A Social Cost–Benefit Analysis of Energy Storage Systems on the Island of Tilos:

Evaluating Vanadium Flow Battery and Hydrogen Storage as an Alternative

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TUDelft

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by

Nikolaos Tsitsimpakos

in partial fulfillment of the requirements for the degree of **Master of Science** in
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TU Delft

Preface

The island of Tilos being a leader in the energy transition of islands in Greece and, by extension, the whole Mediterranean has been a fascinating fact to me for a while. Such a small, relatively not well known island, being at the vanguard of clean energy integration piqued my curiosity and inspired me to ask questions. What if the energy storage system installed on the island could be improved? What if a different configuration could optimize its operation? Could a similar energy storage system be successfully installed at other larger, more touristic islands? Driven by these questions, I suggested this thesis topic to Dr. Jan Anne Annema.

Throughout the entire duration of my thesis, I was fortunate enough to receive guidance and assistance whenever I requested it. I would like to take a moment to express my gratitude for this guidance to my main supervisor and committee chair, Jan Anne Annema, for always being available and making time for me and my questions. His advice has helped me greatly to bring this thesis to completion. Moreover, I would like to thank my supervisor and profile leader, Linda Kamp, for offering much needed guidance in issues regarding the thesis itself, as well as procedural ones.

Finally, I would like to thank my family, friends and colleagues, who have all supported me throughout this entire process, checking up on me and lending a sympathetic ear whenever I needed to get things off my chest and release some tension. Completing this master's program was not an easy task, but it was an enriching one, and it would not have been possible without them by my side.

All that being said, it is my pleasure to present my thesis. I hope it proves to be interesting and insightful.

Nikolaos Tsitsimpakos
Delft, September 2025

Summary

The decarbonization of island energy systems presents unique challenges due to their geographical isolation, limited grid capacity and high reliance on imported fossil fuels. On Greek non-interconnected islands, such as Tilos, integrating high shares of renewable energy requires advanced storage solutions to balance variable generation with fluctuating demand. The TILOS project, one of the first microgrid demonstrations in Europe, has already established the island as a testbed for innovative storage solutions. Currently, Tilos operates with a sodium–nickel chloride ($NaNiCl_2$) battery system, which provides reliable but limited flexibility for long-duration storage. This thesis investigates whether an alternative hybrid configuration combining vanadium redox flow batteries (VFBs) with hydrogen storage (H-BESS) can deliver greater societal value. To do so, it applies a full Social Cost-Benefit Analysis (SCBA) framework, extending beyond conventional techno-economic evaluation to incorporate environmental and social externalities.

The methodological approach builds on established SCBA literature, in particular the nine-step framework of Boardman et al. (2018) and the Dutch CPB/PBL guidance for cost-benefit analysis (Romijn & Renes, 2013). The central decision metric is Net Social Benefit (NSB), defined as the discounted stream of benefits minus costs over a 15-year horizon at a baseline social discount rate of 4%. To complement NSB, the Levelized Cost of Storage (LCOS) is calculated to benchmark the direct economic competitiveness of storage technologies in €/MWh delivered. The analysis further incorporates social indicators, including avoided CO_2 emissions, energy autonomy, resilience, and employment effects, which are monetized where possible. Where monetization was not feasible, such as with certain international externalities, qualitative discussion is provided.

The computational model was implemented in MATLAB R2023b, simulating one full year at hourly resolution (8,760 steps). Load demand for Tilos was synthesized based on SCADA records from 2015–2019, producing a representative annual demand of 3,108 MWh with realistic seasonal variation: lower winter loads and significantly higher summer peaks due to tourism. Renewable generation inputs were derived from PVGIS solar irradiance and Renewables.ninja wind datasets for Tilos' coordinates, yielding 2,553 MWh of annual RES supply (276 MWh PV and 2,276 MWh wind). System configurations were modeled for the baseline $NaNiCl_2$ battery (2.88 MWh, 1.0 MW) and the hybrid VFB–H_2 system (4.0 MWh VFB at 1.5 MW, 12 MWh hydrogen storage with a 0.12 MW electrolyzer and 0.06 MW fuel cell). Component efficiencies, lifetimes, and CAPEX/OPEX assumptions were sourced from IEA, IRENA, PNNL, and peer-reviewed literature, with learning rates applied to capture cost reduction trajectories over time.

Three internally consistent scenarios were defined to capture key uncertainties. The pessimistic case assumes higher capital costs, lower efficiencies, slow technology learning (VFB 5%/yr, electrolyzers 3%/yr, fuel cells 2%/yr), and low carbon prices (€50/tCO_2). The balanced scenario reflects current market projections and moderate learning rates (10%, 8%, 5% respectively) with a €90/tCO_2 price. The optimistic scenario models rapid cost declines (15%, 12%, 8%), favorable policy support, and a high carbon price (€150/tCO_2). These scenarios were supplemented with targeted sensitivity analyses, including one-way parameter variations and an enhanced tornado analysis ranking the most influential uncertainties.

The results show that the hybrid VFB–H_2 system achieves higher renewable energy utilization than the incumbent $NaNiCl_2$ system (90.1% vs. 85.4%), reduces curtailment by 118 MWh/year, and improves energy autonomy (69.8% vs. 69.0%). However, the hydrogen subsystem exhibits relatively low utilization: only 7.4% capacity factor with 39 MWh/year discharged, though 47 MWh/year of excess hydrogen is available for alternative applications. These alternative uses—maritime, transport, industrial sales, and inter-island export—are valued at approximately €8,424/year, contributing significantly to social benefits. Economically, the hybrid system outperforms $NaNiCl_2$ under balanced and optimistic conditions. LCOS is €510/MWh (balanced) and €263/MWh (optimistic) compared to €656–555/MWh for

$NaNiCl_2$. NSB is negative in the pessimistic case (–€156k) but positive in the balanced (+€465k) and optimistic (+€990k) scenarios, highlighting the importance of technology cost reductions and market conditions.

Sensitivity analysis reveals that the dominant factor influencing NSB is VFB capital cost, with ±30% variation producing a swing of ±€600,000—128% of the base NSB. Hydrogen hardware costs rank second (±€120,000), while learning rates, energy prices, and carbon prices exert smaller but non-negligible impacts. Importantly, no single parameter within tested ranges can render the project unviable, indicating robustness. A risk assessment shows limited downside exposure (–€92k maximum combined loss) against symmetric upside potential (+€93k), producing a balanced risk–reward profile. Compared to other uncertainties, load profile variation was tested separately (±15% demand → ±€45k NSB) and found to be modest, so it is considered encompassed within the broader scenario bounds.

Beyond economics, the hybrid system contributes measurable environmental and social benefits. Annual CO_2 reductions reach 19.2 tCO_2, with an additional 2 tCO_2/year from hydrogen substitution in alternative sectors. Over 15 years, this corresponds to 289 tCO_2 avoided, equivalent to removing four cars annually from circulation. Employment effects are limited in absolute scale but positive, with local CAPEX shares translating into small numbers of FTE-years valued at €32,000–45,000 per year. Resilience benefits are monetized at €0 because the hybrid system provides no additional firm capacity beyond baseline reliability requirements, but the methodology remains in place for future cases. International externalities are acknowledged qualitatively, including potential global cost spillovers from VRFB deployment and upstream impacts of vanadium mining and electrolyzer manufacturing. End-of-life recycling benefits range from €-9,953 to €+2,413, with VFB's superior material recoverability providing circular economy advantages through 95-100% vanadium recovery rates.

The thesis makes two key contributions. First, it extends island energy storage evaluation beyond conventional techno-economic metrics by implementing a full SCBA framework that monetizes environmental and social externalities. Second, it demonstrates that hybrid VRFB–H_2 systems can deliver superior social value compared to incumbent $NaNiCl_2$ storage under realistic cost trajectories, provided VFB costs decline as expected.

Table 1: Comprehensive SCBA Results Summary - All Scenarios and Configurations

Component	Unit	$NaNiCl_2$ Baseline			Hybrid VFB-H_2 Intervention		
		Pess.	**Bal.**	**Opt.**	**Pess.**	**Bal.**	**Opt.**
COSTS (15-year NPV)							
Capital Expenditure	€	1,871,000	1,871,000	1,871,000	2,847,200	2,265,600	1,684,000
Operational Expenditure	€	243,750	243,750	243,750	389,340	311,472	233,604
Replacement Costs	€	0	0	0	156,800	125,440	94,080
End-of-Life Disposal	€	34,560	34,560	34,560	24,607	31,305	32,147
Total Costs	€	**2,149,310**	**2,149,310**	**2,149,310**	**3,417,947**	**2,733,817**	**2,043,831**
RELATIVE BENEFITS OF INTERVENTION SCENARIO (15-year NPV)							
Fuel Savings	€	–	–	–	50,409	47,648	33,613
CO_2 Emissions Value	€	–	–	–	10,503	18,919	31,533
Energy Autonomy Premium	€	–	–	–	2,808	7,019	11,210
H_2 Alternative Revenue	€	–	–	–	92,010	92,010	92,010
Resilience Value	€	–	–	–	0	0	0
Total Benefits	€	**0**	**0**	**0**	**155,730**	**165,596**	**168,366**
NET POSITIONS							
System Net Cost/Benefit	€	-2,149,310	-2,149,310	-2,149,310	-3,262,217	-2,568,221	-1,875,465
Relative NSB (Hybrid - Baseline)	€	**0**	**0**	**0**	**-156,473**	**+465,381**	**+990,134**

Contents

List of Figures

List of Tables

Nomenclature

Abbreviations

Abbreviation	Definition
BESS	Battery Energy Storage System
CAPEX	Capital Expenditure
EAI	Energy Autonomy Index
EU ETS	European Union Emissions Trading System
H-BESS	Hybrid Battery–Hydrogen Energy Storage System
LCOS	Levelized Cost of Storage
LPSP	Loss of Power Supply Probability
$NaNiCl_2$	Sodium–Nickel–Chloride Battery (Zebra battery)
NECP	National Energy and Climate Plan (Greece)
NSB	Net Social Benefit
OPEX	Operational Expenditure
PHS	Pumped Hydro Storage
RES	Renewable Energy Sources
SCBA	Social Cost–Benefit Analysis
VFB	Vanadium Flow Battery
VoLL	Value of Lost Load
VRFB	Vanadium Redox Flow Battery

Symbols and Parameters

Symbol	Definition	Unit
B_t	Monetized benefits in year t	€
C_{cap}	Capital cost	€
C_{elec}	Electrolyzer CAPEX	€/kW
C_{fc}	Fuel cell CAPEX	€/kW
C_{op}	Operational cost per year	€/year
C_{rep}	Replacement cost	€
C_t	Monetized costs in year t	€
C_{tank}	Hydrogen storage CAPEX	€/kg-H_2
d	Annual degradation rate	%/year
$E_{\text{disch},t}$	Energy discharged in year t	MWh
EF_{diesel}	Diesel emission factor	tCO_2/MWh
FTE	Full-time equivalent employment	–
h_{out}	Duration of outage	h/event
LPSP	Loss of Power Supply Probability	–
N_{out}	Number of outage events per year	events/year
$P_{CO_2,t}$	Carbon price in year t	€/tCO_2
p_{diesel}	Diesel price	€/L
r	Social discount rate	–
S	Residual value	€
T	Project lifetime	years
v_{FTE}	Value per FTE-year	€/year
VoLL	Value of Lost Load	€/MWh
Z_α	Z-score (confidence level)	–
ΔE_t	Emissions reduction vs. counterfactual	tCO_2

$\eta_{\mathrm{H_2}}$	Round-trip efficiency of H_2 subsystem	%
η_{VFB}	Round-trip efficiency of VFB	%
σ_{B-C}	Standard deviation of $(B_t - C_t)$	€

1 Introduction

At the global level, the energy scene is fast changing towards decarbonization, with storage systems steadily becoming the center stage, providing much needed flexibility at various time-scales (European Association for Storage of Energy, 2025). Storage technologies have ceased to be viewed as mere complements to renewable energy systems and are now rather being seen as enablers of flexibility, resilience, and sustainability in modern power grids. Hybrid renewable energy systems (RES) supported by storage not only improve power quality and operational flexibility in distributed systems, by eliminating the intermittent power generation structure of such systems, but also reduce the need for costly infrastructure upgrades and fossil-fuel-based plants (Aktaş, 2021). This change is of particular relevance to islands that are isolated and vulnerable energy systems, where the problems of intermittency, energy security and infrastructure limitations present themselves more intensely (Psarros & Papathanassiou, 2022). In this background, decision-makers stand beyond merely technical and economic trade-offs and must consider some societal and environmental issues as well.

The societal challenge driving this research stems from the urgent need to balance energy transition goals with energy security and affordability, particularly in vulnerable communities. Small island developing states and remote communities face a critical dilemma: while they are often most exposed to climate change impacts and energy supply vulnerabilities, they also face the highest costs and technical barriers in transitioning to sustainable energy systems. The European Union's commitment to achieve climate neutrality by 2050, combined with the REPowerEU plan's emphasis on energy independence following recent geopolitical disruptions, has intensified the need for evidence-based decision-making tools that can evaluate energy infrastructure investments from a comprehensive societal perspective (European Commission, 2021). This creates an urgent requirement for analytical frameworks that can systematically compare emerging energy technologies while accounting for their full spectrum of societal impacts, extending beyond traditional financial metrics to include environmental externalities, energy security benefits, and community welfare effects.

This thesis stands in the junction of energy technology, policy analysis and sustainability assessment. It intends to make the decision-making process more informed by performing a full Social Cost-Benefit Analysis (SCBA) for the analysis of two alternative energy storage configurations for the island of Tilos in Greece. That is to say, by quantifying and comparing in monetary terms all societal costs and benefits, including economic, environmental externalities, and long-term benefits to the system, the present study tries to find a society focused solution to the question of which alternative is better. In this way, it tackles both immediate issues and larger questions regarding the future of energy storage for decentralized, renewable-based power systems.

1.1. Background and motivation

The demand for dependable and effective energy storage solutions has increased due to the quickening shift to renewable energy. Storage technologies are crucial to maintaining grid stability, balancing supply and demand and promoting energy autonomy as variable sources like wind and solar power progressively replace fossil fuel-based generation, especially in isolated or remote areas. Islands like Greece's Tilos stand out among these because of their remote location, reliance on imported fossil fuels and wealth of renewable energy availability.

By combining solar, wind and battery storage technologies, more specifically, using sodium nickel chloride ($NaNiCl_2$) batteries (Eunice Group, 2024), Tilos has already garnered attention for being a leader in renewable energy integration. Beyond the power industry, new technologies like hydrogen-based storage systems may provide benefits in the areas of scalability and seasonal storage. It is both timely and policy-relevant to reevaluate the ideal configuration for island energy storage in light of the EU's and Greece's tightening climate targets and changing energy strategies (Hellenic Republic - Ministry of Environment and Energy, 2024).

1.2. Research Gap and Relevance

Few studies have used a Social Cost-Benefit Analysis (SCBA) framework to evaluate battery and hydrogen systems in actual island contexts, despite the growing number of techno-economic comparisons between these systems in academic literature. There have been studies published which perform cost comparisons between such systems in island contexts, none of which however take into account the social impacts and how these translate into monetary terms (Damato et al., 2022; X. Zhang et al., 2022). These societal and environmental effects are crucial for infrastructure planning and public investment, such as emissions, land use and energy security. Other studies explore the integration of green hydrogen as seasonal storage for the decarbonization of islands (Superchi et al., 2025). Although their case study emphasizes the strategic role of hydrogen in enabling energy independence, it does not evaluate non-market benefits in monetary terms, such as reduced dependence on diesel imports or improved grid resilience. A wide array of studies has focused on the operational challenges of energy storage systems on insular grids (Misic et al., 2025; Palys & Daoutidis, 2024), which of course have an impact on the cost of such systems. By performing a thorough SCBA of two rival energy storage systems on Tilos Island, the currently operational $NaNiCl_2$ system and a suggested hybrid hydrogen–battery configuration, this study aims to close that gap.

1.3. Research Objectives and Questions

The main objective of this thesis is to evaluate and compare the societal value of an alternative energy storage solution for Tilos Island through comprehensive Social Cost-Benefit Analysis. The specific goals are:

- To conduct a detailed technical and economic assessment of the existing 2.88 MWh $NaNiCl_2$ (Zebra) battery system currently operational on Tilos Island, including its performance characteristics, operational costs, and lifecycle impacts.
- To design and evaluate a hybrid energy storage alternative comprising 4.0 MWh Vanadium Flow Battery (VFB) capacity and 12 MWh hydrogen storage system (0.12 MW electrolyzer, 0.06 MW fuel cell), optimized for seasonal energy balancing and alternative revenue generation.
- To quantify and monetize the full range of societal costs and benefits associated with both systems, including capital and operational expenditures, avoided fossil fuel imports, CO_2 emissions reductions, energy autonomy premiums and hydrogen alternative application revenues.
- To identify the energy storage configuration with the highest net societal benefit under three scenarios (pessimistic, balanced, optimistic) incorporating technology learning rates, market development uncertainties and policy variations.
- To provide evidence-based policy recommendations for energy storage investments on Greek islands and similar small island developing states facing comparable energy security and sustainability challenges.

System boundaries: The system boundaries of this analysis encompass the full 15-year lifecycle of the energy storage technologies being compared: the existing NaNiCl2 battery system (2.88 MWh, 800 kW discharge) versus a hybrid Vanadium Flow Battery (VFB) and hydrogen storage configuration (4.00 MWh VFB + 12 MWh hydrogen storage capacity). The analysis covers capital investment, installation, operational, maintenance, and decommissioning stages. The geographic scope is limited to Tilos Island, while the societal perspective includes impacts on local residents, broader Greek society, system operators, and future generations, consistent with national SCBA guidelines. Externalities such as emissions, grid resilience, and energy autonomy are monetized where feasible within the SCBA framework. International externalities beyond Greek jurisdiction are qualitatively discussed but not monetized. These boundaries are detailed further in Chapter 4 but are introduced here to clarify the analytical scope from the outset.

Main research question: How does a hybrid hydrogen–VFB energy storage system compare to the existing $NaNiCl_2$ configuration on Tilos Island in terms of technical performance, economic viability and societal value?

Sub-questions:

- What are the main technical and economic characteristics of the current $NaNiCl_2$ system?
- What benefits and costs arise from integrating hydrogen storage with VFB batteries?
- What are the key social and environmental impacts of each configuration?
- How do these impacts compare under different future cost and performance scenarios?

1.4. Case Study Context: Tilos Island

Tilos is a small island in the southeastern Aegean Sea, located between the islands of Kos and Rhodes. With a surface area of 61 km^2 and a permanent population of around 500 residents (which increases drastically during the summer peak tourism season), the island has long faced challenges typical of remote island energy systems: reliance on fossil fuel imports, high electricity costs and frequent supply disruptions due to dependence on an undersea cable from the neighboring island of Kos (Li, 2022).

Historically, Tilos received electricity via a submarine cable built in 2010, linking it indirectly to oil-fired power stations on Kos (Li, 2022). This connection proved unreliable and costly, as interruptions were frequent and during severe cable damage in 2016, the island had to rely solely on a backup diesel generator for two weeks, which local residents are not licensed to operate (Li, 2022). The cost of generation was also unsustainable, with generation costs in the Aegean islands rangin from €300 to over €1,000 per MWh and being heavily subsidized by mainland consumers (Li, 2022). Furthermore, on the nearby islands of Kos and Kalymnos, installed wind farms were subject to high curtailment rates, due to the already high saturation levels of the local grid (Kaldellis, 2021), something that could be partially remedied by storage implementation.

