averages, are unable to capture the dynamic and time-dependent behaviour of modern energy systems. This work proposes a dynamic LCA/LCC framework for the environmental and economic evaluation of energy storage systems operating across electrical, thermal, and hydrogen vectors. The methodology combines high-resolution operational data with scenario-based modelling through a dual-path architecture, integrating data-driven inputs, such as IoT and SCADA measurements, with model-driven components, including synthetic load profiles, forecasted parameters, and future system configurations. The framework is implemented in a Python-based environment, enabling flexible data processing, time-resolved simulation, and harmonised computation of life cycle indicators in accordance with ISO 14040/44 and ISO 15686-5 standards. The proposed approach is validated across six heterogeneous demonstration sites, encompassing industrial microgrids, district energy systems, local energy communities, islanded grids, and hydrogen-based transport applications. Results indicate that the framework enables consistent and comparable assessment of both operational and embodied impacts under varying data availability conditions, while capturing temporal dynamics such as renewable generation variability, storage cycling behaviour, and evolving grid emission factors. The analysis highlights the importance of integrating dynamic operational modelling into life cycle methodologies to avoid misrepresentation of long-term environmental and economic performance. The proposed framework supports scalable and replicable sustainability assessment of complex energy systems, providing a robust tool for decision-making, system optimisation, and policy evaluation in the context of the energy transition.

Keywords:

Dynamic Modelling; Energy Storage Systems; Life Cycle Assessment; Life Cycle Costing; Multi-vector Energy Systems.

1. Introduction

1.1. Background and motivation

The ongoing energy transition is characterised by the rapid deployment of renewable energy sources (RES) and the increasing electrification of end-use sectors. Technologies such as photovoltaic systems and wind power are being integrated at large scale [1], driven by ambitious decarbonisation targets and policy frameworks at both European and global levels [2, 3]. However, the inherent variability and intermittency of these resources introduce significant operational challenges for energy systems, including imbalances between supply and demand, grid congestion, and reduced system stability [4, 5, 6].

Energy storage systems (ESS) are widely recognised as a key enabling technology to address these challenges. By providing temporal flexibility, storage systems support the integration of RES, improve self-consumption, and enable new operational strategies such as peak shaving, load shifting, and provision of ancillary services [7, 8, 9]. Beyond electrical storage, modern systems increasingly incorporate thermal storage, hydrogen-based solutions, and hybrid configurations, leading to the emergence of multi-vector energy systems where electricity, heat, and fuels are strongly interconnected [10, 11].

While the technical role of storage in such systems is well established, its broader sustainability implications require careful evaluation. In particular, the environmental and economic performance of storage technologies must be assessed across their full life cycle, considering both embodied impacts and operational behaviour.

1.2. Limitations of conventional LCA/LCC approaches

Life Cycle Assessment (LCA) [12] and Life Cycle Costing (LCC) [13] are widely used methodologies for evaluating environmental impacts and economic performance over the lifetime of energy systems. These approaches provide a structured framework to quantify indicators such as greenhouse gas emissions, primary energy demand, and total system costs, from material extraction and manufacturing to operation, maintenance, and end-of-life stages [14].

However, conventional implementations of LCA and LCC are typically based on static representations of system behaviour [14, 15]. They often rely on annual averages, simplified load profiles, and fixed emission factors, which do not adequately reflect the temporal dynamics of modern energy systems [16, 17]. This limitation is particularly critical for systems with high penetration of RES and storage, where operational conditions vary significantly at sub-hourly time scales.

Several key limitations can be identified. First, static approaches are unable to capture the time-dependent operation of storage systems, including charge–discharge cycles, efficiency losses, and interactions with variable renewable generation. Second, they neglect the evolution of system parameters over time, such as changes in grid emission intensity, technology degradation, and replacement cycles. Third, they struggle to represent interactions across multiple energy vectors, which are increasingly relevant in integrated energy systems combining electricity, heat, and hydrogen.

These limitations can lead to significant inaccuracies in the estimation of both environmental and economic performance, potentially misrepresenting the benefits of storage technologies and hindering informed decision-making.

1.3. Need for dynamic and multi-vector assessment frameworks

To overcome the limitations of static methodologies, there is a growing need for dynamic assessment frameworks capable of capturing the temporal and structural complexity of modern energy systems. Such frameworks must integrate high-resolution operational data, account for time-varying system conditions, and enable the consistent evaluation of both operational and embodied impacts.

In addition, the increasing prevalence of multi-vector energy systems requires methodologies that can simultaneously consider interactions between different energy carriers [18]. For example, the integration of thermal storage in district energy systems, the coupling of electricity and hydrogen production in power-to-X applications, and the coordination of distributed storage in local energy communities all require a unified modelling approach.

A further challenge lies in the heterogeneity of data availability across real-world applications. While some systems provide detailed measurements through IoT and SCADA platforms, others rely on simulated or projected data. Therefore, an effective assessment framework must be flexible enough to accommodate both measured and modelled inputs without compromising methodological consistency.

1.4. Contribution and scope of this work

This paper proposes a dynamic Life Cycle Assessment and Life Cycle Costing (LCA/LCC) framework for the evaluation of energy storage systems in multi-vector energy environments. The methodology is based on a dual-path architecture that combines:

- a data-driven pathway, utilising high-resolution operational data, including IoT and SCADA measurements, bills of quantities, and site-specific parameters; and
- a model-driven pathway, incorporating synthetic load profiles, scenario-based assumptions, and projections of future system conditions.

Both pathways are integrated into a unified life cycle computation framework, enabling the consistent calculation of environmental and economic indicators in accordance with established standards, including ISO 14040/44 for LCA and ISO 15686-5 for LCC.

The proposed methodology is implemented in a flexible computational environment and validated across six heterogeneous demonstration sites, covering a wide range of applications such as industrial microgrids, district heating and cooling systems, local energy communities, islanded grids, and hydrogen-based transport systems. This diversity enables the assessment of the framework's scalability and applicability under different system configurations and data conditions.

The main contribution of this work is the development and validation of a scalable and replicable dynamic LCA/LCC framework that captures the temporal dynamics and multi-vector interactions of modern energy systems, providing a robust basis for sustainability assessment, system optimisation, and decision support.

1.5. Paper organisation

The remainder of the paper is organised as follows. Section 2 presents the proposed methodology, including the dynamic modelling approach and the dual-path framework. Section 3 describes the case study framework and data sources. Section 4 presents the results and discusses the main findings. Finally, Section 5 concludes the paper and outlines directions for future work.

2. Methodology

2.1. Problem formulation

The objective of this work is to evaluate the environmental and economic performance of energy storage systems integrated in multi-vector energy systems over their full life cycle. The assessment must account for both embodied impacts (materials, manufacturing, installation, end-of-life) and operational impacts (energy flows, system operation, and interactions with external systems).

Let the system be defined over a discrete time horizon $t \in \{1, \dots, T\}$, with temporal resolution Δt. The energy balance at each time step is governed by the interaction between load demand, renewable generation, storage operation, and grid exchanges.

The total life cycle impact I can be expressed as the sum of embodied and operational components:

$$I = I_{\text{emb}} + I_{\text{op}} \tag{1}$$

where I_{emb} represents impacts associated with system construction, maintenance, and end-of-life, and I_{op} corresponds to impacts arising from system operation over time.

Similarly, the total life cycle cost C is defined as:

$$C = C_{\text{cap}} + C_{\text{op}} + C_{\text{rep}} + C_{\text{eol}} \tag{2}$$

where C_{cap} is the capital expenditure, C_{op} the operational cost, C_{rep} the replacement cost, and C_{eol} the end-of-life cost.

The challenge lies in accurately computing I_{op} and C_{op}, which depend on time-resolved system operation, especially in systems with variable renewable generation and storage dynamics.

2.2. Dynamic energy system modelling

The proposed framework represents system operation using high-resolution time series. At each time step t, power quantities (MW) are converted into energy (MWh) using (3):

$$E(t) = P(t) \cdot \Delta t \tag{3}$$

Energy storage operation is modelled through charge and discharge processes governed by system constraints. The state of charge (SOC) evolves as:

$$SOC(t+1) = SOC(t) + \eta_{\text{ch}} E_{\text{ch}}(t) - \frac{E_{\text{dis}}(t)}{\eta_{\text{dis}}} \tag{4}$$

where $E_{\text{ch}}(t)$ and $E_{\text{dis}}(t)$ denote charging and discharging energy, and η_{ch}, η_{dis} are the corresponding efficiencies.

The SOC is bounded by:

$$0 \le SOC(t) \le C_{\text{bat}} \cdot DOD \tag{5}$$

where C_{bat} is the storage capacity and DOD corresponds to the depth of discharge.

Grid exchanges are computed as:

$$E_{\text{imp}}(t) = \max[E_{\text{load}}(t) - E_{\text{RES}}(t) - E_{\text{dis}}(t), 0] \tag{6}$$

$$E_{\text{exp}}(t) = \max[E_{\text{RES}}(t) - E_{\text{load}}(t) - E_{\text{ch}}(t), 0] \tag{7}$$

This formulation enables the representation of storage-driven load shifting and renewable self-consumption enhancement.