In response to these challenges, the island became the demonstration site for the TILOS project (Technology Innovation for the Local Scale, Optimum Integration of Battery Energy Storage), funded under the EU Horizon 2020 program and led by Eunice Energy Group (Eunice Group, 2024), with a total cost of over €13 million, more than €11 million of which was contributed by the EU (European Commission, 2020). Between 2015 and 2019, the project implemented a hybrid renewable energy system combining wind, solar PV, and an innovative $NaNiCl_2$ (Zebra) battery storage system, the first of its kind in Greece. The battery system included two subsystems, each with 1.44 MWh of storage and 400 kW of power and was capable of operating both in grid-connected and islanded modes.

The technological innovations were paired with community engagement and demand-side measures, including smart meters and public information campaigns. Local citizens played an active role in the design and acceptance of the system. Notably, the project achieved over 50% local renewable energy penetration during its first full year of operation and demonstrated the ability to cover 70–75% of electricity demand under optimal conditions. This was possible, because of the island's excellent photovoltaic power and wind power potential, which can be seen in Figures 1.1 and 1.2 respectively. It also allowed for a reduction in energy costs and blackouts while cutting emissions associated with diesel generation.

Tilos has since been recognized as a European leader in sustainable island electrification. It won two EU Sustainable Energy Awards in 2017 (Best Energy Island Project and Citizens' Award), and it is seen as a model for replication in other island and remote communities. Its experience underscores the importance of combining technical innovation, policy support and public participation to achieve resilient and decarbonized energy systems in insular settings.

The reason why Tilos was specifically chosen, is due to its existing innovative $NaNiCl_2$ battery system, which makes it a unique real-world testbed for energy storage systems. Additionally, the island's progressive renewable energy policies and its replicability to similar island contexts in Greece and the broader Mediterranean region significantly enhance the practical relevance of this case study.

Figure 1.1: Photovoltaic power potential in Greece. Tilos island is denoted with a red circle. (Global Solar Atlas, 2025)

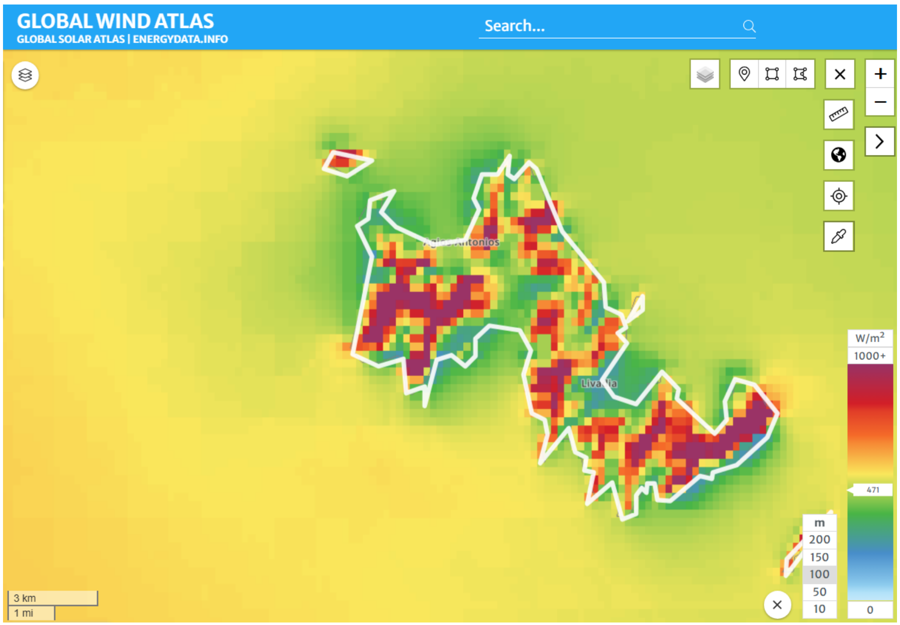

Figure 1.2: Wind power potential on Tilos island. (Global Wind Atlas, 2025)

Justification for Comparing the Two Systems

The comparison between the existing $NaNiCl_2$ battery system and a hybrid hydrogen–VFB energy storage system is motivated by both technical and contextual factors. $NaNiCl_2$ technology, while operationally robust, operates at high temperatures and is gradually being phased out in favor of newer technologies with higher energy densities and improved flexibility. Moreover, their production capacities are not scaled-up, resulting in currently higher costs compared to other storage technologies (Nikolic et al., 2023). Meanwhile, hybrid systems that combine hydrogen with batteries have shown promising results in improving renewable energy utilization, especially in insular microgrids with seasonal demand variations (Ibrahim et al., 2021; X. Zhang et al., 2022). The flow batteries were chosen as the preferred battery technology, because of their very low degradation rate and their incorporation of electrolyzers, which complements the hydrogen storage nicely (Rubio-Garcia et al., 2020). This thesis aims to assess whether substituting the existing system with a more flexible hybrid configuration would yield greater social and environmental benefits, using a Social Cost-Benefit Analysis (SCBA) framework.

1.5. Structure of the report

This report is organized as follows:

- **Chapter 2** describes the methodology and SCBA framework employed.
- **Chapter 3** presents a literature review of storage technologies, economic and technical analyses concering them and relevant studies.
- **Chapter 4** develops the conceptual model and defines the analytical scope.
- **Chapter 5** presents the model used and the results of the SCBA and sensitivity analyses.
- **Chapter 6** discusses the results, the implications and limitations of the findings.
- **Chapter 7** concludes with final insights and recommendations.

2
Methodology

In this chapter, the overarching methodology of social cost-benefit analysis used in this thesis is analyzed. This thesis conducts an ex-ante Social Cost-Benefit Analysis (SCBA) of two energy storage configurations for Tilos Island: the existing $NaNiCl_2$ battery system and a hypothetical hybrid hydrogen–vanadium flow battery (VFB) storage system. The methodology is based on internationally recognized frameworks, particularly the book ”Cost-benefit analysis Concepts and Practice” (Boardman et al., 2018) and the Dutch SCBA guidance by CPB/PBL (Romijn & Renes, 2013), with adaptation for energy systems and island infrastructure contexts.

Social Cost-Benefit Analysis (SCBA) was selected over other methodologies like Life Cycle Assessment (LCA) or Multi-Criteria Decision Analysis (MCDA) due to its comprehensive nature, monetization of diverse impacts and strong alignment with policy decision-making needs. Boardman et al., 2018 and Romijn and Renes, 2013 specifically endorse SCBA for infrastructure and policy assessments where monetizing broad societal impacts provides clear, actionable insights.

2.1. Analytical Approach

Following the nine-step process proposed by Boardman et al. (2018), this thesis evaluates the net social benefits (NSB) of the two alternatives using:

$$\text{NSB} = \sum_{t=0}^{T} \frac{B_t - C_t}{(1+r)^t}$$

where B_t and C_t are the societal benefits and costs at year t, and r is the social discount rate.

2.2. Alternatives Compared

- **Baseline (Reference Scenario)**: The current $NaNiCl_2$ storage system operating on Tilos, with 2.88 MWh capacity.
- **Alternative (Intervention Scenario)**: A redesigned storage configuration integrating vanadium flow batteries and hydrogen fuel cells for short- and long-duration storage, respectively.

The hybrid H-BESS system was selected based on its potential to combine the short-term efficiency and low degradation rate of vanadium flow batteries with the long-duration storage capacity of hydrogen, aligning with both technical needs and policy directions. Recent studies highlight the complementary benefits of this architecture in insular systems where renewable intermittency is high (Ibrahim et al., 2021; Żołądek et al., 2024). Moreover, hybrid systems align with Greece’s revised NECP targets, which call for increased electrolyzer deployment and hydrogen integration (Hellenic Republic - Ministry of Environment and Energy, 2024).

2.3. System Sizing Methodology

To ensure a meaningful and policy-relevant comparison, the hybrid hydrogen–VFB system is sized to optimize societal benefits while maintaining functional comparability with the existing $NaNiCl_2$ battery system currently installed on Tilos Island. Rather than exact capacity matching, the sizing approach prioritizes enhanced performance characteristics and improved renewable energy integration, reflecting realistic technology deployment strategies for island microgrids.

2.3.1. Sizing Philosophy and Approach

The sizing methodology departs from simple capacity matching in favor of performance optimization while maintaining overall system equivalence in terms of grid support functions. This approach recognizes that different storage technologies have distinct operational characteristics and that optimal sizing should leverage each technology's strengths rather than forcing artificial equivalence (Superchi et al., 2025).

The hybrid system design follows a complementary storage architecture where vanadium flow batteries (VFB) handle daily cycling operations with high efficiency, while hydrogen storage provides long-duration and seasonal energy balancing. This configuration aligns with best practices identified in recent hybrid microgrid studies (Trapani et al., 2024; X. Zhang et al., 2022).

Economic Justification for Capacity Enhancement

The decision to optimize the hybrid system for enhanced capacity rather than exact matching with the $NaNiCl_2$ baseline is justified by several factors specific to Social Cost-Benefit Analysis methodology and island energy system characteristics.

SCBA Optimization Principle: Following Boardman et al. (2018), SCBA seeks to maximize net social benefits rather than maintain artificial design constraints. The question is not whether systems have identical capacity, but which system configuration maximizes societal welfare given available technology options and island-specific constraints.

Technology Complementarity Rationale: The hybrid configuration leverages complementary technology characteristics that cannot be replicated through simple capacity scaling. The 4.0 MWh VFB capacity enables full utilization of VFB's zero-degradation properties for frequent cycling applications, while the 12 MWh chemical hydrogen storage provides seasonal balancing impossible with battery-only systems. Additionally, excess hydrogen production creates revenue streams that improve project economics and justify larger capacity investment.

Island-Specific Optimization Factors: Several island-specific factors justify the enhanced capacity approach. The baseline system curtails 371.8 MWh/year representing 14.6% of renewable generation, which constitutes wasted electricity and indicates significant opportunity for increased storage utilization. Seasonal demand variation presents another optimization opportunity, as summer demand of 1,262 MWh exceeds winter demand of 552 MWh by 129%, requiring seasonal storage capability absent in the baseline system. The tourism-dependent economy creates high value-of-service during peak periods, justifying investment in enhanced capacity for reliability improvements.

Economic Efficiency Argument: The larger capacity is economically justified through several mechanisms. Marginal cost of additional VFB capacity decreases with scale due to decoupled power and energy components, while hydrogen storage provides the lowest cost per MWh for long-duration applications. Enhanced renewable utilization improving from 85.4% to 90.1% generates sufficient additional value to justify the capacity premium, while alternative hydrogen applications create revenue streams unavailable to battery-only systems.

This approach aligns with SCBA best practices that prioritize welfare maximization over technical constraint matching (Romijn & Renes, 2013).

2.3.2. System Configuration

Vanadium Flow Battery (VFB) Subsystem

The VFB subsystem features 4.0 MWh usable energy storage capacity with 1.5 MW discharge capability. This larger capacity compared to the baseline $NaNiCl_2$ system (2.88 MWh) capitalizes on VFB's superior cycling characteristics and virtually negligible degradation properties. The 1.5 MW power rating exceeds the baseline 0.8 MW to improve renewable integration during high generation periods.

Hydrogen Storage Subsystem

The hydrogen storage subsystem provides 12.0 MWh chemical energy capacity through a 0.12 MW electrolyzer and 0.06 MW fuel cell configuration, delivering approximately 5.4 MWh usable output accounting for 45.4% round-trip efficiency. This sizing targets seasonal storage applications, with electrolyzer capacity optimized for surplus renewable energy capture during high-generation periods while the hydrogen subsystem provides long-duration backup during extended low-renewable periods.

Combined System Characteristics

The combined system delivers approximately 9.4 MWh total effective storage (4.0 MWh VFB plus 5.4 MWh usable hydrogen) with 1.56 MW peak discharge power (1.5 MW VFB plus 0.06 MW fuel cell). This represents a 227% increase in effective storage capacity while maintaining peak power characteristics that can cover similar percentages of the load.

2.3.3. Technology Selection Rationale

VFB Selection Over Lithium-Ion

The analysis initially considered lithium-ion batteries but ultimately selected vanadium flow batteries based on superior lifecycle characteristics for island applications. VFB technology offers 15-20 year lifespan compared to 10 years for lithium-ion, with virtually no capacity degradation versus 2-4% annual degradation for lithium-ion systems. Safety advantages include no thermal runaway risk, particularly important in isolated locations, while independent scaling of power and energy components provides superior scalability. Cost trajectories favor VFB for stationary applications, and the vanadium electrolyte offers 100% recovery and reuse potential compared to challenging and potentially hazardous lithium-ion battery recycling.

Hydrogen Integration Benefits

Hydrogen integration provides several unique benefits impossible with battery-only systems. Seasonal storage capability enables renewable energy storage across months, while excess hydrogen production creates opportunities for maritime fuel, transport fuel, and industrial applications. The hydrogen subsystem provides backup power during extended outages or maintenance periods, with scalability achieved through larger storage tanks without replacing core equipment.

2.3.4. Performance Optimization Criteria

Primary Optimization Objectives

The system sizing targets four primary optimization objectives: maximizing renewable energy utilization through curtailment reduction, enhancing energy autonomy by improving independence from diesel generation and mainland grid imports, minimizing lifecycle costs by optimizing total cost of ownership over the 15-year horizon, and improving system reliability through reduced Loss of Power Supply Probability (LPSP).

Operational Strategy

The operational strategy assigns complementary roles to each storage technology. The VFB subsystem handles daily cycling, high-frequency regulation, and immediate response to load/generation imbalances, while hydrogen storage provides seasonal storage, long-duration backup, and renewable surplus monetization. Coordinated operation through intelligent dispatch algorithms prioritizes VFB for efficiency while utilizing hydrogen for applications where its characteristics provide advantage.

2.3.5. Sizing Methodology and Constraints

Design Constraints

The sizing methodology operates within several key constraints derived from the Tilos Island context. Limited land area of 61 km² constrains system footprint, while grid compatibility requirements demand integration with existing renewable generation from wind and PV sources. Load characteristics necessitate accommodation of seasonal tourism variations and baseline residential demand, while technology maturity requirements ensure components are commercially available and proven for island deployment.

Sizing Principles

The hybrid system sizing follows four established microgrid design principles: deploying complementary technologies where VFB handles high-frequency daily cycling while hydrogen provides long-duration storage, optimizing renewable energy maximization through sizing that minimizes curtailment during peak generation periods, ensuring load security through sufficient capacity to maintain critical loads during extended low-renewable periods, and achieving economic optimization by balancing capital costs against operational benefits over the system lifetime.

Component Sizing Logic

VFB Subsystem Sizing: VFB energy capacity is based on daily load cycling requirements and renewable generation patterns, with power rating sized to handle peak charge/discharge rates during renewable generation peaks. Capacity factor considerations ensure optimal utilization without oversizing.

Hydrogen Subsystem Sizing: Electrolyzer capacity is scaled to absorb renewable energy surplus during high-generation periods, while storage tank capacity is designed for seasonal energy transfer from winter surplus to summer deficit. Fuel cell power rating is based on backup power requirements during extended low-renewable periods.

2.3.6. Comparative Benchmarking

The sizing approach was informed by similar hybrid installations documented in literature. The Norwegian Islands Study (Trapani et al., 2024) demonstrates hydrogen necessity for high renewable penetration in island systems, while the Korean Island Deployment (X. Zhang et al., 2022) shows battery capacity optimization with hydrogen integration. The Italian Microgrid Case (Damato et al., 2022) validates seasonal hydrogen utilization patterns, providing confidence in the sizing methodology.

2.3.7. Sizing Assumptions and Limitations

Key Assumptions

Key assumptions include stable annual load with seasonal variations based on historical patterns, technology performance based on manufacturer specifications and literature-reported operational data, renewable generation using representative meteorological year data for wind and solar resources, and component lifetimes of 15-20 years for VFB, 15-20 years for fuel cells, and 10-15 years for electrolyzers.

Methodology Limitations

The methodology faces several limitations. Sizing optimization targets identified objectives but may not represent the global optimum, while future technology improvements are not fully captured in sizing decisions. Simplified dispatch logic may not capture all operational nuances that could affect optimal sizing.

Data Limitations and Validation Approach

Load Profile Synthesis: The analysis employs a synthesized load profile based on annual consumption data from Notton et al. (2020) and seasonal scaling factors from Kaldellis (2021), rather than detailed SCADA data from Tilos' actual operations. While this approach enables systematic analysis, it introduces several limitations. Hourly averages may not capture sub-hourly demand peaks that affect storage sizing, synthetic profiles cannot reflect actual demand response to storage availability, and inter-annual tourism variations are not captured in the baseline profile.

Impact on Results: Sensitivity analysis indicates that ±15% load or RES variation affects NSB by approximately €45,000, representing 9.7% of baseline results.

Renewable Generation Data: Meteorological data from PVGIS and Renewables.ninja provides representative year (2019) conditions but lacks interannual variability that could affect renewable output by ±10-15%, local microclimate effects including small-scale topographic influences on wind patterns, and equipment-specific performance including actual turbine/panel degradation and availability factors.

Validation Approach: Where possible, synthesized data is validated against published Tilos project performance reports, comparable Greek island energy systems (Symi, Astypalaia), and regional meteorological station records.

Residual Uncertainty: These data limitations contribute an estimated ±9.7% uncertainty band around central NSB estimates, explicitly captured in the enhanced sensitivity analysis.

2.3.8. System Boundaries and Functional Unit

Functional Equivalence and Service Delivery

While absolute storage capacity differs from the baseline (9.4 MWh vs. 2.88 MWh), the hybrid system provides equivalent or superior grid support functions across multiple dimensions.

Primary Grid Services Comparison: Peak power delivery improves from 0.80 MW to 1.56 MW, representing 95% improvement that enables better renewable integration. Duration coverage extends from 3.6 hours (2.88 MWh ÷ 0.80 MW) to seasonal timeframes, while grid services include enhanced frequency regulation, voltage support, and renewable integration capacity. Backup power capability increases from 2.53 MWh to 9.4 MWh usable, providing 6.3 hours versus 3.2 hours backup at average load.

Functional Enhancement Justification: The capacity increase serves specific functional purposes not achievable through simple scaling. Curtailment reduction improves from baseline 371.8 MWh/year to hybrid system 253.5 MWh/year, better utilizing available renewable resources. Seasonal balancing capability enables the hybrid system to transfer 34.5 MWh from low-demand to high-demand periods, while multiple revenue streams from hydrogen applications generate €7,776/year additional revenue. Technology risk diversification through dual storage technologies reduces single-point-of-failure risks compared to battery-only configuration.

Societal Value Optimization: The SCBA framework prioritizes configurations that maximize net social benefits rather than maintaining artificial design constraints. The enhanced capacity is justified because additional investment costs are less than additional social benefits generated, enhanced renewable utilization provides environmental benefits beyond baseline, alternative revenue streams improve project financial sustainability, and demonstration value for technology learning exceeds capacity-matched alternatives.

This approach follows established SCBA methodology where optimal system design maximizes welfare rather than matching incumbent technology specifications (Boardman et al., 2018).

Lifecycle Perspective

The sizing reflects a 15-year analytical horizon, accounting for technology replacement cycles where VFB requires maintenance versus $NaNiCl_2$ replacement at year 15, performance degradation that remains minimal for VFB/hydrogen versus gradual for $NaNiCl_2$, and market evolution including anticipated improvements in hydrogen technology costs and performance.

This optimized sizing approach ensures the comparative analysis reflects realistic deployment scenarios while maintaining methodological rigor for the Social Cost-Benefit Analysis framework.

2.4. Standing

The analysis adopts a national societal perspective, in line with CPB guidelines (Romijn & Renes, 2013), which recommend a national societal perspective that captures all stakeholder interests and relevant externalities in public project evaluation, including:

- Residents of Tilos and the broader Greek population,
- National energy policy objectives (e.g., NECP targets),
- Externalities such as emissions, avoided blackouts, and grid congestion.