2.3. Dual-path LCA/LCC framework

To address the challenges associated with heterogeneous data availability and the need for both retrospective and prospective analysis, the proposed methodology adopts a dual-path architecture that integrates data-driven and model-driven approaches within a unified life cycle assessment framework. This structure enables consistent evaluation of environmental and economic performance across diverse system configurations while maintaining methodological flexibility.

The data-driven pathway relies on empirical information derived directly from the demonstration systems. This includes high-resolution operational data obtained from IoT devices and SCADA platforms, as well as system-specific inputs such as bills of quantities, measured energy flows, and locally relevant emission factors and energy tariffs. By incorporating real operational behaviour, this pathway allows for the accurate representation of system dynamics and supports the calculation of life cycle indicators based on observed performance.

In parallel, the model-driven pathway supports the analysis of systems where measured data are incomplete or unavailable and enables the exploration of alternative or future scenarios. This pathway incorporates synthetic or estimated inputs, including reconstructed load and generation profiles, projected demand patterns, expected system lifetimes, and assumptions regarding future energy mixes, costs, and policy conditions. As such, it extends the applicability of the framework beyond purely data-rich environments and allows for forward-looking assessments.

Both pathways converge within a common life cycle computation layer, where environmental and economic indicators are evaluated using harmonised system boundaries, consistent functional units, and standardised calculation procedures. This integration ensures that results derived from different data sources remain comparable, while preserving the ability to reflect the specific characteristics of each system.

The combined use of empirical and model-based inputs provides a robust foundation for assessing complex energy systems operating across multiple energy vectors. By capturing both real-time operational behaviour and potential future developments, the dual-path framework enables comprehensive and scalable evaluation of energy storage technologies under varying conditions of data availability and system complexity. The methodology is implemented in a flexible computational environment, allowing efficient processing of time-resolved data and seamless integration of multi-source inputs.

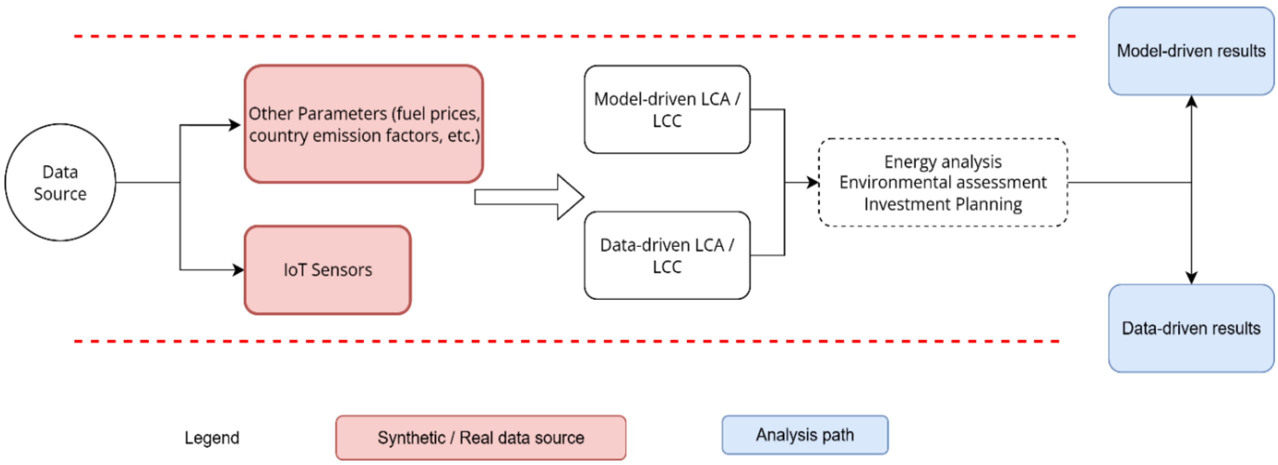

Figure. 1. *Dual-path LCA/LCC workflow combining data-driven and model-driven analyses.*

2.4. Life cycle impact and cost assessment

Key performance indicators (KPIs) are employed to quantify a system's performance and can be classified into five main categories, encompassing technical, environmental, economic, social, and platform engineering aspects [19]. Within the scope of this study, the proposed evaluation framework focuses on environmental and economic KPIs.

In order to establish the specific KPIs used for assessment in this paper, the CO_2 emissions and the annual energy cost are defined by equations (8) and (9), respectively:

$$CO_2\ emissions = \sum_{i=1}^{N} E_i \cdot EF_i \tag{8}$$

$$C_{\text{energy}} = p_{\text{imp}} \cdot \sum_{t}^{T} E_{\text{imp}}(t) - p_{\text{exp}} \cdot \sum_{t}^{T} E_{\text{exp}}(t) \tag{9}$$

where E_i corresponds to the annual energy consumption of energy carrier i, EF_i corresponds to the emission factor of energy carrier i (measured in kg CO_2 per kWh), N is the number of energy carriers, p_{imp} and p_{exp} are the import and export electricity tariffs (measured in € per kWh), and $E_{\text{imp}}(t)$ and $E_{\text{exp}}(t)$ are the imported and exported energy quantities at time step t.