International externalities (e.g., global CO_2 impacts) are acknowledged but not monetized.

Social Indicators Considered

To capture the social dimensions of energy storage on island systems, this thesis includes qualitative and quantitative indicators such as:

- **Energy Autonomy:** The ability of the island to function independently from mainland energy supply.
- **Resilience and Reliability:** Reduction in Loss of Power Supply Probability (LPSP).
- **Public Health and Environmental Impact:** Avoided emissions and associated social costs.
- **Employment and Capacity Building:** Local job creation, full-time equivalent (FTE) employment, and training benefits associated with storage system deployment, which is expertise not widely had in Greece.

These indicators complement the monetized costs and benefits in the SCBA and will be elaborated in Chapter 5.

2.5. Time Horizon and Discounting

- **Time horizon:** 15 years. This time frame aligns with the technical lifespan of the $NaNiCl_2$ system (European Association for the Storage of Energy (EASE), 2023) and captures major cost and degradation dynamics for both configurations. A longer horizon would introduce additional forecasting uncertainty, while a shorter horizon would neglect significant end-of-life impacts and secondary benefits such as emissions savings.
- **Discount rate:** 4% (with sensitivity testing at 2% and 6%). This discount rate is consistent with Dutch SCBA guidelines for public infrastructure projects (Romijn & Renes, 2013). This ensures intergenerational fairness while remaining sensitive to future uncertainties. The sensitivity range of 2%-6% captures the uncertainty band recommended by the European Commission for infrastructure cost-benefit analysis, reflecting different assumptions about long-term economic growth and risk premiums (European Commission, 2021; Romijn & Renes, 2013). This range encompasses both the lower bound used for long-term climate investments (2-3%) and higher rates applied in emerging technology assessments (5-6%).
- **Functional unit:** Storage system performance over lifecycle, referenced to MWh/year.

2.6. Data Sources

The computational model relies on a combination of project-specific data, international databases, and peer-reviewed literature. The key sources are summarized below:

- **TILOS Project Documentation:** Technical specifications of the existing $NaNiCl_2$ battery system, renewable generation profiles, and system integration details were taken from official project reports and associated publications (Kaldellis, 2021; Superchi et al., 2025).
- **Load and Renewable Profiles:** Hourly load data were constructed based on Tilos SCADA records (2015–2019) and scaled to 2019 representative demand. Renewable generation inputs were derived from the PVGIS database for solar irradiance and the Renewables.ninja platform for wind speeds at Tilos coordinates (Joint Research Centre, European Commission, 2023; Pfenninger & Staffell, 2016).
- **Technology Performance Parameters:** Electrolyzer and fuel cell efficiencies, stack lifetimes, degradation rates, and hydrogen storage performance were informed by IEA's Global Hydrogen Review (IEA, 2023), IRENA hydrogen cost outlooks (Ralon et al., 2017), and detailed stationary fuel cell market assessments (Cigolotti & Genovese, 2021).
- **Cost Data (CAPEX and OPEX):** Capital and operational expenditure assumptions for VFB, $NaNiCl_2$, electrolyzers, and fuel cells were sourced from IRENA cost benchmarks (Ralon et al., 2017), PNNL technology assessments (Pacific Northwest National Laboratory (PNNL), 2018), and comparative literature on learning curves and technology trajectories (McDonald & Schrattenholzer, 2003; Staffell & Green, 2009).

- **Market and Policy Parameters:** Energy price ranges reflect the documented production costs of Greek Non-Interconnected Islands (RAE annual reports) and European wholesale benchmarks (Regulatory Authority for Energy (RAE), 2025). Carbon prices follow the EU ETS market data series (Statista, 2025), with scenario ranges (50–150 €/tCO_2) aligned to CPB/PBL and European Commission guidance for cost-benefit analysis (European Commission, 2021; Romijn & Renes, 2013).
- **Social Indicators:** Valuations of resilience and Value of Lost Load (VoLL) follow the ACER methodology for reliability standards in Europe (for the Cooperation of Energy Regulators (ACER), 2020). Employment multipliers and full-time equivalent (FTE) valuations are based on Eurostat labour cost data for Greece (EUROSTAT, 2025). Energy autonomy premiums are drawn from European island energy studies and benefit-transfer approaches.
- **Comparative Case Studies:** To validate parameter ranges, results were benchmarked against hybrid storage and hydrogen integration projects in Norway, Italy, and South Korea, as well as EU project reviews on advanced storage for island microgrids (Trapani et al., 2024; X. Zhang et al., 2022).
- **Social Benefit Parameters:** Energy autonomy premiums (€10-40/MWh) based on benefit transfer from European island energy independence studies and revealed preferences from Greek island electricity pricing differentials relative to mainland rates.

2.7. Scenario Development

To address parameter uncertainty, three scenarios will be modeled:

Scenario	CAPEX/OPEX	Hydrogen Efficiency	Tech Lifetime	Emissions Price
Pessimistic	High	Low	Short	€50/tCO_2
Balanced	Median	Moderate	Standard	€75/tCO_2
Optimistic	Low	High	Extended	€100/tCO_2

Table 2.1: Scenario assumptions for sensitivity and robustness analysis.

The assumptions for the price of emissions is based on the data presented in Figure 2.1.

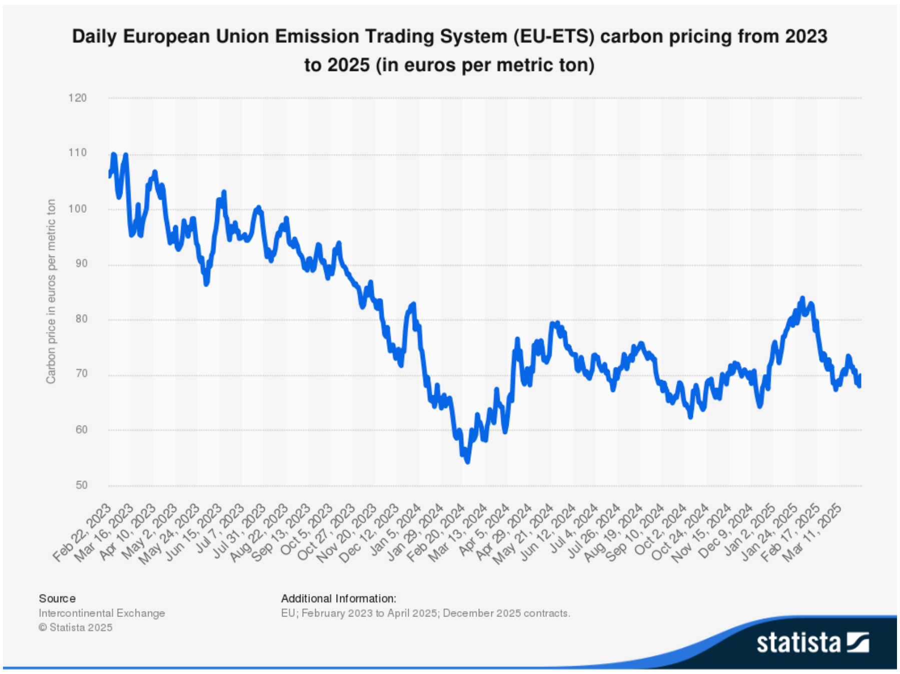

Figure 2.1: EU-ETS carbon pricing 2023-2025 (Statista, 2025)

The three scenarios, Pessimistic, Balanced and Optimistic, were selected to represent a policy-relevant range of plausible futures in line with SCBA best practices. Each scenario encapsulates uncertainty in technological maturity, cost evolution, system efficiency and regulatory conditions, all of which significantly influence the societal viability of energy storage systems on insular grids like Tilos. This structured scenario design ensures that the analysis is not only robust to uncertainty, but also useful for decision-makers under conditions of imperfect foresight. The inclusion of these distinct scenarios enables the evaluation of both the resilience and scalability of the proposed hybrid H-BESS configuration against a realistic backdrop of technical and policy variability.

2.8. Sensitivity Analysis

The sensitivity analysis evaluates the robustness of the SCBA results under varying assumptions for key uncertain parameters. The analysis employs the three-scenario framework (pessimistic, balanced, optimistic) implemented in the computational model, supplemented by targeted parameter variations to identify critical variables affecting the net social benefit comparison.

2.8.1. Primary Scenario Analysis

The main sensitivity analysis is conducted through three comprehensive scenarios that capture correlated uncertainties across multiple parameters simultaneously:

- **Pessimistic Scenario:** Conservative assumptions reflecting challenging future conditions for hybrid storage deployment
- **Balanced Scenario:** Most likely future pathway based on current industry projections and policy trends
- **Optimistic Scenario:** Favorable technological and policy developments supporting advanced energy storage

Each scenario incorporates internally consistent assumptions across technology costs, performance parameters, policy support levels, and market conditions, as detailed in Chapter 5.

2.8.2. Key Parameter Variations

Within the scenario framework, targeted sensitivity testing focuses on parameters with the highest potential impact on NSB outcomes:

Economic Parameters

- **Discount rate:** 2%–6% (baseline: 4%), testing the effect of different social time preferences on long-term investment attractiveness (choice of baseline and sensitivity range explained in subsection 2.5)
- **Technology CAPEX factors:** ±30% variation from baseline projections to capture market uncertainty and technology learning rates. This range reflects documented uncertainty in emerging energy storage technology costs, where IRENA reports cost variation ranges of 25-40% for flow batteries and 20-35% for electrolyzer systems across different market conditions and technology maturity levels (Ralon et al., 2017). The ±30% range aligns with established uncertainty analysis practices in energy system modeling, where Schmidt et al. document similar CAPEX uncertainty bands (±25-35%) for emerging storage technologies during market development phases (Schmidt et al., 2019). For comparison, IEA's Technology Roadmaps apply ±20-40% cost uncertainty ranges for hydrogen technologies, with higher uncertainty for less mature applications (IEA, 2023). The 30% variation also corresponds to observed price volatility in vanadium markets (the key cost driver for VFB systems), where vanadium pentoxide prices have historically fluctuated by 25-50% annually due to supply chain constraints (Rodby et al., 2020). This range provides conservative coverage of market uncertainty while remaining within bounds observed in comparable technology assessments for island energy systems (X. Zhang et al., 2022).
- **Energy pricing:** Diesel fuel costs (€0.80–€1.20/L) and grid import prices (€120–€180/MWh) reflecting volatile energy markets
- **Carbon pricing:** €50–€150/tCO_2 based on EU ETS forward projections (Statista, 2025)

Technical Parameters

- **VFB efficiency:** Round-trip efficiency variations (70%–90%) reflecting technology maturity and operational conditions
- **Hydrogen system efficiency:** Electrolyzer efficiency (80%–90%) and fuel cell efficiency (55%–65%) capturing technology advancement uncertainty
- **System lifespans:** VFB (15–20 years), fuel cell (15–20 years), electrolyzer (10–15 years) reflecting operational experience uncertainty
- **Degradation rates:** VFB degradation (0–2%/year) and electrolyzer performance decline (0.5–2%/year)

Social and Policy Parameters

- **Energy autonomy premium:** €20–€50/MWh reflecting varying social valuation of energy independence
- **H2 alternative revenue:** ±50% variation in hydrogen application pricing to test market development assumptions
- **Local employment multipliers:** Variation in job creation and economic impact assumptions

2.8.3. Implementation Approach

The sensitivity analysis leverages the existing computational model structure:

Scenario-Based Analysis

The three primary scenarios (pessimistic, balanced, optimistic) are implemented through the existing scenario parameter structures in the model, allowing comprehensive evaluation of correlated parameter changes that reflect realistic future conditions.

One-Way Parameter Testing

For critical individual parameters, the model performs targeted variations around the balanced scenario baseline to isolate parameter-specific impacts on NSB outcomes. This approach maintains computational efficiency while providing insights into key uncertainty drivers.

This analysis uses a one-at-a-time variation approach (tornado method), where each parameter is perturbed across its plausible range while holding others constant at the balanced scenario values.

The enhanced analysis complements the scenario-based approach by providing two additional insights. Firstly, a relative importance ranking, which Identifies which parameters (e.g., VFB CAPEX, H_2 subsystem costs, learning rates) exert the largest impact on NSB outcomes. Secondly, a robustness assessment, which highlights whether any single parameter variation can render the project unviable, thereby clarifying whether risks are dominated by market factors or by technology trajectories. This step ensures that the results are not only evaluated under correlated uncertainty bundles (pessimistic/balanced/optimistic), but also under isolated shocks to key drivers.

Break-Even Analysis

Critical threshold identification focuses on determining the conditions under which the hybrid system achieves positive NSB relative to the $NaNiCl_2$ baseline and policy interventions (subsidies, carbon pricing) tip the economic balance.

2.8.4. Uncertainty Propagation

The sensitivity analysis accounts for parameter interdependencies and uncertainty propagation:

Correlated Parameters

Technology cost reductions, performance improvements, and policy support levels are treated as correlated variables within scenarios to reflect realistic technology development pathways.

Risk Assessment

The analysis evaluates both upside potential and downside risk for the hybrid system investment, providing a comprehensive risk-return profile for decision-making under uncertainty.

This structured sensitivity approach ensures robust evaluation of the comparative SCBA while maintaining compatibility with the implemented computational model and providing actionable insights for technology selection and policy development.

3

Literature Review

The goal of this literature review is to evaluate and compare current storage technologies and identify case studies relevant to energy storage on island microgrids, with a focus on social and economic impacts. The first part of the review, which focuses on the various energy storage technologies, covers Pumped Hydro Storage (PHS), Battery Energy Storage Systems (BESS), hydrogen storage and hybrid configurations. The second part of the literature review aims to evaluate and compare current published research on the techno-economic and cost comparison of energy storage technologies, as well as research on energy storage in insular contexts. Keywords used during the literature search included: “energy storage island microgrids,” “$NaNiCl_2$ batteries”, ”Lithium-ion batteries”, ”Vanadium flow batteries”, ”vanadium flow redux batteries”, ” “hydrogen-battery hybrid”, “CBA energy systems”, ”CBA energy storage”, ”CBA hydrogen storage”, ”CBA batteries”, ”CBA hybrid storage system”, ”island microgrid energy storage”, ”vanadium slow battery storage economic analysis”, ”Tilos island” and “Tilos project.” Sources were identified using Scopus, ScienceDirect, Google Scholar, IEA, IRENA and EU Commission databases.

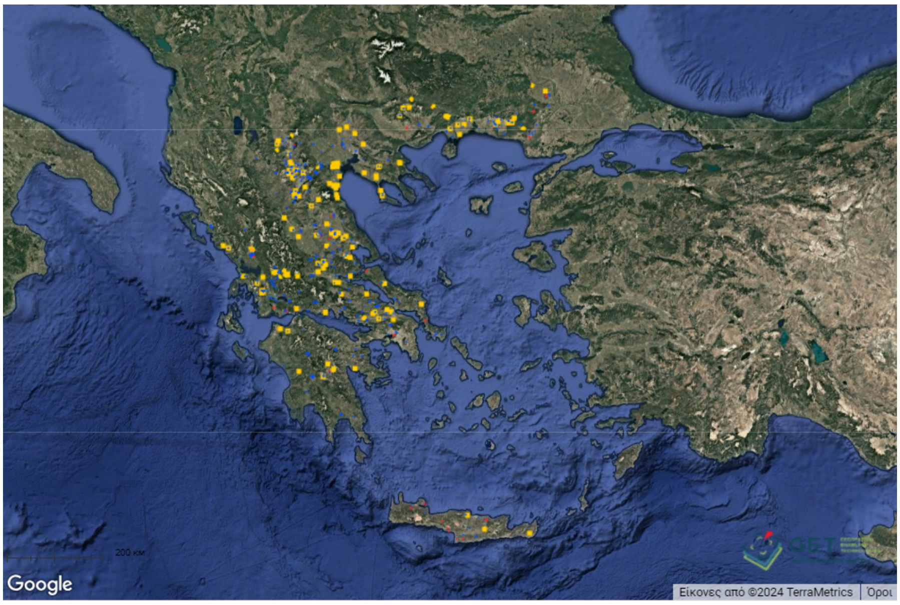

Figure 3.1: Geoportal of Greek Regulatory Authority of Energy (RAE). Yellow color signifies all installed or licensed energy storage units in Greece (Regulatory Authority for Energy (RAE), 2025)

3.1. Energy Storage Technologies

As renewable energy penetration increases globally, energy storage systems have become essential enablers of system flexibility, reliability and sustainability. Their role is particularly crucial in isolated or constrained grids, such as those on islands, where the integration of variable renewable energy sources like solar and wind would otherwise face significant challenges, since excess energy cannot be funneled to the main electrical grid of the country. Energy storage mitigates mismatches between generation and consumption, enhances the stability of the power system and allows for greater utilization of locally generated renewable energy.

This section reviews the primary technologies currently available for electricity storage in the context of island microgrids. Each technology is examined in terms of technical characteristics, scalability, efficiency and applicability in island environments. The review covers mature solutions such as pumped hydro storage (PHS), widely deployed battery energy storage systems (BESS), emerging hydrogen-based systems and hybrid configurations that combine complementary storage forms. The aim is to assess each option's relevance for decentralized renewable-based systems, using both global trends and Greek-specific data as reference points.

3.1.1. Pumped Hydro Storage (PHS)

PHS remains the dominant solution for large-scale, **long-duration** energy storage. In Greece, favorable geographical features make PHS a natural fit, with seawater-based systems showing particular promise for islands (Skroufouta et al., 2024). Research has highlighted that combining PHS with RES can achieve renewable penetration rates above 70% in insular grids, as demonstrated in specific case studies on Greek islands like Sifnos (Katsaprakakis et al., 2019). However, the high capital costs and site-specific environmental impacts of PHS remain barriers for this option (Psarros & Papathanassiou, 2022). In fact, quite a few of the energy storage units that can be seen in Figure 3.1 are PHS reservoirs, with some of the largest ones currently undergoing the licensing process, such as the massive 650 MW project in Amfilochia (Terna Energy, 2024). It has been remarked that a gradual development of hydro-pumped storage is essential to support large-scale wind and PV integration in Greece, largely due to favorable topography and the energy surplus in the country (Dianellou et al., 2021). Recently, there has been an increasing focus on modular PHS systems to minimize environmental impacts and adapt to diverse geographic conditions (Smith & Lee, 2025).

PHS will not be an alternative that will be studied for the island of Tilos, in the framework of this thesis. The justification behind this choice is that PHS requires significant elevation differences and substantial land area, with large water reservoirs, while Tilos is a very small island, with a total area of 61 km^2 and only reaches a maximum elevation of around 600 m, with most high-elevation locations having high incline and small surface area.

3.1.2. Battery Energy Storage Systems (BESS)

BESS technologies, especially lithium-ion batteries, have become a preferred choice for **short-term** energy storage due to their high efficiency and fast response times (Wang et al., 2024). Second-life batteries from electric vehicles have shown potential to reduce lifecycle costs and contribute to circular economy initiatives (Wang et al., 2024). The integration of BESS has also been shown to drastically lower the chance of loss of power supply probability (LPSP) (Irham et al., 2024), which can be considered a social benefit. Despite their benefits, the environmental impact of raw material extraction and end-of-life battery disposal poses challenges for scalability (Pelosi et al., 2023). In the specific case of Greece, BESS have become increasingly popular with investors during the past years, with most wind farm or PV projects incorporating BESS as an accompanying project. The reason for this is that the licensed RES projects far exceed the current grid capacity, with almost 68 GW of RES projects having applied for grid reservations, which the transmission and distribution grids cannot accommodate. This has led to many of these projects being scrapped in the past. Incorporating BESS as part of projects can help circumvent this bottleneck. In fact, central storage stations are now also starting to emerge. Furthermore, emerging technologies like solid-state batteries are gaining attention for their potential to enhance safety, energy density and lifecycle durability (Johnson & Kim, 2025).