One of the main KPIs defined is the reduction in energy cost ($ECRed$) or alternatively the reduction in electricity bill for operational and industrial users, and it is expressed as:

$$ECRed = \frac{C_{\text{base}} - C_{\text{upg}}}{C_{\text{base}}} \cdot 100 \tag{10}$$

where C_{base} corresponds to the total annual cost in the baseline scenario (subsection 3.2) and C_{upg} corresponds to the total annual cost in the upgrade scenario (subsection 3.2).

Another important KPI is the reduction of environmental footprint ($EnvF$) and it evaluates the percentage improvement in the environmental footprint compared to the baseline scenario, considering the relative CO_2 savings:

$$EnvF = \frac{CO_{2,\text{base}} - CO_{2,\text{upg}}}{CO_{2,\text{base}}} \cdot 100 \tag{11}$$

where $CO_{2,\text{base}}$ and $CO_{2,\text{upg}}$ correspond to the baseline and storage-enhanced CO_2 emissions, respectively. These indicators enable the evaluation of storage benefits relative to baseline system configurations. Additionally, the difference $CO_{2,\text{base}} - CO_{2,\text{upg}}$ represents the CO_2 savings achieved by energy storage systems, i.e.,

$$CO_{2,\text{saved}} = CO_{2,\text{base}} - CO_{2,\text{upg}} \tag{12}$$

$C_{\text{cap,red}}$ quantifies the reduction in grid capacity costs achieved through the use of energy storage. It is calculated using the following empirical formula:

$$C_{\text{cap,red}} = \alpha_{\text{peak}} \cdot \frac{\sum_t^T E_{dis}(t)}{H_{\text{peak,month}} \cdot 12} \cdot C_{\text{cap}} \tag{13}$$

where α_{peak} is a dimensionless coefficient, $H_{\text{peak,month}}$ represents the average number of hours at peak demand per month, and C_{cap} is the unit capacity cost. This indicator should be interpreted as a simplified proxy rather than a direct market-based valuation.

To estimate the overall cost efficiency of the applied energy storage technologies, expressed as cost per MWh of load, equation (14) is used:

$$C_{\text{efficiency}} = \frac{C_{reno}}{\frac{E_{load}}{1000}} \tag{14}$$

where E_{load} is the load in MWh.

The increase in RES self-consumption, i.e., the total amount of renewable energy produced and consumed locally rather than exported to the grid, is calculated using (15) as follows:

$$\Delta E_{\text{RES}} = E_{\text{supply,upg}} - E_{\text{supply,base}} \tag{15}$$

where $E_{\text{supply,upg}}$ is the annual renewable electricity allocated to on-site consumption in the upgrade scenario (subsection 3.3), and $E_{\text{supply,base}}$ is the corresponding value for the baseline (subsection 3.3).

RES penetration is also an environmental KPI that expresses the share of renewable or (in the context of this paper) storage-based supply relative to total electricity demand, as defined by (16):

$$RES\ Penetration = \frac{E_{supply}}{E_{demand}} \cdot 100 \tag{16}$$

From an economic aspect, one of the most important indicators is Return on Investment (ROI), which expresses how efficiently an investment generates yearly returns. It is calculated using formula (17):

$$ROI = \frac{C_{\text{base}} - C_{\text{upg}}}{Investment} \cdot 100 \tag{17}$$

Furthermore, another common economic KPI is the Net Present Value (NPV) defined as follows:

$$NPV = \sum_i^n \frac{CF_i}{(1 + r)^i} - Investment \tag{18}$$

where CF corresponds to the cashflow in year *i*, i.e., $C_{\text{base}} - C_{\text{upg}}$, r is the discount rate during the investment's lifetime, and n represents the years comprising the investment's lifetime.

The Internal Rate of Return (IRR) reflects an investment's intrinsic profitability and is calculated using equation (19) as follows:

$$\sum_i^n \frac{CF_i}{(1 + IRR)^i} = Investment \tag{19}$$

2.5. Implementation and computational workflow

The proposed methodology is implemented within a modular computational environment based on Python, enabling flexible integration of heterogeneous data sources and efficient processing of time-resolved information. This implementation supports the consistent application of the framework across multiple case studies, while maintaining transparency and reproducibility in the assessment process.

The workflow begins with the acquisition and preprocessing of input data, including measured operational time series, system specifications, and external parameters such as energy tariffs and emission factors. Where necessary, incomplete datasets are reconstructed or extended to ensure temporal consistency, allowing the representation of system behaviour over a full annual cycle. Attention is given to preserving the statistical characteristics and intra-day variability of the original data.

Following data preparation, the operational behaviour of the energy system is simulated using the dynamic modelling approach described in Section 2.2. This includes the calculation of energy balances at each time step, as well as the representation of storage operation through charging and discharging processes subject to technical constraints. The resulting time series of grid imports, exports, and storage states provide the basis for subsequent impact and cost calculations.

The life cycle assessment and costing stages are then performed by combining time-resolved operational results with system-level information related to materials, installation, maintenance, and end-of-life processes. Environmental indicators, such as greenhouse gas emissions and primary energy demand, are computed using standardised emission factors and life cycle inventories, while economic indicators are derived from cost parameters associated with system investment, operation, and replacement.

Finally, the KPIs defined in subsection 2.4 are calculated to quantify the relative benefits of energy storage integration with respect to baseline system configurations. These indicators enable a structured comparison of different scenarios and support the interpretation of results across diverse applications. The modular structure of the computational workflow allows the methodology to be readily adapted to different system types, data conditions, and analysis objectives, making it suitable for large-scale and multi-site assessments.

3. Case study framework and data description

3.1. Demonstration sites overview

The proposed methodology is validated across six heterogeneous demonstration sites, developed within the 'SINNOGENES' project, representing a wide range of applications, system configurations, and energy vectors. These sites include industrial microgrids, district heating and cooling systems, local energy communities, islanded energy systems, and hydrogen-based transport applications. The diversity of the demonstration environments enables the assessment of the framework under varying operational conditions, levels of data availability, and system scales. The location and typical characteristics of the six demonstration sites are presented in Table 1.

Table 1. *Location and type of the six demonstration sites of the 'SINNOGENES' project used for evaluation.*

Demo site	Location	Type	Storage systems in baseline scenarios	Storage systems in upgrade scenarios
Demo#1	Porto Metropolitan Area, Portugal	Industrial microgrid	--	Li-ion 2nd life battery and a (VRFB)
Demo#2	Soria, Spain	Research facility/Bioclimatic building	Limited electrical storage	Geothermal infrastructure, heat pumps, high-power electrical storage
Demo#3	Walqa Technology Park, Spain	Local Energy Community (LEC)	Existing hydrogen storage system	Expansion of the configuration with a second Hydrogen Refuelling Station (HRS)
Demo#4	Herzberg, Germany	Industrial site	--	Heat pumps, multiple thermal storage units
Demo#5	Ikaria, Greece	Islanded grid	Hydro-Pumped Storage (PHS)	No added storage units, but optimization of Ikaria's power system & interconnection with Samos Island
Demo#6	ZIMEYSA industrial park, Geneva, Switzerland	Localized H_2 ecosystem for decarbonisation of mobility	--	Compression and storage of H_2

3.2. Data sources and system representation

The assessment relies on a combination of measured and modelled data, consistent with the dual-path framework described in Section 2.3. For several demonstration sites, high-resolution operational data are available through IoT and SCADA systems, providing time series of renewable generation, energy consumption, and grid exchanges at sub-hourly resolution. These datasets enable the direct application of the data-driven pathway and allow the representation of actual system behaviour over time.

In cases where full datasets are not available, the analysis is complemented by model-driven inputs, including reconstructed load profiles, synthetic generation patterns, and scenario-based assumptions regarding system operation. These inputs are derived from system specifications, historical data, and relevant external sources, ensuring consistency with the physical and operational characteristics of each site.

All datasets are processed to ensure temporal consistency and compatibility with the dynamic modelling framework. When necessary, partial time series are extended to represent full-year operation using replication and scaling techniques, preserving the statistical properties of the original data while enabling annual performance assessment.

3.3. Scenario definition and evaluation approach

For each demonstration site, the analysis is structured around the comparison of at least two configurations: a baseline scenario representing the system without advanced storage integration or extensions in infrastructure, and one or more upgrade scenarios incorporating new energy storage technologies. This comparative approach enables the quantification of the benefits of energy storage systems in terms of environmental and economic performance.

The evaluation is performed on the six demonstration sites presented in Table 1, and is based on a set of harmonised KPIs, formulated in section 2.4, as well as derived indicators expressing relative improvements with respect to the baseline configuration. This approach ensures consistent comparison across demonstration sites while allowing the identification of system-specific performance characteristics.