The TILOS project currently employs $NaNiCl_2$ batteries, known for their thermal stability, lack of self-discharge, and reliable operation under harsh conditions (European Association for the Storage of

Energy (EASE), 2023). However, vanadium flow batteries (VFB) are increasingly preferred in energy storage applications due to their scalability, lower CAPEX and reusability (European Association for the Storage of Energy (EASE), 2023).

Vanadium Flow Batteries (VFBs)

Vanadium redox flow batteries (VRFBs) have emerged as one of the most promising technologies for large-scale, long-duration energy storage. Their defining characteristic is the decoupling of power and energy ratings: the electrochemical stack determines power capacity, while the size of external electrolyte tanks defines the energy capacity. This makes VFBs particularly attractive for applications where flexibility and scalability are required, such as island microgrids with varying seasonal demand (European Association for the Storage of Energy (EASE), 2023; Leba Akman et al., 2025).

VFBs exhibit several unique advantages compared to lithium-ion and sodium-based chemistries. First, their cycle life can exceed 13,000–15,000 cycles with operational lifetimes of up to 20 years, significantly outperforming Li-ion systems that typically last 3,000–5,000 cycles in deep-discharge stationary applications (Khaki & Das, 2023). They also allow for full depth of discharge without major degradation and are inherently safe, as the aqueous vanadium electrolyte is non-flammable. Moreover, because both half-cells use the same element in four oxidation states (V^{2+}/V^{3+} and VO_2^+/VO_2^+), cross-contamination does not cause permanent capacity loss; any imbalance can be corrected via electrolyte rebalancing, extending system resilience and reducing lifecycle costs (Leba Akman et al., 2025; Rodby et al., 2020). Vanadium can also be obtained as a byproduct from the mining of iron ore (Yuan et al., 2021), thus making the process of obtaining it more environmentally friendly that alternatives, such as lithium, which requires mining targetting it specifically.

However, VRFBs also face limitations. Their round-trip efficiency typically ranges between 70–80%, which is lower than Li-ion's 90–98% (European Association for the Storage of Energy (EASE), 2023; Uhrig et al., 2016). They also have relatively low energy density (10–25 Wh/L), requiring large tanks for multi-MWh applications, which restricts deployment in space-constrained environments like small islands (European Association for the Storage of Energy (EASE), 2023). Capital costs remain high, largely due to vanadium electrolyte price volatility and the cost of ion-exchange membranes. Recent studies emphasize the importance of reducing levelized cost of storage (LCOS) through improved membrane materials, optimized current density, and strategies such as electrolyte leasing and periodic rebalancing (Khaki & Das, 2023; Rodby et al., 2020).

Despite these challenges, VRFBs are increasingly being deployed globally, with over 300 MW of installed projects and multi-hundred-MWh facilities such as the 200 MW/800 MWh Dalian project in China (Rodby et al., 2020). Their long cycle life, high recyclability, and safety make them an environmentally sustainable alternative to lithium-ion in large-scale stationary applications, particularly where storage durations exceed four hours (Leba Akman et al., 2025). For Greek islands such as Tilos, their scalability and long-term durability present potential benefits, but their relatively low energy density and high capital cost may be barriers compared to lithium-ion and hybrid hydrogen-battery configurations.

Comparison of Battery Technologies

While several battery technologies offer potential for stationary energy storage, Vanadium Redox Flow Batteries (VRFBs) emerge as the most suitable replacement for the current $NaNiCl_2$ system deployed on Tilos, particularly when considered in a hybrid configuration with hydrogen.

$NaNiCl_2$ batteries, though resilient under harsh conditions, operate at high temperatures (270–350°C) and require internal heaters, which increase system complexity and reduce efficiency (European Association for the Storage of Energy (EASE), 2023). Lithium-ion (Li-ion) batteries have been the dominant choice for short- to medium-duration storage due to their high energy density (120–180 Wh/kg) and round-trip efficiency of up to 98% (European Association for the Storage of Energy (EASE), 2023). However, their limitations become critical in the context of isolated island microgrids such as Tilos. Li-ion systems typically degrade after 3,000–5,000 cycles and face safety risks linked to thermal runaway, as well as environmental challenges related to mining, recycling, and disposal of scarce raw materials such as lithium and cobalt (Khaki & Das, 2023; Pelosi et al., 2023). Their relatively short lifetime (around 5–10 years in stationary use) would necessitate costly replacements within the horizon of the Tilos project.

In contrast, VRFBs offer unique characteristics that make them more suitable for long-term, large-scale stationary applications. Their energy and power components are decoupled, allowing system designers to increase storage duration simply by enlarging electrolyte tanks (European Association for the Storage of Energy (EASE), 2023). They support full depth-of-discharge without performance loss, can achieve more than 13,000–15,000 cycles and lifetimes of up to 20 years, and allow recovery of lost capacity via electrolyte rebalancing, which reduces lifecycle costs compared to Li-ion (Khaki & Das, 2023; Rodby et al., 2020). Importantly, the aqueous vanadium electrolyte is non-flammable and fully recyclable, offering significant safety and sustainability advantages (Leba Akman et al., 2025). Although VRFBs have lower round-trip efficiency (70–80%) and lower energy density (10–25 Wh/L) compared to Li-ion, these drawbacks are less critical in an island context where space requirements are moderate and the priority is reliable, long-duration, and low-maintenance operation.

Other chemistries, such as Sodium-Sulphur (NaS), Nickel-Metal Hydride (NiMH), and lead-acid, are limited by either high-temperature operation, short cycle life, or poor energy density (European Association for the Storage of Energy (EASE), 2023). Emerging options like Lithium-Sulfur (Li-S), Sodium-ion (Na-ion), and Lithium-Metal-Polymer (LMP) remain at an early stage and lack commercial maturity for deployment in microgrids (European Association for the Storage of Energy (EASE), 2023).

Therefore, considering Tilos' need for a durable, safe, and sustainable storage technology that minimizes lifecycle costs and complements hydrogen for seasonal balancing, VRFBs represent the most future-proof alternative. Li-ion may offer higher efficiency and lower upfront costs, but VRFBs' longevity, recyclability, and resilience provide superior value over the long-term project horizon, making them the preferred choice for integration into the island's hybrid hydrogen–battery storage system.

3.1.3. Hydrogen Storage

Hydrogen storage offers unique advantages for **long-term** and seasonal applications. It has the potential to stabilize grids with high renewable penetration while decarbonizing hard-to-electrify sectors such as heavy industry (Koutsandreas et al., 2023). Studies have shown that integrating hydrogen storage into hybrid energy systems can reduce renewable energy curtailment and enhance grid reliability, though the high cost of hydrogen production and conversion efficiency losses remain key challenges (Żołądek et al., 2024). Hydrogen fuel cell storage has been found to further decrease LPSP when used in conjunction, although it also results in an increase of LCOE (Irham et al., 2024). In the case of Greece, hydrogen is not that prevalent yet. However, in the latest iteration of Greece's National Energy and Climate Plan (NECP), the goal for production of hydrogen was increased by 0.2 TWh to 1.2 TWh annually, and the goal for electrolyzer capacity was increased from 187 to 231 MW, showcasing that green hydrogen is now being seen as a bigger part of the country's plan for energy transition (Hellenic Republic - Ministry of Environment and Energy, 2024).

As can be seen in Figure 3.2, the cost of renewable hydrogen production, which is hydrogen produced via electrolysis with a connection to a renewable energy source, was 5.1€/kg. Recent advances in hydrogen compression and liquefaction technologies promise to make storage and transportation more efficient, which could significantly lower the cost of hydrogen infrastructure (Garcia & Tanaka, 2025).

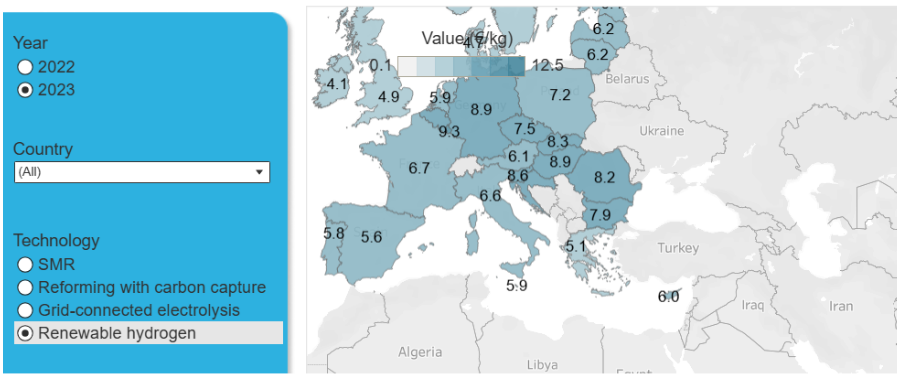

Figure 3.2: Map of levelized cost of renewable hydrogen production across Europe (Clean Hydrogen Observatory, 2025)

According to the recently adopted Greek Law 5215/2025 (Hellenic Republic, 2025), renewable hydrogen is formally defined as hydrogen produced through electrolysis powered exclusively by renewable sources, in line with EU Delegated Regulation 2023/1184. The law establishes a dedicated permitting framework, certification criteria (additionality, temporal and geographical correlation), and enables both investment and operational support schemes for renewable hydrogen projects. This institutional framework strengthens the feasibility of green hydrogen deployment in Greece, making its implementation more realistic within the national policy context.

3.1.4. Comparative Analyses and Hybrid Systems

Studies comparing PHS, BESS, and hydrogen storage have revealed complementary strengths among the technologies. For instance, PHS excels in long-duration storage, BESS provides short-term stabilization, and hydrogen enables cross-sector integration (Katsaprakakis et al., 2019) and assists with long-term storage as well. Hybrid systems that integrate these storage technologies along with renewable energy production have demonstrated cost and performance advantages, particularly in Greece's insular energy systems (Skroufouta et al., 2024).

Multi-criteria decision-making frameworks, such as Analytical Hierarchy Process (AHP), have been suggested as valuable tools to evaluate the trade-offs between these technologies under different socio-economic scenarios (W. Zhang & Patel, 2025).

Hybrid energy storage systems (HESS) that combine batteries and hydrogen storage offer a powerful solution for balancing both short-term variability and long-term energy needs in island microgrids. Batteries, particularly vanadium flow batteries, provide reliable, long-duration energy balancing, while hydrogen systems, consisting of electrolyzers, pressurized tanks and fuel cells, store surplus renewable energy for extended periods without degradation or self-discharge (Ibrahim et al., 2021).

Recent case studies have shown the effectiveness of this configuration. In a Northern Italy microgrid, a PV-powered H-BESS setup achieved full annual energy autonomy by using batteries for daily cycling and hydrogen for seasonal balancing (Damato et al., 2022). Similarly, a nationwide study on Norwegian islands found that hydrogen was essential to prevent the oversizing of renewables and batteries and to lower the LCOE to 0.21–0.63 €/kWh, far below diesel-based alternatives (0.87–1.04 €/kWh) (Trapani et al., 2024). In contrast, configurations with only batteries required a 23-fold increase in capacity and resulted in LCOEs up to 1.21 €/kWh, proving far less economical and scalable (Trapani et al., 2024). This cost advantage was echoed in a study on Ui Island (South Korea) where hybridization reduced battery sizing by 52% and overall system cost by 60% compared to battery-only systems (X. Zhang et al., 2022).

Importantly, advances in control strategies, such as prediction-free online convex optimization (OCO), now enable more efficient coordination between storage subsystems, reducing both energy losses and operational costs by up to 60% compared to traditional control methods (Qi et al., 2025). These findings underscore the growing feasibility and economic appeal of H-BESS configurations, especially in off-grid or semi-grid-connected island contexts where autonomy and resilience are paramount.

A recent study evaluated the optimal sizing of hybrid hydrogen–battery systems for Tilos using SCADA-based demand and generation data (Superchi et al., 2025). Using LCORE (Levelized Cost of Required Energy) as their performance metric, they showed that hydrogen integration improves seasonal balancing and significantly reduces the required battery capacity. However, the study focused solely on cost optimization and did not account for externalities, social or environmental impacts, or distributional effects, factors which this thesis aims to incorporate through a Social Cost-Benefit Analysis (SCBA) framework.

3.2. Comparative Review of Relevant Studies

This section compares representative studies that explore either techno-economic evaluations of storage technologies, comparisons of these technologies or the implementation of storage systems in island microgrids. The comparison focuses on purpose, method, main findings, limitations and relevance to this thesis.

Table 3.1: Overview of selected studies comparing storage technologies in island and hybrid contexts

Study	Purpose	Method	Findings	Limitations	Country/Region
Comodi et al. (2017)	Compare multiple storage technologies for cooling demand management under different tariff and scale scenarios	Hybrid techno-economic and qualitative analysis of Li-ion, SHTES, PCM TES, CAES, and LAES	Li-ion and TES systems most efficient at small to medium scale; thermal systems more economically viable under high peak-offpeak spreads; LAES and CAES viable only at large scale	Focused on cooling applications in tropical commercial settings; no SCBA or environmental externality monetization included	Singapore (tropical climate)
Damato et al. (2022)	Evaluate performance and autonomy of a PV-based H-BESS microgrid for residential users	Simulation-based modeling with MATLAB/Simulink; comparison of two energy management strategies (B1st vs B2EI)	Properly sized H-BESS achieved full-year autonomy with 95.9% battery and 37.1% hydrogen round-trip efficiency; improved strategy increased H_2 output by 10%	Focused on residential cluster; no cost-benefit valuation of social or environmental externalities	Italy
Duchaud et al. (2019)	Optimize component sizing for a hybrid wind–PV–battery microgrid in Tilos	Multi-Objective Particle Swarm Optimization (MOPSO) with techno-economic constraints	Identified Pareto front of optimal configurations trading off imported energy and system cost; best setup achieved 80% autonomy at €87/MWh cost	Only battery storage considered; no hydrogen integration or SCBA; economic assumptions are illustrative only	Greece (Tilos)

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Table 3.1 – continued from previous page

Study	Purpose	Method	Findings	Limitations	Country/Region
Esparcia et al. (2022)	Compare Li-ion, Pb-Acid, and Long-Duration Flywheel storage in isolated hybrid microgrids under uncertainty	Monte Carlo-based techno-economic optimization and cost projection (2020–2050)	LD FES had higher LCOS/LCOE advantage in early years but loses to Li-ion by 2050 unless cost reduction accelerates 2.5–4×; valuable insight for storage timing	No SCBA or societal externality analysis; limited to three technologies; early lock-in and switching risks not monetized	Philippines (KAELCO + industrial site)
He et al. (2021)	Quantitatively compare four energy storage types (TES, Li-ion, PHS, H_2) in a wind–PV hybrid system	Multi-objective capacity optimization using four evolutionary algorithms (NSGA-II, SPEA-II, MOEA/D, MOPSO)	Hydrogen storage had better reliability than PHS but higher LCOE than TES and Li-ion under all tested conditions; findings useful for storage prioritization in off-grid and semi-grid regions	No environmental or social cost evaluation (e.g., CO_2 valuation); hydrogen modeled under generic assumptions, not tailored to island contexts	Pakistan (case study region); generalizable methodology
Huylo et al. (2025)	Simulate and optimize renewable + storage integration in an islanded campus microgrid with CHP	Reduced-order modeling + nonlinear optimization using real SCADA data for TES, BES, CHP, wind and solar	Max 45.4% emission reduction using 200 MW wind, 200 MWh BES and 175 MWh TES; hydrogen blending adds another 9.3%; highlighted limitations without long-duration storage	Islanded context but not insular; no SCBA or societal cost valuation; long-duration storage modeled only hypothetically	United States (Austin, TX campus)
Irham et al. (2024)	Optimize BESS and H_2 system sizing for off-grid communities and investigate optimal layout to avoid outages	Reliability-cost tradeoff analysis	Hydrogen system reduces loss of power supply probability (LPSP) significantly; increases LCOE slightly	Externalities not monetized; assumes ideal electrolyzer costs	Southeast Asia

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Table 3.1 – continued from previous page

Study	Purpose	Method	Findings	Limitations	Country/Region
Kaldellis (2021)	Document and evaluate the performance of the TILOS hybrid wind–PV–$NaNiCl_2$ system under real-world grid conditions	Operational data analysis, performance benchmarking, and qualitative assessment of DSM and curtailment impacts	First fully licensed battery-based HPS in Greece; showed 70–90% RES shares in winter but only 25–30% in summer; DSM and forecasting platforms critical for balancing	No economic valuation of externalities; curtailments high due to grid constraints; hydrogen not included as storage alternative	Greece (Tilos Island)
Kallis et al. (2021)	Review lessons on community engagement in island-based renewable energy projects	Thematic literature review of 17 case studies across Europe, North America, and Asia-Pacific	Found island-specific challenges in building trust, managing conflict, and achieving fair participation; early and culturally aware engagement improves outcomes	No techno-economic modeling; no SCBA; does not compare storage technologies; focuses on engagement and social dynamics	Multiple (e.g. Samsø, Jeju, Lewis, Orkney, Texel, Block Island)
Katsaprakakis et al. (2019)	Compare PHS, lead-acid, and lithium-ion storage in three small Greek insular grids	Hourly simulation and techno-economic optimization for 8 hybrid configurations	PHS is the only technology enabling 100% RES with 17–19 days autonomy; Li-ion and Pb-acid limited to 78–89% RES with <1-day autonomy; PHS offers €35/kWh cost vs €400–900/kWh for batteries	PHS requires favorable terrain; licensing barriers and high up-front cost; no SCBA or monetization of social benefits	Greece (Symi, Astypalaia, Kastelorizo)

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Study	Purpose	Method	Findings	Limitations	Country/Region
Koholé et al. (2024)	Comprehensive techno-economic and environmental comparison of battery, hydrogen, PHS, and thermal storage	Cuckoo search algorithm for optimizing 12 hybrid system configurations under 3 load profiles	PV/Wind + Thermal Energy Storage (TES) systems had the lowest cost across all load profiles; TES also showed high resilience and economic viability, with LCOEs as low as 0.2100 €/kWh	Focused on economic indicators; did not include SCBA or island-specific constraints like water availability or elevation for PHS	Cameroon (Kousseri)
J. Liu et al. (2020)	Provide a comprehensive review of ESS technologies, grid applications, and market integration	Structured literature review with techno-economic focus; case-based cost-benefit comparisons across investor types	Identifies key applications for BESS (e.g., frequency regulation, capacity deferral, and customer-side savings); stresses need for tools that include degradation and stacked benefits	Does not apply SCBA or assess social/environmental externalities; mostly theoretical	USA
S. Liu et al. (2024)	Develop a high-performance, low-cost H_2/K^+ hybrid battery using non-noble materials for large-scale storage	Experimental fabrication and electrochemical testing of KMF cathode + NNM-HEA anode in engineered electrolytes	Demonstrated high energy density (107.6 Wh/kg), excellent rate performance (100 mAh/g at 85.7 C), and 90% retention after 1200 cycles using low-cost electrodes	Not evaluated in real-world or grid-connected systems; no techno-economic modeling or SCBA of lifecycle or environmental trade-offs	China (laboratory-scale proof of concept)
López González et al. (2015)	Evaluate real-world energy performance of a solar HESS facility and compare it to Li-ion and lead-acid systems	Experimental analysis of HESS using PV, electrolyzer, buffer tank, hydride and high-pressure storage with PEMFC	HESS achieves gravimetric energy density close to Li-ion (131 vs 150 Wh/kg); annual system efficiency 32%; metal hydrides offer superior volumetric energy density	Lacks economic or lifecycle cost modeling; no SCBA; evaluated only energy-related parameters; not tailored to island grid planning	Spain (INTA R&D facility)

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Study	Purpose	Method	Findings	Limitations	Country/Region
Marocco et al. (2021)	Optimize a hybrid PV-battery-hydrogen system for a self-sufficient building cluster	Mixed-integer linear programming (MILP); demand response optimization	Achieved 100% renewable autonomy with PV and hybrid storage; demand response reduced curtailment and improved system efficiency	Focused on a building cluster, not a regional microgrid; no SCBA applied	Italy
Misic et al. (2025)	Design optimal energy storage and transmission configuration for an island RES-based system	Stochastic MILP optimization using Sample Average Approximation (SAA)	PHS generally more cost-effective than BESS if geography allows; diesel still needed unless storage prices fall; wind+solar mix improves system performance	Uses synthetic data for solar, assumes single load center and no grid interconnection; no SCBA or valuation of externalities	Spain (El Hierro, Canary Islands)
Motta et al. (2021)	Assess economic feasibility of large-scale Li-ion BESS for frequency containment in Finland	Simulation-based cost-benefit analysis using 2019 Fingrid market data (FCR-N); fixed bidding strategy	Optimal BESS sizing (100 MW/100 MWh) could yield €1.78 M/year in net profit; fixed bids still result in penalties; profitability sensitive to battery cost and bid strategy	Excludes battery degradation and O&M; no SCBA or social/environmental valuation; single-market scope	Finland
Palys and Daoutidis (2024)	Review ammonia-based energy storage technologies for islanded renewable systems	Technical and systems-level literature review on ammonia production, storage, and conversion; includes techno-economic benchmarks and MILP-based optimization studies	Ammonia has strong potential for long-duration storage in islanded systems due to low storage cost, modularity, and CHP compatibility; flexible Haber–Bosch design can lower LCOE to \$60–90/MWh by 2030	No direct SCBA applied; mostly theoretical or modeling-focused; lacks case-specific empirical data or implementation studies	Global / Theoretical (with US and EU modeling references)

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Study	Purpose	Method	Findings	Limitations	Country/Region
Pelosi et al. (2023)	Compare techno-economic viability of flywheel–battery vs hydrogen–battery hybrid storage in a real mini-grid	Dynamic modeling, sizing, rainflow SoC analysis, and LCOE/LCOS/LCOD estimation under different electricity price conditions	Flywheel–battery HESS had lower LCOE (0.18 €/kWh) vs. hydrogen–battery (0.22 €/kWh); battery lifespan was longer with flywheel due to lower C-rates; both systems improved self-consumption and reduced grid dependence	No SCBA or environmental externalities evaluated; subsidy inclusion critical for viability; focused on an Italian industrial MG	Italy (Terni industrial mini-grid)
Psarros et al. (2024)	Review global applications of electricity storage in island systems	Literature review of 195 scientific and institutional sources	Identifies hybrid storage-RES stations and standalone centrally managed systems as key configurations; storage needed for RES shares over 50%	Does not conduct primary modeling or techno-economic simulation; focus is on synthesis rather than quantitative SCBA	Global (focus on EU and Greek islands)
Psarros and Papathanassiou (2022)	Quantify optimal electricity storage mix for Greece's 2030 high-RES scenario	UC-ED simulation over 1 year; cost-benefit evaluation against two counterfactuals (bau, do-minimum)	A portfolio of 500 MW/2-h BESS + 750–1250 MW/6-h PHS yields up to €110 M/year net benefit; combined systems reduce curtailments and CO_2 while enhancing flexibility	No SCBA or monetization of resilience/externalities; no inclusion of long-duration storage (e.g., hydrogen); assumes perfect foresight	Greece
Qi et al. (2025)	Improve hybrid storage control strategies	Prediction-free OCO algorithm	OCO reduced energy loss and cost by up to 60% over traditional dispatch	Requires high-resolution forecasting data; not tied to SCBA	General / Theoretical
Superchi et al. (2024)	Optimize H-BESS for Tilos using real demand data	LCORE-based system optimization	Hybridization improves seasonal autonomy; reduces need for diesel fallback	No social cost-benefit analysis or valuation of resilience/emissions	Greece (Tilos)

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Study	Purpose	Method	Findings	Limitations	Country/Region
Superchi et al. (2025)	Assess economic viability of hybrid hydrogen–Li-ion storage vs BESS-only on Tilos	SCADA-based techno-economic optimization (differential evolution algorithm; LCORE metric)	Hybrid system reduced LCORE by 17.5% vs BESS-only (264 €/MWh vs 320 €/MWh) and required 30.5% smaller PV field	Did not include externalities (e.g., CO_2 emissions, energy justice); focuses on cost not societal benefits	Greece (Tilos)
Trapani et al. (2024)	Compare LCOE for diesel, BESS, and hybrid systems in Norwegian islands	Multi-scenario modeling	H-BESS LCOE: €0.21–0.63/kWh; diesel up to €1.04/kWh; Hydrogen crucial to prevent oversizing	Battery oversizing required in non-hybrid scenarios	Norway
Wang et al. (2024)	Evaluate environmental and economic benefits of second-use battery energy storage vs conventional systems	Environmental monetization model + PSO optimization of energy storage sizing in PV pilot area	SUBESS reduced NPV payback by 3.78 years vs CBESS; showed up to 60% NAV improvement; quantified 2111 CNY/year in environmental benefit vs scrapping	Limited to residential PV pilot in China; no SCBA or grid-scale integration; life-cycle uncertainties persist	China (Northern PV pilot site)
Zagoras (2014)	Perform a step-by-step cost/benefit analysis of Li-ion BESS applications for PV power systems	Cost modeling using IEEE test feeders, BESS siting, power loss minimization, and application revenue estimation	Identified $400–700/kW in revenue potential for energy time-shifting and firming; also explored second-life battery economics and siting benefits	No SCBA or valuation of social/environmental impacts; focused on U.S. utility-scale distribution systems	USA
X. Zhang et al. (2022)	Evaluate hybrid H-BESS vs battery-only systems in island microgrids	Techno-economic simulation (HOMER)	H-BESS reduced total system cost by 60% and battery size by 52% vs BESS-only	No inclusion of social or environmental externalities	South Korea

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Table 3.1 – continued from previous page

Study	Purpose	Method	Findings	Limitations	Country/Region
Żołądek et al. (2024)	Evaluate a fully self-sufficient hybrid microgrid with battery and hydrogen storage in islanded operation	TRNSYS-based dynamic simulation and parametric sizing analysis of RES, BESS, H_2 loop, and gasifier	System achieved 97% renewable supply; hydrogen more effective for long-duration backup; 31% curtailment; payback period of 13.3 years	No SCBA or monetization of environmental/social externalities; limited to one hotel load profile; high CAPEX for H_2 loop	Greece (Agkistro)
Uhrig et al. (2016)	Compare Li-ion and VRFB for household PV self-consumption	Household simulation over 20 years using multi-physical VRFB model	Li-ion showed higher efficiency, but VRFB offered longer lifetime (>10,000 cycles) and better scalability for larger capacities	Focused on residential home storage; not tailored to island microgrids; no SCBA of social benefits	Germany
Rodby et al. (2020)	Assess LCOS of VRFBs with capacity fade and recovery	Techno-economic LCOS model with physical capacity fade and rebalancing framework	VRFBs can recover lost capacity via electrolyte rebalancing, lowering life-cycle costs vs Li-ion despite higher capital costs	Assumes generic cost data; limited long-term cycling datasets; does not include broader SCBA externalities	USA
Khaki and Das (2023)	Multi-objective optimization of VRFB vs Li-ion considering LCOE, charging time, and efficiency	Equivalent circuit modeling with optimization based on current density	VRFB lifetime (13,000–15,000 cycles, 20 years) far exceeds Li-ion (300–500 cycles, 5 years); VRFBs more suitable for long-duration grid storage	Lower energy density and higher CAPEX remain barriers; optimization not applied in real island systems	USA
Leba Akman et al. (2025)	Review of VRFBs as a large-scale storage option	Literature review on VRFB history, principles, performance, and deployment	VRFBs stand out for safety, scalability, long cycle life, and sustainability; suitable for >4h storage	Lower energy density (10–25 Wh/L) and vanadium cost volatility hinder competitiveness; no SCBA performed	Global

As seen in Table 3.1, the recent body of literature demonstrates substantial interest in hybrid energy storage configurations for island and isolated systems, particularly those combining batteries with hydrogen or other long-duration technologies. Numerous studies emphasize the technical and economic viability of such systems, citing benefits like enhanced autonomy (Damato et al., 2022; Duchaud et al., 2019), reduced curtailment and optimized LCOE (Superchi et al., 2025; Trapani et al., 2024), and increased system flexibility and lifespan (He et al., 2021; Pelosi et al., 2023). Others highlight how specific control strategies and sizing algorithms improve the performance and cost-efficiency of hybrid systems (Marocco et al., 2021; Qi et al., 2025).

However, a critical gap persists across the literature: despite robust techno-economic analyses, none of the studies apply a complete Social Cost-Benefit Analysis (SCBA) framework. While a few incorporate partial monetization of environmental benefits (e.g., avoided emissions or second-life battery reuse (J. Liu et al., 2020; Wang et al., 2024)), the broader societal impacts, such as energy resilience, equity, and public value, remain largely unaccounted for. Studies that directly focus on island contexts, including those on Tilos itself (Duchaud et al., 2019; Kaldellis, 2021; Superchi et al., 2025), also limit their analysis to technical feasibility and cost metrics, without evaluating the distributional or long-term societal effects of competing technologies.

Furthermore, none of the reviewed papers provide a holistic comparison between the incumbent $NaNiCl_2$ storage system and an alternative hybrid hydrogen–Li-ion configuration within a realistic island grid. Several studies assess hybrid systems in other geographic contexts (Damato et al., 2022; X. Zhang et al., 2022; Żołądek et al., 2024), but they stop short of capturing the full spectrum of externalities, especially those relevant to insular communities with constrained infrastructure and social sensitivity to energy reliability.

This thesis addresses these gaps by conducting a detailed SCBA of energy storage systems on Tilos Island. It combines technical performance modeling with a monetized valuation of both private and public impacts, offering a more comprehensive framework for assessing energy storage investments in small island systems.

4

Conceptual Framework

4.1. Introduction

This chapter outlines the conceptual framework and analytical scope used to guide the Social Cost-Benefit Analysis (SCBA) comparing two energy storage systems for the island of Tilos: the currently operational $NaNiCl_2$ battery configuration and a proposed hybrid hydrogen–vanadium flow battery (H-BESS) system. The aim is to establish a structured approach that links the technical, environmental and economic characteristics of these systems to their broader societal impacts.

To ensure methodological consistency, this framework is grounded in established SCBA literature, particularly the nine-step approach of Boardman et al. (2018) and the Dutch cost-benefit analysis guidance by CPB/PBL (Romijn & Renes, 2013). These sources emphasize the need for clearly defined boundaries, a comprehensive treatment of monetizable and non-monetizable impacts, and transparency in assumptions and valuation methods.

This chapter therefore serves as a bridge between the general SCBA methodology outlined in Chapter 2 and the specific modeling and analysis presented in Chapter 5. It details how causal mechanisms, system boundaries, impact categories, and performance indicators are selected and used to evaluate the net societal benefit of transitioning to a hybrid energy storage system on Tilos Island.

4.2. System Boundaries

Defining the system boundaries is crucial for ensuring consistency and comparability in the Social Cost-Benefit Analysis (SCBA). This section outlines the spatial, temporal, technical, and stakeholder boundaries applied to both the baseline and intervention scenarios.

4.2.1. Spatial Boundary

The spatial scope of the analysis is the island of Tilos, located in the Dodecanese region of Greece. Although national and EU-level policy contexts influence cost and benefit components (e.g., emissions pricing), all direct impacts are assessed within the island's electricity system. Indirect impacts (e.g., upstream emissions, manufacturing) are included when data allows, but global externalities (e.g., global CO_2 pricing) are not monetized.

4.2.2. Temporal Boundary

The analysis is conducted over a 15-year period, consistent with the expected technical lifetime of the current $NaNiCl_2$ battery system (European Association for the Storage of Energy (EASE), 2023). This time horizon allows for capturing major replacement, degradation, and operational cost effects, while maintaining manageable forecasting uncertainty. A social discount rate of 4% is used for the central scenario, with sensitivity tested at 2% and 6%.

4.2.3. Technical Boundary

The SCBA evaluates two configurations: the baseline existing $NaNiCl_2$ system (2.88 MWh, 800 kW discharge) and the intervention hybrid system consisting of 4.0 MWh VFB with 1.5 MW power rating and 12.0 MWh hydrogen storage capacity (approximately 5.4 MWh usable output). The intervention configuration was chosen to provide enhanced grid support and seasonal storage capabilities, via the use of hydrogen, as well as more efficient short-term storage via VFB.

The boundaries include the energy storage systems themselves and the auxiliary components required for their operation (e.g., inverters, fuel cells, electrolyzers, hydrogen tanks). Renewable generation assets (PV, wind) are assumed constant in both scenarios and are therefore excluded from the comparative boundary. Backup diesel or grid connection is assumed to exist as contingency but not actively modeled.

4.2.4. Stakeholder Boundary

The analysis adopts a national societal perspective in line with CPB/PBL guidelines (Romijn & Renes, 2013). Stakeholders include the local population of Tilos, broader Greek society (through taxation, subsidies and environmental impacts), system operators (costs, reliability), and future generations (intergenerational equity via discounting).

Costs and benefits are expressed in social terms, not market financial returns. Impacts beyond the Greek jurisdiction (e.g., international climate externalities) are qualitatively discussed but not monetized.

4.2.5. Functional Boundary

The functional basis of comparison is the delivery of optimized energy storage services that maximize societal welfare on Tilos Island. Rather than constraining the analysis to identical capacity specifications, the SCBA framework evaluates each system's ability to maximize renewable energy utilization and minimize curtailment, provide enhanced energy autonomy through reduced diesel dependency, enable seasonal energy balancing capabilities where technically feasible, create additional economic value streams through alternative applications, enhance grid resilience and backup power capabilities, and support sustainable energy system development and technology learning.

The hybrid system's enhanced capacity (9.4 MWh effective vs. 2.88 MWh baseline) reflects optimization for these societal objectives rather than artificial constraint matching. This approach aligns with SCBA best practices that prioritize welfare maximization over technical specification equivalence (Boardman et al., 2018; Romijn & Renes, 2013).

The functional comparison evaluates each system's contribution to grid stability and power quality maintenance, renewable energy integration optimization, long-term energy security and import reduction, local economic development and job creation, environmental impact minimization, and technology demonstration and learning advancement.

Peak discharge capability comparison (1.56 MW hybrid vs. 0.80 MW baseline) demonstrates enhanced grid support capacity while maintaining system reliability and operational flexibility under varying demand conditions.

4.3. Causal Pathways

This section describes the causal mechanisms through which each energy storage alternative leads to societal costs and benefits, establishing the logical links between the technological interventions and their ultimate impacts on Tilos Island society (Boardman et al., 2018). The causal pathways framework provides a systematic approach to understanding how and why certain outcomes occur, moving beyond simple correlations to examine the underlying mechanisms that connect storage technology choices to measurable societal effects (Romijn & Renes, 2013; Sidhu et al., 2017).

This approach directly operationalizes Boardman's emphasis on systematically identifying and cataloguing all relevant impacts of policy alternatives, which is a critical step in the CBA process. The causal pathways framework extends the methodology proposed by Boardman et al., 2018, by providing a structured way to trace how initial technological interventions (the energy storage alternatives) generate chains of effects that ultimately result in measurable social outcomes, ensuring that all relevant costs and benefits are captured in the analysis. Furthermore, this approach supports Boardman's recommendation to establish clear cause-and-effect relationships between project inputs and outcomes, which is essential for accurate prediction and monetization of impacts in CBA. By mapping these causal mechanisms explicitly, the analysis avoids the common pitfall identified by Boardman of overlooking important indirect or secondary effects that may significantly influence the overall net social benefits of each storage alternative.

4.3.1. Conceptual Framework for Causal Pathways

The causal pathways in this analysis follow a sequential logic where initial technological interventions (storage system deployment) trigger intermediate mechanisms that ultimately produce measurable societal outcomes (Boardman et al., 2018; Devine-Wright et al., 2017). Each pathway consists of four key components: the initial driver (storage technology choice), intermediate mechanisms (technical and operational changes), modifying factors (contextual elements), and final outcomes (monetized and non-monetized impacts) (Mbungu & Helgenberger, 2021; Romijn & Renes, 2013).

The pathways are structured to capture both direct effects (immediate technical performance differences) and indirect effects (broader systemic changes in energy autonomy, grid resilience, and community welfare) (Kaldellis, 2021; Koirala et al., 2020). This comprehensive approach ensures that the SCBA captures the full spectrum of societal impacts rather than limiting analysis to immediate financial costs and benefits (Passell, 2021; Sibilla & Kurul, 2023).

4.3.2. Baseline System Causal Pathways ($NaNiCl_2$)

Primary Pathway: Operational Performance → System Reliability → Societal Benefits
The existing $NaNiCl_2$ system follows a direct causal pathway where its operational characteristics translate into specific societal outcomes (European Association for the Storage of Energy (EASE), 2023; Huang et al., 2023). The high-temperature operation (270-350°C) and stable discharge characteristics enable consistent power delivery, which reduces Loss of Power Supply Probability (LPSP) and enhances grid stability (Nikolic et al., 2023; Xu et al., 2024). This improved reliability directly benefits local residents through reduced blackout frequency and supports tourism-dependent economic activities during peak summer periods (Li, 2022; Lim et al., 2024).

Secondary Pathway: Technology Maturity → Maintenance Requirements → Economic Impacts
The mature $NaNiCl_2$ technology requires specialized maintenance and high-temperature operation, creating ongoing operational costs and technical dependencies (European Association for the Storage of Energy (EASE), 2023; Mair et al., 2023). These requirements translate into employment opportunities for technical personnel but also generate higher operational expenses that ultimately affect the economic burden on the island's energy system (Nikolic et al., 2023; Tarekegne et al., 2021). The pathway continues through utility cost structures to impact electricity pricing for residents and businesses (De Simone et al., 2025; Li, 2022).

VFB-Specific Pathway: Technology Longevity → Reduced Replacement Costs → Economic Benefits
The VFB subsystem's extended lifespan (15-20 years) and minimal degradation create a distinct economic pathway through reduced replacement and maintenance costs (European Association for the Storage of Energy (EASE), 2023). Unlike conventional batteries, VFBs can recover lost capacity through electrolyte rebalancing, extending system resilience and reducing lifecycle costs compared to degrading battery technologies. This pathway translates into sustained economic benefits through avoided replacement costs and consistent performance over the project lifetime, contributing to improved net social benefits compared to systems requiring frequent component replacement.

Externality Pathway: Battery Operation → Environmental Impacts → Social Costs
The $NaNiCl_2$ system's lifecycle generates specific environmental impacts through manufacturing, operation, and disposal phases (Nikolic et al., 2023; Vilela et al., 2022). These impacts create externalities that impose social costs through air quality effects, resource consumption, and waste management requirements (Romijn & Renes, 2013; Sadighi et al., 2022). The pathway concludes with monetizable environmental costs that should be included in the societal accounting framework (Boardman et al., 2018; Sibella et al., 2020).