Given the diversity and scale of the demonstration activities, it is not feasible to present a detailed analysis of all the calculated KPIs for each one of the six demonstration sites. Therefore, this work focuses on a representative subset of results that illustrate the capabilities of the proposed framework and highlight key insights related to the operation and impact of energy storage systems.

The selected results emphasise differences in system behaviour across applications, the influence of storage technology characteristics, and the role of dynamic modelling in capturing temporal effects that would be overlooked by static approaches. This selective presentation ensures clarity and conciseness, while preserving the generality and validity of the conclusions.

4. Results and discussion

The following section presents the results of the comparative analysis between the baseline configurations mentioned in subsection 3.3 and upgrade scenarios for the six ‘SINNOGENES’ demonstration sites. The evaluation focuses on environmental and economic KPIs to quantify the impact of the integrated energy storage solutions.

4.1. Demo#1

Table 2 presents indicative assessment results of the Demo#1 site based on the KPIs described by formulas (10)–(14) in subsection 2.4.

Table 2. *Assessment results of Demo#1.*

Description of KPI	Unit	Upgrade – Li-ion 2nd life battery (vs baseline)	Upgrade – VRFB (vs baseline)
Reduction in users’ energy bill	%	0.5%	0.2%
Reduction in excess capacity planning cost	%	Small positive proxy benefit	Small positive proxy benefit
CO_2 savings	tCO_2/year	19.1 tCO_2/year	18.1 tCO_2/year
Increase in renewable self-consumed energy	MWh	4.3 MWh	2.5 MWh
Reduction in environmental footprint	%	6.3%	6.0%
Minimise cost	€/MWh	215.43 €/MWh (slightly lower)	215.94 €/MWh (slightly higher)

The results demonstrated in Table 2 highlight the framework’s ability to differentiate between chemical storage systems behind the meter. Table 2 indicates that while both storage technologies contribute to annual CO_2 mitigation, the 2nd-life Li-ion configuration achieves a slightly higher environmental footprint reduction (6.3%) compared to the VRFB (6.0%), primarily due to its superior round-trip efficiency in short-term balancing [20].

From an economic perspective, the reduction in the annual energy bill remains marginal (0.2–0.5%), reflecting the challenge of monetizing storage in industrial environments with already optimized load profiles. However, the proposed framework successfully captures a consistent decrease in the total energy cost per MWh, providing a verified baseline for future industrial microgrid scaling.

4.2. Demo#2

In Table 3, the indicative results of the evaluation framework applied in the Demo#2 site are demonstrated, where the KPIs were calculated based on equations (8)–(10), and (15), described in subsection 2.4.

Table 3. *Assessment results of Demo#2.*

Description of KPI	Unit	Baseline scenario	Upgrade scenario	Change
Total Annual CO_2 Emissions	Kg	58,356	46,289	-20.5%
RES Self-Consumed	kWh	244,749	292,979	+19.7%
Total Annual Energy Cost	€	74,219	59,971	-19.2%
Electricity Bill	€	66,344	54,619	-17.7%
RES Generation	kWh	382,430	457,791	+19.7%

The results in Table 3 suggest that the transition from a pellet-based baseline to a geothermal-coupled system in Demo#2 affects significantly both the energy efficiency of the system and the CO_2 emissions. The assessment framework records a 20.5% reduction in total CO_2 emissions and a nearly 20% increase in RES self-consumption, driven by the electrification of the heating load via high-efficiency heat pumps. From an economic aspect, the upgrade scenario achieves a 19.2% decrease in total energy expenditure, primarily driven by reduced lower pellet consumption, and improved self-consumption of renewable electricity. These findings demonstrate that the proposed evaluation method can effectively quantify the cross-vector benefits of integrating geothermal and thermal storage with high-power electrical flexibility assets.

4.3. Demo#3

The assessment results of the demonstration site Demo#3 are shown in Table 4, based on the KPIs defined by equations (10)–(13) and (15).

Table 4. *Assessment results of Demo#3.*

Description of KPIs	Unit	Upgrade scenario #1	Upgrade scenario #2
Reduction in electricity cost per kWh for users	%	-31.21% vs baseline	-31.21% vs baseline
Increase in revenues from energy storage / flexibility services	€	7,462.72 €	5,552.75 €
Reduction in net planning / operation costs for engaged system operators	%	+93.61% vs baseline	+19.18% vs baseline
Annual CO_2 savings	tCO_2	969 tCO_2	447 tCO_2
Increase in RES energy self-consumed / locally used	MWh	+5,401.42 MWh vs baseline	+2,610.62 MWh vs baseline
Reduction in environmental footprint (net annual emissions)	%	+550.61% vs baseline	-108.67% vs baseline