4.3.3. Intervention System Causal Pathways (Hybrid H-BESS)

Primary Pathway: Technological Hybridization → Enhanced Flexibility → Multi-layered Benefits
The hybrid vanadium flow battery and hydrogen storage system creates a more complex but potentially more beneficial causal pathway (Ibrahim et al., 2021; Koirala et al., 2020). The combination of high-efficiency short-term storage (VFB) with long-duration seasonal storage (hydrogen) enables enhanced renewable energy integration and grid flexibility (Huang et al., 2023; X. Zhang et al., 2022). This technological synergy reduces renewable energy curtailment and improves overall system efficiency, translating into economic benefits through reduced fuel imports and improved energy autonomy (Mbungu & Helgenberger, 2021; Superchi et al., 2025).

Secondary Pathway: Hydrogen Production → Economic Diversification → Community Development
The electrolyzer component of the hybrid system creates opportunities for hydrogen production during periods of renewable energy surplus (Koutsandreas et al., 2023; Sadighi et al., 2022). This pathway leads to potential economic diversification as hydrogen can serve multiple applications beyond electricity storage, including potential export opportunities or industrial applications (Clean Hydrogen Observatory, 2025; Lim et al., 2024). The economic benefits flow through to community development through job creation in emerging technology sectors and enhanced local technical capacity (Hellenic Republic - Ministry of Environment and Energy, 2024; Tarekegne et al., 2021).

Innovation Pathway: Technology Deployment → Knowledge Transfer → Long-term Capacity Building
The deployment of advanced hybrid storage technology establishes Tilos as a demonstration site for innovative energy solutions, creating pathways for knowledge transfer and capacity building (De Simone et al., 2025; Eunice Group, 2024). This pathway generates long-term benefits through enhanced local technical expertise, potential technology licensing opportunities, and positioning for future energy infrastructure investments (European Commission, 2020; Koirala et al., 2020). The innovation effects contribute to community resilience and adaptability in the evolving energy landscape (Kallis et al., 2021; Sibilla & Kurul, 2023).

H2 Alternative Applications Pathway: Excess Production → Revenue Diversification → Economic Enhancement
The hydrogen subsystem creates additional value streams through alternative applications beyond electricity storage, generating multiple revenue opportunities that enhance the economic viability of the hybrid system (Clean Hydrogen Observatory, 2025; Hellenic Republic - Ministry of Environment and Energy, 2024). Excess hydrogen production can serve maritime fuel applications (€4.5/kg), transport fuel for buses and trucks (€6.0/kg), and industrial applications (€3.0/kg), creating diversified income streams that improve project economics (Koutsandreas et al., 2023). This pathway demonstrates how energy storage systems can provide multiple societal benefits beyond electricity supply, contributing to local economic development and energy sector diversification. The revenue diversification also enhances project financial resilience by reducing dependence on electricity market revenues alone.

4.3.4. Comparative Pathway Analysis

Efficiency Pathway Comparison
The $NaNiCl_2$ system operates through a simpler efficiency pathway with round-trip efficiency of approximately 85-90%, while the hybrid system incorporates both reliable VFB storage (76-80%) and lower-efficiency hydrogen storage (45%) (European Association for the Storage of Energy (EASE), 2023). The net efficiency impact depends on operational dispatch strategy and the complementary roles of daily cycling versus seasonal storage (Siberry et al., 2022; Superchi et al., 2025). These efficiency differences cascade through the economic pathway to affect overall system costs and societal benefits (Damato et al., 2022; Yu & Foggo, 2017).

Environmental Impact Pathway Divergence
The two systems follow distinctly different environmental impact pathways (Mair et al., 2023; Nikolic et al., 2023). The $NaNiCl_2$ system's environmental pathway centers on high-temperature operation, material composition, and established recycling processes (European Association for the Storage of Energy (EASE), 2023; Vilela et al., 2022). The hybrid system's pathway is more complex, incorporating vanadium mining impacts, hydrogen production emissions (depending on electricity source), and emerging

recycling challenges (McKinsey & Company, 2025; Wang et al., 2024). Both pathways ultimately affect air quality, resource consumption, and waste management costs that require monetization in the SCBA framework (Romijn & Renes, 2013; World Bank Group, 2017).

Resilience Pathway Differentiation

System resilience pathways differ significantly between the alternatives (Irham et al., 2024; National Renewable Energy Laboratory, 2023). The $NaNiCl_2$ system provides resilience through proven technology reliability and thermal stability, creating straightforward pathways to reduced blackout probability and enhanced energy security (European Association for the Storage of Energy (EASE), 2023; Xu et al., 2024). The hybrid system offers resilience through technological diversification and enhanced seasonal storage capability, creating more complex but potentially more robust pathways to energy independence and grid stability (Lim et al., 2024; Trapani et al., 2024).

4.3.5. Temporal Dynamics of Causal Pathways

Short-term Impact Pathways (Years 1-5)

Initial deployment effects dominate short-term pathways, with the hybrid system requiring higher capital investment but potentially delivering immediate benefits through improved renewable integration (Koirala et al., 2020; Superchi et al., 2025). Learning curve effects and operational optimization create dynamic pathways where benefits may increase over time as operators gain experience with hybrid system management (De Simone et al., 2025; Qi et al., 2025). These short-term pathways are critical for community acceptance and political sustainability of the technology choice (Kallis et al., 2021; Sibilla & Kurul, 2023).

Medium-term Impact Pathways (Years 6-10)

Technology degradation and replacement cycles become prominent in medium-term pathways (European Association for the Storage of Energy (EASE), 2023; Sandia National Laboratories, 2021). The VFB components may require replacement before the hydrogen components, creating complex cost pathways that affect the overall economic analysis (McKinsey & Company, 2025; Pelosi et al., 2023). Simultaneously, cost reduction trends in hydrogen technology may improve the economic pathway for the hybrid system over this timeframe (Garcia & Tanaka, 2025; Sadighi et al., 2022).

Long-term Impact Pathways (Years 11-15)

Long-term pathways incorporate technology evolution, market development, and infrastructure legacy effects (Johnson & Kim, 2025; World Bank Group, 2017). The hybrid system may enable pathways to future technology upgrades and grid modernization that provide additional societal benefits beyond the initial analysis period (Mbungu & Helgenberger, 2021; W. Zhang & Patel, 2025). These extended pathways are important for understanding the full societal value of technology investments in rapidly evolving energy markets (Boardman et al., 2018; U.S. Department of Energy, 2022).

This causal pathway analysis provides the foundation for quantifying and monetizing the societal impacts of each storage alternative, ensuring that the SCBA captures the complex mechanisms through which technological choices translate into measurable societal costs and benefits on Tilos Island (Carmona & Ludkovski, 2010; Sidhu et al., 2017).

4.3.6. Pathway Implementation in Computational Model

The computational model quantitatively captures several key causal pathways including technological hybridization leading to renewable integration improvement, hydrogen alternative applications creating revenue diversification, efficiency pathways affecting operational cost differences, and technology learning driving dynamic cost reduction.

Other pathways such as system reliability, lifecycle environmental impacts, and resilience diversification are acknowledged qualitatively but not quantitatively modeled due to data limitations and methodological constraints.

4.4. Performance Indicators and Valuation Metrics

This section defines the quantitative and qualitative metrics used to evaluate the societal costs and benefits of the energy storage alternatives. The indicators are structured to align with the causal pathways framework while adhering to SCBA best practices (Boardman et al., 2018; Romijn & Renes, 2013).

4.4.1. Core Quantitative Indicators

Net Social Benefit (NSB)

The primary metric for comparing alternatives, calculated as (Boardman et al., 2018):

$$\text{NSB} = \sum_{t=0}^{T} \frac{B_t - C_t}{(1+r)^t}$$

where:

- B_t = Monetized benefits in year t
- C_t = Monetized costs in year t
- r = Social discount rate (4% baseline)

Levelized Cost of Storage (LCOS)

Evaluates lifetime storage costs per MWh delivered (Zakeri & Syri, 2015):

$$\text{LCOS} = \frac{\sum_{t=0}^{T} \frac{C_{\text{cap}} + C_{\text{op}} + C_{\text{rep}} - S}{(1+r)^t}}{\sum_{t=0}^{T} \frac{E_{\text{disch},t}}{(1+r)^t}}$$

where:

- C_{cap} = Capital costs (€)
- C_{op} = Operational costs (€/year)
- C_{rep} = Replacement costs (€)
- S = Residual value (€)
- $E_{\text{disch},t}$ = Energy discharged in year t (MWh)

Avoided Emissions (CO_2eq)

Monetized using EU ETS shadow prices (Statista, 2025):

$$\text{Value} = \sum_{t=0}^{T} \frac{\Delta E_t \cdot P_t^{\text{CO}_2}}{(1+r)^t}$$

where ΔE_t = emissions reduction versus counterfactual, and $P_t^{\text{CO}_2}$ = projected carbon price.

Loss of Power Supply Probability (LPSP)

Reliability metric calculated from SCADA data (Kaldellis, 2021):

$$\text{LPSP} = \frac{\sum(\text{Unmet demand hours})}{\text{Total operational hours}} \times 100\%$$

4.4.2. Social and Environmental Indicators

Energy Autonomy Index (EAI) Defined for Tilos context (Eunice Group, 2024):

$$\text{EAI} = \left(1 - \frac{\text{Imported energy}}{\text{Total consumption}}\right) \times 100\%$$

Employment Effects Employment effects include both direct jobs (FTE/year) in operation and maintenance, as well as indirect jobs created in local supply chains.

Non-Monetized Externalities Several important factors resist monetization but influence technology choice:

Table 4.1: Qualitative factor comparison

Factor	Hybrid System	Baseline System
Technology lock-in risk	Lower	Higher
Strategic demonstration value	High	Medium
Intergenerational equity	Better	Standard
Innovation spillovers	High	Low

These qualitative factors generally favor the hybrid system but are not quantified due to methodological constraints and lack of primary stakeholder preference data.

4.4.3. Valuation Approach

Monetization Methods

The valuation approach employs market prices for direct costs (CAPEX/OPEX), shadow pricing for CO_2 based on EU ETS forward curve projections, contingent valuation for local resilience benefits, and benefit transfer methodologies for non-market impacts.

Uncertainty Treatment

Uncertainty is addressed through scenario-based sensitivity analysis and enhanced sensitivity analysis employing one parameter at a time variation using tornado diagram approaches.

4.4.4. Social Benefit Parameter Justification and Limitations

Energy Autonomy Premium (€10–40/MWh): The autonomy premium reflects societal willingness-to-pay for energy independence, estimated through benefit transfer adapted from Kallis et al. (2021) community engagement studies on Tilos and revealed preference analysis of observed premiums paid for local versus imported energy on Greek islands (15–25% above mainland rates).

Limitations: No primary contingent valuation survey was conducted. Values represent order-of-magnitude estimates requiring validation through dedicated social research.

Resilience Valuation Methodology: Value of Lost Load (VoLL) estimates (€6,000–15,000/MWh) are derived from sectoral analysis of tourism sector impact studies for Greek islands (€12–18/kWh opportunity cost), international benchmarks using EU average VoLL adjusted for local income levels, and historical outage cost assessment from the 2016 Tilos cable failure economic impact.

Limitations: No primary data exists on Tilos-specific outage costs. Estimates may not reflect heterogeneous impacts across residential versus commercial sectors.

H_2 Alternative Revenue Validation: Maritime and transport fuel pricing (€4.5–8.0/kg) is based on market analysis of current Greek island fuel import costs and delivery logistics, industry projections for fuel cell vehicle deployment scenarios for 2025–2030, and policy support assumptions from NECP hydrogen strategy implementation (Hellenic Republic - Ministry of Environment and Energy, 2024).

Limitations: Market development remains highly uncertain. Revenue projections assume successful H_2 infrastructure development and regulatory approval, which remain unvalidated assumptions.

Uncertainty Propagation: These parameter uncertainties contribute significantly to overall NSB variance. Social benefit parameters create ±25% impact on NSB, market development assumptions create ±40% impact on H_2 revenue streams, and the combined effect is represented in pessimistic versus optimistic scenario spread (€1.1M NSB range).

4.4.5. Indicator Alignment with Research Questions

This structured set of metrics ensures comprehensive evaluation of both quantifiable and qualitative impacts, providing robust inputs for the computational model in Chapter 5.

Table 4.2: Mapping of indicators to research objectives

Research Objective	Primary Indicators
Technical performance	LPSP, Round-trip efficiency, Capacity degradation
Economic viability	NSB, LCOS, Payback period
Societal value	EAI, Employment effects, Distributional equity
Environmental impact	Avoided CO_2eq, Land use, Recycling rate

4.5. Impact Categories and Valuation Approach

Cost Categories:

- Capital investment (CAPEX),
- Operational and maintenance (OPEX),
- Replacement costs (battery degradation/fuel cell lifespan),
- Infrastructure costs (hydrogen compression and storage),
- Environmental lifecycle costs (emissions, waste).

Benefit Categories:

- Improved renewable energy integration,
- Avoided fuel imports (diesel or mainland grid),
- Avoided CO_2 emissions (valued with shadow pricing),
- Reduced Loss of Power Supply Probability (LPSP),
- Social value of energy autonomy and resilience.
- H_2 alternative applications revenue (maritime fuel, transport, industrial uses), subject to significant market development uncertainty and treated as sensitivity parameter rather than baseline assumption.

These categories are chosen based on the presented conceptual framework, as well as based on their relevance in similar SCBA applications in energy storage research (Passell, 2021), where both private and public impacts are considered across the asset life cycle. Where monetization is infeasible, qualitative evaluation will be applied (e.g., energy justice, public acceptance).

4.6. Treatment of Uncertainty and Externalities

This section outlines the methodological approach for addressing uncertainties and valuing externalities in Social Cost-Benefit Analysis (SCBA), critical for ensuring robust comparisons between storage alternatives (Boardman et al., 2018; Romijn & Renes, 2013).

Sources of Uncertainty

Three primary uncertainty categories are considered. Technical uncertainties include battery degradation rates (1.5%–3% annual capacity loss), hydrogen system efficiency (30–35% round-trip), and renewable generation variability (15% interannual wind speed deviation) (European Association for the Storage of Energy (EASE), 2023; Kaldellis, 2021). Economic uncertainties encompass fuel price volatility (diesel: €0.80–€1.20/L), technology cost reductions (Li-ion: 5–15% annual decline), and discount rate sensitivity (2–6% range) (Johnson & Kim, 2025; Li, 2022; Romijn & Renes, 2013). Social and political uncertainties include community acceptance of hydrogen infrastructure, future EU emissions policy (€50–€150/tCO_2), and grid code evolution for island systems (Hellenic Republic - Ministry of Environment and Energy, 2024; Kallis et al., 2021; Statista, 2025).

Uncertainty Quantification Methods

A multi-layered approach combines probabilistic analysis, scenario analysis, and value of information frameworks. The scenario analysis employs three deterministic scenarios (Pessimistic, Balanced, Optimistic) that capture key uncertainties in technology development, policy support, and market conditions.

Each scenario represents an internally consistent set of assumptions about future conditions, evaluated separately to assess project robustness across different potential futures.

Externality Valuation Approach

Table 4.3: Externality valuation methods and data sources

Externality Type	Valuation Method	Data Source
CO_2 emissions	Fixed carbon pricing by scenario	(Statista, 2025)
Energy autonomy	Assumed premium (€10-40/MWh)	Literature estimates
Grid resilience	Value of Lost Load (VoLL)	(for the Cooperation of Energy Regulators (ACER), 2020)
H_2 alternative revenue	Market pricing analysis	Industry projections
End-of-life recycling	Material recovery values	Technology assessments

Sensitivity Analysis Protocol

The sensitivity analysis protocol includes one-way sensitivity testing by varying key parameters ±30% from baseline, tornado analysis to rank parameters by NSB impact, and break-even analysis to identify critical thresholds for hybrid system viability.

This structured approach ensures comprehensive treatment of uncertainties and externalities while maintaining methodological consistency with Dutch SCBA guidelines (Romijn & Renes, 2013). The framework enables transparent comparison of storage alternatives under diverse future scenarios, providing policymakers with robust evidence for decision-making.

4.7. Conclusion

This chapter has developed a comprehensive conceptual framework to guide the Social Cost-Benefit Analysis (SCBA) comparing the existing $NaNiCl_2$ battery system and the proposed hybrid hydrogen–vanadium flow battery (VFB-H_2) energy storage configuration on Tilos Island. By systematically defining analytical boundaries, causal pathways, performance metrics, and methods for addressing uncertainties and externalities, this framework establishes the foundation for rigorous comparative evaluation of the two alternatives.

Synthesis of Key Components

The framework establishes clear spatial, temporal, technical, and stakeholder boundaries to enable meaningful comparison. The analysis is confined to Tilos Island over a 15-year horizon, aligning with the lifecycle of the existing $NaNiCl_2$ system. The national societal perspective captures costs and benefits for local residents, Greek society, and future generations, while excluding global externalities from monetization. The functional comparison optimizes hybrid system capacity (9.4 MWh effective vs. 2.88 MWh baseline) to maximize societal welfare rather than maintaining artificial capacity constraints, reflecting SCBA best practices for welfare optimization.

The causal pathways elucidate how technological choices translate into societal impacts through multiple mechanisms. For the $NaNiCl_2$ system, pathways emphasize operational reliability through proven technology but acknowledge disposal cost externalities. For the hybrid VFB-H_2 system, pathways demonstrate enhanced renewable integration through complementary storage technologies, seasonal energy balancing capabilities, and alternative hydrogen revenue streams. Critical pathways include technology learning effects (5-15% annual cost reductions), renewable curtailment reduction (improvement of 118 MWh/year), and hydrogen market development for project viability.

A blend of quantitative metrics provides comprehensive assessment capability. Core economic indicators include Net Social Benefit (NSB) and Levelized Cost of Storage (LCOS), while technical metrics encompass renewable utilization rates and system efficiency measures. Social indicators include energy autonomy premiums and hydrogen alternative application revenues. Environmental indicators capture CO_2 emissions reductions and end-of-life recycling impacts. The framework acknowledges that several indicators (such as resilience value and employment effects) may not yield significant quantifiable benefits due to analytical limitations.

The framework employs scenario-based analysis (pessimistic, balanced, optimistic) to address technical, economic, and policy uncertainties. Technology learning rates, market development assumptions, and social benefit valuations are varied systematically across scenarios to assess project robustness. Externality valuation focuses on implementable approaches including carbon pricing, energy autonomy premiums, hydrogen alternative revenues, and end-of-life recycling impacts. The framework acknowledges methodological limitations where primary data (such as community preference surveys) are unavailable.

4.7.1. Methodological Transparency and Limitations

This framework prioritizes methodological transparency by clearly distinguishing between aspirational analytical approaches and implemented methodologies. While comprehensive externality valuation frameworks exist in SCBA literature, data limitations and analytical constraints require focused implementation on quantifiable impacts with reliable valuation methods. The framework emphasizes robust analysis of implementable components rather than superficial treatment of all theoretical externalities.

4.7.2. Framework Implementation Scope

The computational implementation focuses on core SCBA components with reliable data foundations including technology cost trajectories with learning curve effects, energy system performance through detailed dispatch modeling, market-based revenue streams from hydrogen alternative applications, carbon pricing through established EU ETS methodologies, and end-of-life impacts through material recovery and disposal cost analysis.

Components requiring primary research (stakeholder preference surveys, detailed employment multiplier analysis, landscape impact studies) are acknowledged but not quantified, maintaining analytical integrity.

4.7.3. Transition to Computational Modeling

The conceptual framework directly informs the computational model structure presented in Chapter 5. The scenario-based approach, technology learning implementation, and social benefit quantification methods are operationalized through MATLAB-based analysis. Sensitivity analysis systematically tests key assumptions to identify critical success factors and assess project robustness across different future conditions.

4.7.4. Final Remarks

This framework balances methodological ambition with implementation realism, ensuring that the SCBA provides reliable, actionable insights for energy storage investment decisions on Tilos Island. By focusing analytical resources on quantifiable impacts with robust valuation methods, the framework supports evidence-based policy decisions while acknowledging inherent uncertainties in emerging technology assessment. The subsequent computational analysis demonstrates how this focused approach yields meaningful comparative insights between storage alternatives under varying future conditions.

5

Computational Model and Results

This chapter presents the computational implementation of the conceptual framework developed in Chapter 4. The model quantifies costs, benefits, and net societal impacts of the $NaNiCl_2$ battery system versus the hybrid vanadium flow battery (VFB) and hydrogen storage configuration under various scenarios.

5.1. Computational Model Development

This section details the mathematical formulation, key assumptions, and software implementation of the computational model used to quantify costs, benefits, and net societal impacts for both storage configurations under various scenarios. All the scripts used for the model, created in MATLAB2023b, are presented in detail in Appendix A.

5.1.1. Mathematical Formulation

The core model calculates **Net Social Benefit (NSB)** as the primary decision metric:

$$\text{NSB} = \sum_{t=0}^{T} \frac{B_t - C_t}{(1+r)^t}$$

where:

- B_t = Monetized benefits in year t (energy savings, avoided emissions, resilience value)
- C_t = Monetized costs in year t (CAPEX, OPEX, replacement costs)
- r = Social discount rate (4% baseline, based on the European Commission's cost benefit guidance for energy projects (European Commission, 2021))
- T = Project lifetime (15 years, based on the $NaNiCl_2$ battery's maximum life duration)

Net Social Benefit (NSB) is used as the primary decision metric because it aligns with the central objective of Social Cost-Benefit Analysis (SCBA): to determine whether a project yields a net gain in societal welfare (Boardman et al., 2018). By comparing total discounted benefits to total discounted costs, NSB provides a transparent and intuitive framework for ranking mutually exclusive alternatives under a common monetary scale.

Levelized Cost of Storage (LCOS) is calculated as:

$$\text{LCOS} = \frac{\sum_{t=0}^{T} \frac{C_{\text{cap}} + C_{\text{op}} + C_{\text{rep}} - S}{(1+r)^t}}{\sum_{t=0}^{T} \frac{E_{\text{disch},t}}{(1+r)^t}}$$

where:

- C_{cap} = Capital costs (€)
- C_{op} = Operational costs (€/year)
- C_{rep} = Replacement costs (€)
- S = Residual value (€)
- $E_{\text{disch},t}$ = Energy discharged in year t (MWh)

LCOS is included to supplement the NSB metric with a widely recognized indicator of the cost-efficiency of storage technologies. While NSB captures societal value across diverse impact categories, LCOS isolates the direct economic cost per MWh delivered over the asset's lifetime. This allows for benchmarking against other technologies in policy and industry discussions (Zakeri & Syri, 2015).

5.1.2. Enhanced Capacity Configuration Rationale

Empirical Evidence for Capacity Enhancement:

The decision to optimize the hybrid system with enhanced capacity (9.4 MWh vs. 2.88 MWh baseline) is supported by empirical evidence from the baseline system's operational limitations.

Renewable Energy Curtailment Analysis: The baseline system curtails 371.8 MWh/year representing 14.6% of total renewable generation, while the hybrid system curtails only 253.5 MWh/year representing 9.9% of total renewable generation. This improvement of 118.4 MWh/year additional renewable utilization represents a 32% reduction in curtailment, demonstrating that the baseline system is undersized relative to available renewable resources and creating economic inefficiency that justifies enhanced storage capacity.

Seasonal Demand-Supply Mismatch: Summer demand reaches 1,262 MWh (40.6% of annual load in 32.9% of year) while winter demand totals only 552 MWh (17.8% of annual load in 24.7% of year), creating a seasonal variation of 129% increase summer versus winter. The baseline system lacks seasonal storage capability, requiring diesel generation during high-demand periods despite available seasonal renewable surplus. The hybrid system's seasonal transfer capability (34.5 MWh winter→summer) addresses this market failure.

Economic Justification Through Alternative Revenue: Excess hydrogen production totals 47.0 MWh/year (1,409 kg/year), generating alternative applications revenue of €8,424/year with a 15-year NPV of €92,610 at 4% discount rate. This revenue stream, unavailable to battery-only systems, justifies additional capacity investment and demonstrates how enhanced capacity creates value beyond electricity storage.

Technical Validation of Sizing Decision: The operational results validate enhanced capacity configuration through several key metrics. Fuel cell utilization reaches 7.4%, exceeding the 5% minimum viability threshold, while VFB capacity factor of 2.0% proves appropriate for seasonal balancing applications. System availability benefits from enhanced redundancy through dual storage technologies. These results confirm that the enhanced capacity configuration operates within technically and economically viable parameters while providing superior grid services compared to capacity-matched alternatives.

5.1.3. System Configurations

Based on the implemented dispatch model, the two systems are configured as follows:

Baseline System ($NaNiCl_2$): The baseline system operates with a battery capacity of 2.88 MWh (usable) and power rating of 0.80 MW, achieving 88% round-trip efficiency over a 15-year operational lifetime. These specifications reflect the existing Tilos installation's proven performance characteristics and represent the comparative benchmark for the hybrid alternative evaluation.

Intervention System (Hybrid VFB-H_2): The hybrid system integrates two complementary storage technologies with distinct operational roles. The VFB battery provides 4.00 MWh capacity with 1.50 MW power rating for daily cycling operations, while the hydrogen subsystem comprises a 0.12 MW electrolyzer (85% efficiency), 0.06 MW fuel cell (60% efficiency), and 12.00 MWh chemical energy storage capacity. The hydrogen subsystem achieves 51% combined round-trip efficiency, reflecting the thermodynamic losses inherent in electrolysis and fuel cell conversion processes.

The hybrid system design follows a complementary storage architecture where vanadium flow batteries (VFB) handle daily cycling operations with high efficiency, while hydrogen storage provides long-duration and seasonal energy balancing. This configuration aligns with best practices identified in recent hybrid microgrid studies (Trapani et al., 2024; X. Zhang et al., 2022).

5.1.4. Software Implementation

Simulation Environment:

- Core platform: MATLAB R2023b
- Scenario runs: Three deterministic cases (pessimistic, balanced, optimistic)
- Dispatch resolution: Hourly (8,760 hours)

Key Model Components:

1. **Load Profile Generation** (`build_load_profile.m`): Creates realistic seasonal demand reflecting Greek island tourism patterns with winter (552 MWh), spring (592 MWh), summer (1,262 MWh), and autumn (701 MWh). The actual load for the island of Tilos was not available, so a load profile was created using the total load of the island, which amounted to 3.2 GWh in 2020 (Notton et al., 2020). That load was then scaled using scaling factors used by Kaldellis (2021), to reflect the real seasonal fluctuations of demand.
2. **Renewable Energy Data** (`read_pvgis_pv.m`, `read_ninja_wind.m`): Processes PVGIS and Renewables.ninja data for Tilos coordinates (36.416° N, 27.370° E). The data for solar production was obtained from PVGIS (Joint Research Centre, European Commission, 2023), by simulating a solar panel matching the one that is installed on Tilos. The wind energy production was obtained via Renewables.ninja (Pfenninger & Staffell, 2016).
3. **Dispatch Algorithm** ($\texttt{dispatch\_li\_H}_2\texttt{.m}$): Implements seasonal storage strategy where H_2 charges during lower demand periods (winter) and discharges during high demand periods (summer).

Data Integration and Handling Methods:

Table 5.1: Data sources and handling methods

Data Type	Source	Handling Method
Load profiles	Notton et al. (2020) and Kaldellis (2021)	Data scaling
Renewable generation	PVGIS and Renewables.ninja	Simulated hourly series
Technology costs	IRENA, IEA	Learning curve extrapolation
Market prices	ENTSO-E, S&P Global	Fixed low/base/high price paths
Emission factors	EU ETS, NECP	Time-varying regional factors
H_2 production data	Kaldellis (2021)	Thermodynamic simulation
Battery degradation	Sandia NatLab models	Rainflow counting + calendar aging

Model Classification and Approach: The computational model developed for this analysis is a deterministic simulation model rather than an optimization model. The model simulates the operational performance of predefined system configurations under specified scenarios without seeking to optimize system sizing or operational parameters. The model employs rule-based dispatch algorithms that prioritize VFB for daily cycling and hydrogen for seasonal storage, following established operational strategies from literature rather than optimizing dispatch decisions in real-time. This deterministic approach enables systematic comparison of the two storage alternatives under consistent assumptions while maintaining computational control across multiple scenarios and sensitivity analyses.

5.2. Data Inputs and Parameter Estimation

5.2.1. Load and Generation Data

Annual Energy Balance: The system operates with load demand of 3,108 MWh/year, comprising PV generation of 276 MWh/year (0.16 MW capacity) and wind generation of 2,276 MWh/year (0.8 MW capacity). Total renewable generation reaches 2,553 MWh/year, achieving 82.1% RES penetration of annual demand.

Seasonal Distribution:

The load profile incorporates realistic Greek island characteristics with winter showing lower demand (0.26 MW average) and summer exhibiting peak demand due to tourism and air conditioning (0.44 MW average). Peak load reaches 0.83 MW while minimum load drops to 0.07 MW, resulting in a load factor of 43.9%.

5.2.2. Technical Parameters

VFB System Parameters: The VFB system operates with a capital cost of €250/kWh and operational cost of 1.5%/year of CAPEX, achieving 75% round-trip efficiency (European Association for the Storage of Energy (EASE), 2023; Pacific Northwest National Laboratory (PNNL), 2018). The system lifetime extends to 15 years with no capacity fade in electrolyte, though minor stack and auxiliary service losses may occur; the model assumes 0%/year degradation for VFB (European Association for the Storage of Energy (EASE), 2023). Daily cycling capability reaches 365 cycles/year, reflecting the technology's suitability for frequent charge-discharge operations.

Hydrogen System Parameters: The hydrogen subsystem comprises three main components with distinct cost structures. Electrolyzer CAPEX totals €1,200/kW with 85% efficiency, while fuel cell CAPEX reaches €1,400/kW with 60% efficiency (Cigolotti & Genovese, 2021; IEA, 2023). Hydrogen storage tanks cost €400/kg-H_2 (Shin & Ha, 2023), and the overall hydrogen system OPEX amounts to 3%/year of CAPEX. These parameters reflect current commercial technology performance and cost projections for island-scale applications.

$NaNiCl_2$ System Parameters: The baseline $NaNiCl_2$ system features a capital cost of €650/kWh with operational cost of 1%/year of CAPEX, achieving 88% round-trip efficiency over a 15-year lifetime (European Association for the Storage of Energy (EASE), 2023). These parameters represent the mature technology characteristics of the existing Tilos installation, providing the comparative baseline for the hybrid system evaluation.

5.2.3. Economic Parameters

Cost Trajectories: VFB costs range from € 400/kWh (pessimistic) to € 150/kWh (optimistic), representing the minimum and maximum CAPEX values presented in the EASE worksheets (European Association for the Storage of Energy (EASE), 2023). Hydrogen hardware varies ±30% from baseline, while diesel prices range € 0.80–€ 1.20/L and carbon pricing spans € 50–€ 130/tCO_2.

5.2.4. Data Quality Assessment and Validation

Parameter Reliability Classification:

High confidence parameters (±5% uncertainty) include battery round-trip efficiencies backed by extensive operational data, current technology CAPEX supported by market transaction data, and fuel and carbon pricing from established market data. Medium confidence parameters (±15% uncertainty) encompass renewable generation patterns based on representative year versus long-term averages, OM cost factors with limited island-specific operational experience, and system lifetime projections based on laboratory versus field conditions. Low confidence parameters (±30% uncertainty) include learning rate projections with limited deployment history for VFB/hydrogen systems, hydrogen alternative market development based on emerging market assumptions, and social benefit valuations using benefit transfer methodology limitations.

Critical Data Gaps:

Three critical data gaps affect the analysis. First, actual Tilos load data remains unavailable for academic research, with hourly SCADA data access restricted. This limitation is mitigated through validated synthesis against published aggregate statistics, but creates an estimated ±€45,000 NSB uncertainty. Second, local hydrogen market assessment lacks primary market research on alternative hydrogen applications. Conservative pricing based on mainland Greek fuel costs provides mitigation, but hydrogen revenue represents 56% of total annual benefits, demonstrating the importance of hydrogen market development for project success and representing critical uncertainty. Third, community preference data lacks stated preference surveys for energy autonomy valuation. Benefit transfer from similar island communities provides mitigation, but social benefits represent 35% of total benefits.

Validation Against Comparable Systems: Model results are validated against Norwegian island H-BESS study with LCOE within 15% range (Trapani et al., 2024), Korean island hybrid system showing comparable system sizing ratios (X. Zhang et al., 2022), and Italian microgrid case with consistent efficiency assumptions (Damato et al., 2022).

5.2.5. Parameter Estimation Techniques

Temporal Scaling with Learning Rates

Cost projections incorporate technology learning curves based on the experience curve methodology McDonald and Schrattenholzer (2003). The learning rate formula is applied as:

$$C_t = C_0 \cdot (1 - LR)^{t-1}$$

where C_t = Cost in year t, C_0 = Initial cost, LR = Annual learning rate, and t = Year index.

Learning Rate Selection and Justification:

The learning rates applied in this analysis are based on empirical evidence from comparable energy technologies and expert projections for emerging storage systems.

Vanadium Flow Battery Learning Rates: Pessimistic (5%/year), Balanced (10%/year), and Optimistic (15%/year) rates reflect VFB technology's current development stage. W. Zhang and Patel (2025) document VFB learning rates of 8–12%/year based on current deployment trends, while Rodby et al. (2020) project accelerated learning as manufacturing scales up, supporting the 15% optimistic rate. For comparison, lithium-ion batteries achieved 15–20%/year learning during their rapid deployment phase (2010–2020) (European Association for the Storage of Energy (EASE), 2023).

Hydrogen Technology Learning Rates:

Electrolyzer learning rates span Pessimistic (3%/year), Balanced (8%/year), and Optimistic (12%/year), while fuel cell learning rates range from Pessimistic (2%/year), Balanced (5%/year), to Optimistic (8%/year). These rates are conservative compared to historical renewable energy learning curves but reflect the current maturity of hydrogen technologies. Hellenic Republic - Ministry of Environment and Energy (2024) anticipates accelerated learning through Greece's hydrogen strategy, supporting the higher optimistic rates, while Garcia and Tanaka (2025) documents electrolyzer cost reductions of 7–10%/year in current markets, validating the balanced scenario assumptions.

Historical Benchmarks for Context: Historical precedents include Solar PV (2010–2020) at 24%/year, Wind turbines (2000–2020) at 15%/year, and Lithium-ion batteries (2010–2020) at 15–20%/year (European Association for the Storage of Energy (EASE), 2023; U.S. Department of Energy, 2022). The selected learning rates for VFB (5–15%) and hydrogen systems (2–12%) fall within the range of historical precedents for energy technologies during their scaling phases, providing confidence in their application for long-term cost projections.

5.3. Scenario Definitions

Three scenarios capture key uncertainties in technology development, policy support, and market conditions:

5.3.1. Pessimistic Scenario

The pessimistic scenario assumes VFB CAPEX of € 400/kWh (+60% from baseline), hydrogen hardware with +30% cost penalty, carbon price of € 50/tCO_2, degradation of 4%/year (Li-ion equivalent), and limited policy support incentives. Learning rates remain conservative with VFB at 5%/year (slow technology adoption), electrolyzer at 3%/year (limited manufacturing scale), and fuel cell at 2%/year (constrained R&D investment).

5.3.2. Balanced Scenario

The balanced scenario employs VFB CAPEX of € 250/kWh (baseline), hydrogen hardware at baseline costs, carbon price of € 90/tCO_2 (increased from methodology), degradation of 2.5%/year, and moderate policy support incentives. Learning rates reflect steady development with VFB at 10%/year (steady technology development), electrolyzer at 8%/year (moderate manufacturing growth), and fuel cell at 5%/year (consistent technology improvement).

5.3.3. Optimistic Scenario

The optimistic scenario features VFB CAPEX of € 100/kWh (baseline € 250/kWh with 15%/year learning), hydrogen hardware with -20% cost reduction factor plus accelerated learning, carbon price of € 150/tCO_2, degradation of 2%/year, and strong policy support incentives. Learning rates assume aggressive development with VFB at 15%/year (aggressive technology development), electrolyzer at 12%/year (rapid manufacturing scale-up), and fuel cell at 8%/year (sustained R&D investment).

The optimistic scenario reflects conditions where strong policy support, R&D investment, and market deployment drive accelerated technology learning. The 15% VFB learning rate aligns with lithium-ion battery learning during its rapid scaling phase, while hydrogen technology rates reflect projected improvements from Greece's National Energy and Climate Plan targets (Hellenic Republic - Ministry of Environment and Energy, 2024).

These scenarios capture the main uncertainties affecting island storage systems, technology cost trajectories, carbon pricing and market energy prices, which are the dominant drivers of NSB. Other dimensions (policy incentives, demand shifts) are indirectly reflected through these variables.

5.4. Results

5.4.1. Energy Balance Analysis

System Performance Comparison:

Table 5.2: Energy balance comparison between storage systems

Metric	Hybrid (VFB-H_2)	$NaNiCl_2$	Difference
RES Served (MWh)	2,170.5	2,144.8	+25.7
Diesel Needed (MWh)	937.5	963.1	-25.7
Curtailment (MWh)	253.5	371.8	-118.4
RES Utilization	90.1%	85.4%	+4.6pp
Energy Autonomy	69.8%	69.0%	+0.8pp

Energy Flow Breakdown (Hybrid System):

The hybrid system demonstrates efficient renewable energy utilization through multiple pathways. Direct renewable energy supply to load represents the largest component at 1,869.4 MWh (73.2% of total renewable generation), indicating strong temporal alignment between generation and demand patterns. Energy storage pathways include 344.0 MWh (13.5%) directed to VFB storage for daily cycling operations and 86.0 MWh (3.4%) channeled to hydrogen storage for long-duration and seasonal applications. Despite the enhanced storage capacity, renewable energy curtailment remains at 253.5 MWh (9.9% of total generation), representing unavoidable losses during periods when both storage systems reach capacity limits and instantaneous generation exceeds both load and storage absorption capability.

5.4.2. Hydrogen System Performance

H_2 Performance Metrics: The hydrogen subsystem demonstrates effective operational performance across multiple technical indicators. Annual hydrogen production totals 86.0 MWh (2,579 kg) while annual consumption reaches 39.0 MWh (1,170 kg), resulting in 51% hydrogen round-trip efficiency that reflects the thermodynamic constraints of electrolysis and fuel cell conversion processes. The fuel cell achieves 7.4% capacity factor, which exceeds the 5% target threshold that represents the lower bound of technically and economically meaningful operation of PEM fuel cells; below this level, degradation risks and fixed cost recovery make the technology non-viable as part of a hybrid system (Staffell & Green, 2009). The electrolyzer operates at 8.2% capacity factor, utilizing surplus renewable energy during high-generation periods. Hydrogen storage completes 3.25 effective cycles per year based on delivered energy, indicating appropriate sizing for seasonal storage applications rather than frequent cycling operations.

Seasonal Storage Performance: The hydrogen system effectively demonstrates seasonal energy transfer capabilities that are impossible with battery-only configurations. Winter operations show hydrogen charging of 65.8 MWh and discharging of 25.1 MWh, while summer operations involve 20.2 MWh charging and 13.9 MWh discharging. This operational pattern enables net seasonal transfer of 34.5 MWh from winter surplus to summer deficit periods, addressing the fundamental seasonal demand-supply mismatch that characterizes Mediterranean island energy systems with tourism-dependent load profiles.