The assessment of the Walqa LEC represents the staged integration of additional hydrogen refueling stations into the existing hydrogen storage system. The evaluation results in Table 4 indicate a persistent 31.21% reduction in energy costs per kWh across both the 2024 and 2025 operational periods. As far as the environmental KPIs are concerned, the proposed framework distinctly captures the transition from the commissioning phase (2024) to full operation (2025). In 2024, the high electricity demand of the newly installed alkaline electrolyser led to a temporary 550.6% increase in the system's carbon footprint, even though it generated 969 tons of CO_2 savings and self-consumed an additional 5,401.4 MWh of renewable energy. On the other hand, the 2025 scenario corresponds to the fully operational configuration, where a further 2,610.6 MWh of RES utilization and 447 tons of CO_2 savings completely offset the footprint, achieving a reduction of -108.7%. This assessment framework provides a comprehensive evaluation of the upgraded configuration's decarbonisation effect and resulting electricity bill implications, validating the role of Power-to-gas within a LEC context.

4.4. Demo#4

Table 5 demonstrates the evaluation results of the KPIs described by (8), (10) and (17)–(19) applied to the Demo#4 site.

Table 5. *Assessment results of Demo#4.*

Description of KPIs	Unit	Upgrade scenario	Interpretation
Annual Energy Cost Savings	%	>35% reduction vs baseline (46,810 € - 65,231 € saved/year)	Energy-cost target largely surpassed due to fuel and grid savings
Return on Investment (ROI)	%	8.77% vs baseline (12.22% with green electricity)	Financially viable investment
Internal Rate of Return (IRR)	%	8.75% vs baseline (green electricity case)	Project is value-creating under standard financing
Net Present Value (NPV)	€	+143,313 € (at 5% discount rate)	Positive NPV confirms financial attractiveness
CO_2 Reduction	%	38-40% reduction	Significant decarbonisation

The evaluation of the Herzberg industrial demonstration site illustrates the proposed framework's capacity to assess integrated renewable electricity systems and thermal storage technologies. By modelling the gradual replacement of fossil-fuel-based generation with solar thermal collectors, a heat pump, and multiple thermal storage units, the analysis indicates a reduction in the annual energy bill (35-40%) and the overall environmental footprint (38-40%). Furthermore, the evaluation framework evaluates the long-term techno-economic feasibility of such decarbonisation investments. The calculated ROI of 8.77% and an IRR of 8.75% mathematically confirm that the upgraded multi-energy facility is economically viable within the asset lifetime. Ultimately, the assessment of these specific metrics provides a concrete, validated example for industrial decarbonisation.

4.5. Demo#5

Table 6 provides the assessment results of Demo#5 utilizing, among others, the KPIs described by equations (11), (12), (15), and (16).

Table 6. *Assessment results of Demo#5.*

Description of KPIs	Unit	Upgrade scenarios vs baseline
Potential CO_2 savings thanks to more efficient energy management through storage	tCO_2/yr	812 tCO_2 avoided
Increase in RES self-consumed	MWh	2,508 MWh additional RES (wind) used
Reduction of environmental footprint in demonstrators	%	7–8% CO_2 reduction
RES penetration	%	40.40%

The evaluation results of Demo#5 in Ikaria Island assesses the operational dynamics of a hybrid power system undergoing a transition towards digital-twin-assisted optimal control and submarine interconnection with Samos Island. By quantifying the shift from the baseline to the fully interconnected configuration, the framework captures a substantial environmental improvement, specifically a 7-8% reduction in the overall carbon footprint. This footprint mitigation is mathematically driven by an avoidance of 812 tons of CO_2 annually and a massive increase in wind energy absorption (+2,508 MWh). Furthermore, the analysis validates the effectiveness of the updated dispatching strategy; the relaxation of legacy constraints and the activation of inter-island exchanges allow the system's total RES penetration to reach 40.40. This assessment demonstrates the framework's ability to mathematically verify how advanced control and interconnection fundamentally transform an islanded grid's capacity to minimize wind curtailment and reduce thermal generation dependency.

4.6. Demo#6

Indicative assessment results of the Demo#6 site are provided in Table 7.

Table 7. *Assessment results of Demo#6.*

Description of KPIs	Formula	Upgrade scenario #1
Annual CO_2 avoided by substituting diesel with green-H_2 FCEV at the same distance	$\Delta CO_2 = Emissions_{Diesel} - Emissions_{H2}$	14,980 kgCO_2 per vehicle-year avoided;8 vehicles → 120 tCO_2/year.
Renewable electricity implicitly used to produce the vehicle's annual hydrogen demand (RES self-consumption)	RES (MWh) = H_2 mass (kg) × 33.33 kWh/kg ÷ 1000	37.7 MWh per vehicle-year; 5–6 vehicles → 200 MWh.
Relative reduction of operational CO_2 vs diesel baseline at the same distance (footprint reduction)	%reduction = 1 − ($Emissions_{H2}$ / $Emissions_{Diesel}$).	≈100% within this boundary (depends on PV share and any grid backup).
Energy bill reduction for the operator at the same distance.	%ΔCost = 1 − ($Cost_{H2}$ / $Cost_{Diesel}$).	36% (6,768 € vs 10,586 €).
Increase in RES energy self-consumed / locally used	MWh	+5,401.42 MWh vs baseline
Reduction in environmental footprint (net annual emissions)	%	+550.61% vs baseline

The mobility-focused analysis of the Geneva localized hydrogen ecosystem provides a comparative techno-economic and environmental assessment within an industrial park context. By benchmarking a fuel-cell electric vehicle (FCEV) against a conventional diesel alternative under high-mileage duty cycles (91,481 km annually), the framework quantifies a 36% reduction in annual energy costs, which fall from €10,586 to €6,768. Environmentally, the evaluation suggests an almost complete elimination of operational CO_2 emissions, avoiding 14,980 kg of CO_2 annually per vehicle. These results confirm the techno-economic viability of green hydrogen production and dispensing for industrial mobility. The results in Table 7 verified the framework's capacity to identify how localized hydrogen solutions can effectively decarbonize intensive transport services while achieving significant operational cost parity.

5. Conclusions

This paper presented a dynamic LCA/LCC framework for the evaluation of energy storage systems in multi-vector energy environments. The proposed assessment framework addresses basic limitations of conventional static approaches by integrating high-resolution temporal modelling with a dual-path architecture that combines data-driven and model-driven inputs within a unified life cycle framework. This structure successfully combines data-driven empirical measurements with model-driven scenario inputs, enabling a comprehensive life cycle evaluation under varying conditions of data availability.

The proposed framework was applied to six demonstration sites from the 'SINNOGENES' project which correspond to an industrial microgrid, a research facility, a LEC, an industrial site, an islanded grid, and a local H_2 ecosystem for decarbonisation of mobility. The different technical characteristics of the six demonstration sites confirm the framework's scalability and adaptability. By systematically evaluating specific economic and environmental KPIs, the results demonstrate that capturing dynamic system behavior significantly improves the accuracy of sustainability assessments. The representation of time-dependent interactions between renewable generation, load demand, and storage operation, assists the evaluation framework in capturing effects that are not reflected in traditional methodologies based on annual averages.

The KPIs assessment results presented in section 4 indicate that the integration of energy storage technologies consistently enhances RES self-consumption and yields substantial environmental footprint reductions across all tested scenarios. However, the economic benefits, that are expressed through energy bill reductions, ROI, NPV, and IRR, are more context-dependent, relying heavily on local market conditions, electricity tariffs, and the operational characteristics of the storage assets, such as round-trip efficiency. Furthermore, the results highlight the necessity of integrated assessment approaches for multi-vector systems, where interactions between different energy carriers introduce additional complexity.

Overall, the proposed LCA/LCC framework provides a robust and flexible tool for the sustainability assessment of modern energy systems, supporting informed decision-making in system design and operation, and optimal investment planning. Future work will focus on extending the methodology to include more advanced operational strategies, uncertainty analysis, and the integration of additional sustainability dimensions, such as social impact indicators.

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Nomenclature

C	cost of energy, €
CF	cashflow, €
CO_2	carbon dioxide emissions, kg
DOD	depth of discharge, %
E	energy, kWh (or MWh)
$ECRed$	energy cost reduction, %
EF	emission factor, $kgCO_2/MWh$
$EnvF$	environmental footprint reduction, %
H	average number of hours, h
I	life cycle impact, various units
$Investment$	initial investment cost, €
IRR	internal rate of return, %
N	number of energy carriers, dimensionless
n	project lifetime, year
NPV	net present value, €
P	power quantities, MW
p	electricity tariff, €/kWh
r	discount rate, %
RES	renewable energy sources, dimensionless
ROI	return on investment, %
SOC	state of charge, %
T	total time steps, dimensionless
t	time index or time steps, dimensionless

Greek symbols

a	coefficient, dimensionless
Δ	difference or change, dimensionless

Subscripts and superscripts

base	baseline scenario
bat	battery
cap	capacity
ch	charging
dis	discharging
emb	embodied
eol	end-of-life
exp	exported
i	index for energy carrier or year
imp	imported
month	monthly
op	operational
peak	peak demand
red	reduction
upg	upgrade scenario
rep	replacement

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