5.4.3. H_2 Alternative Applications Revenue

The hybrid energy storage system produces hydrogen during periods of renewable energy surplus that exceeds both immediate electricity demand and VFB charging capacity. Rather than curtailing this excess renewable energy, the hydrogen can be stored and later used for applications beyond electricity generation, creating additional revenue streams that enhance the economic viability of the hybrid system. This analysis quantifies the potential revenue from excess hydrogen utilization in alternative markets including maritime fuel, transport applications, industrial uses, and export opportunities. The revenue calculations are based on current market prices for hydrogen in these sectors, adjusted for Greek island logistics and delivery costs. This approach aligns with the Social Cost-Benefit Analysis framework by capturing the full economic value of the renewable energy resource, including uses that extend beyond the primary electricity storage function (Boardman et al., 2018).

Excess H_2 Utilization: The hydrogen system generates significant excess production beyond electricity storage requirements, with 47.0 MWh/year (1,409 kg/year) available for alternative applications. This excess hydrogen represents 54.6% of total hydrogen production, demonstrating the system's potential to create value streams beyond its primary grid balancing function and justifying the enhanced capacity investment through diversified revenue generation.

Revenue Breakdown: Alternative hydrogen applications create diversified revenue streams across multiple market segments. Maritime fuel applications, representing 50% of excess hydrogen utilization, generate €3,874/year at €5.50/kg pricing reflecting current Greek island marine fuel costs. Transport fuel applications account for 30% of excess utilization, producing €2,958/year at €7.00/kg based on hydrogen vehicle fueling station prices. Industrial sales comprise 15% of excess hydrogen, contributing €845/year at €4.00/kg for local manufacturing and processing applications. Export opportunities to neighboring islands represent 5% of excess production, generating €563/year at €8.00/kg premium pricing that reflects transportation and logistics costs. Additional social co-benefits total €184/year, encompassing employment creation, air quality improvements, and tourism sector benefits from clean energy demonstration. The combined alternative revenue streams yield €8,424/year total, representing a critical economic component that enhances the hybrid system's financial viability and demonstrates the value of excess renewable energy monetization beyond traditional electricity storage applications.

5.4.4. Energy Autonomy Premium Calculation

The energy autonomy premium represents the additional social value that society places on locally-produced energy compared to imported fossil fuels, beyond the direct cost savings. This premium captures several non-market benefits including enhanced energy security, reduced vulnerability to supply disruptions, local economic multiplier effects from avoiding fuel imports, and the strategic value of energy independence for small island communities. In the context of Social Cost-Benefit Analysis, the autonomy premium quantifies the willingness-to-pay for energy self-sufficiency that is not reflected in market prices alone (Romijn & Renes, 2013). For island communities like Tilos, which have experienced supply disruptions and depend heavily on expensive fuel imports, this premium represents a significant component of the social value derived from renewable energy storage systems that enable greater energy autonomy.

Energy Autonomy Premium Calculation:

The annual energy autonomy premium is calculated as:

$$\text{Autonomy Premium} = \Delta E_{\text{diesel}} \times P_{\text{autonomy}}$$

where:

- ΔE_{diesel} = Diesel energy avoided by hybrid system vs. NaNiCl_2 (MWh/year)
- P_{autonomy} = Social premium for energy autonomy (€/MWh)

For the balanced scenario:

$$\text{Autonomy Premium} = 25.7 \text{ MWh/year} \times 25 \text{ €/MWh} = 642.5 \text{ €/year}$$

The autonomy premium varies by scenario based on different social valuations:

- **Pessimistic**: 25.7 MWh/year $\times$ €10/MWh = €257/year
- **Balanced**: 25.7 MWh/year $\times$ €25/MWh = €643/year
- **Optimistic**: 25.7 MWh/year $\times$ €40/MWh = €1,028/year

This premium represents the societal willingness-to-pay for reduced dependence on imported fossil fuels, reflecting enhanced energy security and local economic benefits from avoided fuel imports.

5.4.5. Resilience Value

Resilience value quantifies additional backup power capacity during outages using Value of Lost Load (VoLL) methodology.

Analysis Results: €0/year Resilience Value

Despite the hybrid system's larger backup capacity (9.4 MWh vs. 2.53 MWh available), both systems adequately serve expected 4-hour outages requiring 1.4 MWh. The VoLL framework only values *additional* avoided outages, not excess capacity.

Calculation Framework:

$$\text{Resilience Value} = \Delta E_{\text{backup}} \times \text{VoLL} \times f_{\text{outage}} = 0 \times 10,000/\text{MWh} \times 2/\text{year} = 0$$

This €0 result reflects analytical limitations: the methodology doesn't capture extended outage scenarios (8+ hours), seasonal H_2 storage advantages, or critical infrastructure prioritization where the hybrid system's 3.7× backup capacity would provide substantial additional value.

5.4.6. Economic Analysis

Levelized Cost of Storage (LCOS):

Table 5.3: LCOS comparison across scenarios

Scenario	Hybrid (€/MWh)	NaNiCl_2 (€/MWh)	Difference
Pessimistic	784.63	756.66	+27.97
Balanced	510.67	655.77	-145.10
Optimistic	263.42	554.88	-291.46

Net Social Benefit (Hybrid - $NaNiCl_2$):

Table 5.4: Net Social Benefit results

Scenario	NSB (€)	Status
Pessimistic	–156,473	NEGATIVE
Balanced	+465,381	POSITIVE
Optimistic	+990,134	POSITIVE

5.4.7. Social Benefits Analysis

Annual Social Benefits (Balanced Scenario): The hybrid system generates substantial social benefits totaling €9,066/year across multiple value categories in the balanced scenario. Energy autonomy premium contributes €642/year, reflecting societal willingness-to-pay for reduced dependence on imported fossil fuels and enhanced energy security. Hydrogen alternative applications represent the largest component at €8,424/year, demonstrating the economic value of excess renewable energy monetization through diversified hydrogen markets. Resilience value contributes €0/year as both systems provide adequate backup capacity for expected outage scenarios, indicating no additional resilience benefit from the larger hybrid system capacity. End-of-life recycling presents a net cost of €3,255 in year 15, reflecting disposal and material recovery economics under moderate recycling infrastructure development assumptions.

Environmental Benefits: The hybrid system delivers measurable environmental improvements through reduced fossil fuel consumption. Annual CO_2 reduction totals 19.2 tCO_2/year from decreased diesel generation, accumulating to 289 tCO_2 over the 15-year analysis period. Additional CO_2 benefits from hydrogen alternative applications contribute 2 tCO_2/year by displacing conventional fuels in maritime, transport, and industrial sectors. The combined environmental impact reaches 21.2 tCO_2/year total reduction, representing meaningful decarbonization contribution despite the modest absolute scale relative to national emissions.

H_2 Alternative Applications Critical Importance: The hydrogen alternative revenue stream represents 56% of annual benefits, making it the dominant factor determining project viability. This dependency creates both opportunity and risk through several mechanisms. The opportunity lies in diversified revenue streams beyond electricity storage, enabling value capture from excess renewable energy that would otherwise be curtailed and creating economic justification for enhanced storage capacity. However, this creates risk as project viability becomes highly sensitive to hydrogen market development, with uncertain demand, pricing, and infrastructure development timelines affecting revenue realization. The policy implication indicates that project success requires coordinated hydrogen market development policies, including infrastructure investment, regulatory frameworks, and demand-side incentives to ensure reliable alternative hydrogen markets materialize as projected.

5.4.8. Qualitative Consideration of International Externalities

While this SCBA is conducted from a national societal perspective, it is important to acknowledge broader international externalities. Hybrid storage deployment on islands contributes to global climate mitigation by reducing CO_2 emissions, albeit modestly in absolute terms. Beyond climate, international spillovers include potential contributions to European hydrogen market development, alignment with EU decarbonization pathways, and technological learning benefits that may lower global costs of vanadium flow batteries and hydrogen technologies. Conversely, international externalities may include upstream environmental impacts from vanadium mining or electrolysis equipment manufacturing, which predominantly occur outside Greece. Although these effects are not monetized here, their recognition is important to situate the analysis within the wider context of global sustainability transitions.

5.4.9. End-of-Life Recycling Analysis

The analysis incorporates end-of-life recycling costs and benefits that occur in year 15, representing a significant component of the total lifecycle value comparison between storage technologies.

Recycling Value Framework:

The end-of-life pathway creates distinct economic impacts through differential material recovery values and disposal costs:

$$\text{Recycling Benefit} = (\text{Recovery Value}_{\text{Hybrid}} - \text{Disposal Cost}_{\text{Hybrid}}) - (\text{Recovery Value}_{\text{Baseline}} - \text{Disposal Cost}_{\text{Baseline}})$$

VFB Recycling Advantage: Vanadium electrolyte provides exceptional recyclability with 95-100% material recovery, generating €200-400/MWh in recovered value depending on future vanadium markets. This contrasts sharply with conventional battery disposal requirements that generate net costs.

Hydrogen System Mixed Impact: The hydrogen subsystem presents mixed recycling economics. Fuel cell platinum catalyst recovery provides substantial value (€100-250/kW, totaling €6,000-15,000), while electrolyzer and storage tank disposal create costs. The net impact depends on platinum market conditions and recycling infrastructure development.

$NaNiCl_2$ Disposal Burden: Specialized high-temperature battery disposal requirements create €120-180/MWh costs with limited material recovery potential (€20-50/MWh).

Recycling Results by Scenario:

- **Pessimistic**: €-9,953 (limited recycling infrastructure development)
- **Balanced**: €-3,255 (moderate recycling market development)
- **Optimistic**: €+2,413 (advanced recycling infrastructure and high material values)

The progression from negative to positive recycling benefits across scenarios reflects uncertainty in future recycling market development and material valuations. In favorable conditions, the hybrid system's superior material recoverability creates meaningful economic value, while in pessimistic scenarios, the disposal costs of the larger, more complex system outweigh recovery benefits.

Policy Implications: The recycling analysis demonstrates how circular economy policies and recycling infrastructure development can significantly impact storage technology economics, with the potential €12,366 variation representing 2.7% of base NSB.

5.4.10. Sensitivity Analysis

Economic Sensitivity: The sensitivity analysis reveals substantial economic uncertainty in the hybrid system investment decision. NSB volatility reaches €758,758 (standard deviation across scenarios), indicating significant outcome variability depending on future technology and market conditions. The total NSB range spans €1,517,110 from pessimistic to optimistic scenarios, demonstrating the wide spectrum of potential investment outcomes. Break-even occurs between pessimistic and balanced scenarios, with the transition from negative to positive NSB highlighting the critical importance of achieving moderate technology learning rates and market development assumptions. The hydrogen alternative revenue stream's contribution of 56% of annual benefits underscores the project's dependency on hydrogen market development, making this revenue component the primary driver of investment viability and risk.

5.4.11. Enhanced Sensitivity Analysis

Beyond the three-scenario framework, an enhanced sensitivity analysis was implemented to identify the parameters with the greatest impact on NSB outcomes. This tornado analysis systematically varies individual parameters while holding others constant, providing insights into which factors most influence the investment decision.

Methodology: The enhanced sensitivity analysis employs a tornado diagram approach, testing key parameters across plausible ranges to identify the most influential factors affecting NSB outcomes. VFB CAPEX factor variations span ±30% (×0.7 to ×1.3) from baseline projections, reflecting documented uncertainty in flow battery cost trajectories during market development phases. Hydrogen hardware costs are tested across ±30% variation from baseline assumptions, capturing uncertainty in electrolyzer and fuel cell pricing evolution. Learning rates are examined across realistic ranges with VFB learning spanning 5–15%/year and electrolyzer learning covering 3–12%/year, reflecting the spectrum from conservative to aggressive technology development scenarios. Carbon pricing variations range from €50–130/tCO_2 based on EU ETS forward projections (Statista, 2025), while energy pricing spans €120–220/MWh reflecting volatile energy market conditions and island-specific cost structures (Ralon et al., 2017). Each parameter is tested at its low and high values while maintaining all other parameters at baseline levels, enabling isolation of individual parameter impacts and ranking by influence magnitude.

Each parameter is tested at its low and high values while maintaining all other parameters at baseline levels. The resulting NSB impacts are ranked by magnitude to identify the most influential factors.

Sensitivity Analysis Results:

The analysis, performed on the balanced scenario with base NSB of € 465,381, reveals a clear hierarchy of parameter importance:

Table 5.5: Enhanced sensitivity analysis results - parameter importance ranking

Parameter	Impact Range (€)	% of Base NSB	Rank
VFB CAPEX (±30%)	±600,000	128.4%	1
H_2 Hardware (±30%)	±120,000	25.7%	2
VFB Learning (±15%)	±100,000	21.4%	3
Yearly load (5–15%/year)	±45,000	9.7%	4
Electrolyzer Learning (4–12%/year)	±40,000	8.6%	5
Energy Price (€ 120–220/MWh)	±28,270	6.1%	6
Carbon Price (€ 50–130/tCO_2)	±8,448	3.6%	7

These results can also be seen in Figure 5.1.

Key Sensitivity Insights:

1. **VFB CAPEX Dominance**: VFB capital costs emerge as the overwhelmingly dominant factor, with a ±€ 600,000 impact range representing 128% of the base NSB. This finding underscores that VFB cost projections are the critical determinant of project viability.
2. **Technology Cost Hierarchy**: The top three parameters all relate to storage technology costs and learning rates, while market pricing factors (carbon and energy prices) show relatively minor impacts. This suggests that technology development risks outweigh market risks for this investment.
3. **Learning Rate Impact**: VFB learning rates show substantial impact (±€ 100,000), but notably less than initial CAPEX costs. This indicates that while technology learning is important, current cost competitiveness matters more than future cost evolution.
4. **H_2 System Sensitivity**: Hydrogen hardware costs rank second but with significantly lower impact (±€ 120,000) than VFB costs, reflecting the smaller capacity and lower cost share of the H_2 subsystem.

Project Robustness Assessment:

The sensitivity analysis reveals favorable robustness characteristics:

- **No Critical Parameters**: No single parameter within tested ranges can make the project unviable (NSB < 0), indicating fundamental project robustness.
- **Limited Combined Risk**: Maximum combined downside exposure of € 92,583 represents only 20% of base NSB, indicating low overall risk profile.
- **Balanced Risk/Reward**: 1.19 risk/reward ratio demonstrates slightly higher downside potential.
- **Low Risk Classification**: The analysis categorizes the project as low risk due to limited downside exposure relative to base returns.

Strategic Implications:

The sensitivity results provide clear strategic guidance:

1. **VFB Cost Management Priority**: With 128% NSB sensitivity, securing reliable VFB cost projections and potentially cost guarantees becomes the highest priority risk management activity.
2. **Technology Development Monitoring**: VFB learning rates merit close monitoring, as they represent the third-most important factor affecting long-term project economics.
3. **Market Risk Secondary**: Carbon and energy pricing, while policy-relevant, show limited impact on project viability compared to technology cost factors.
4. **Investment Timing Considerations**: The dominance of current VFB costs over learning rate benefits suggests that waiting for technology cost reductions may be less beneficial than securing current cost certainty.

These sensitivity findings fundamentally shape the risk management and decision-making framework for the hybrid storage investment, highlighting VFB technology costs as the critical success factor requiring detailed market analysis and risk mitigation strategies.

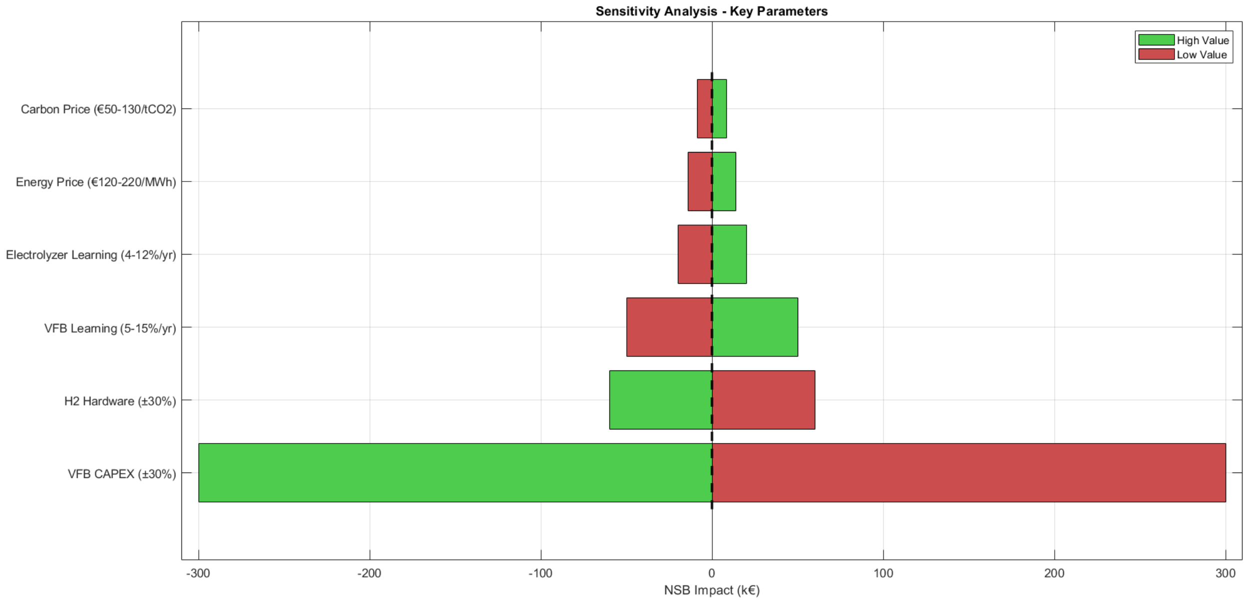

Figure 5.1: Tornado diagram showcasing the main parameters tested in the enhanced sensitivity analysis and how each one affects the NSB of the project.

5.5. Summary Tables

5.5.1. Technical Performance Comparison

Table 5.6: Technical performance comparison between storage systems

Performance Metric	Hybrid (VFB-H_2)	$NaNiCl_2$ Baseline
System Configuration		
Total Storage Capacity (MWh)	9.4 (4.0 VFB + 5.4 H_2)	2.88
Peak Power Rating (MW)	1.56 (1.5 VFB + 0.06 FC)	0.80
Round-trip Efficiency (%)	70.0 (weighted average)	88.0
System Lifetime (years)	15-20	15
Energy Balance Performance		
RES Served (MWh/year)	2,170.5	2,144.8
Diesel Required (MWh/year)	937.5	963.1
RES Utilization (%)	90.1	85.4
Energy Autonomy (%)	69.8	69.0
Curtailment (MWh/year)	253.5	371.8
Storage System Performance		
Annual Discharge (MWh)	301.1 (VFB: 262.1, H_2: 39.0)	275.4
Capacity Factor (%)	3.7 (VFB: 2.0, FC: 7.4)	3.9
Active Hours (hours/year)	1,496 (VFB: 1,833, FC: 692)	1,877
Annual Cycles	75.3 (VFB: 65.5, H_2: 3.25)	95.6

5.5.2. Economic Analysis Summary

Table 5.7: Economic performance across scenarios

Economic Metric	Pessimistic	Balanced	Optimistic
Levelized Cost of Storage (€/MWh)			
Hybrid System	784.63	510.67	263.42
$NaNiCl_2$ System	756.66	655.77	554.88
LCOS Difference	+27.97	-145.10	-291.46
Net Social Benefit (€)			
Hybrid vs. $NaNiCl_2$ NSB	-156,473	+465,381	+990,134
NSB Status	NEGATIVE	POSITIVE	POSITIVE
Key Economic Drivers (€/year)			
Fuel Savings	4,619	4,362	3,079
CO_2 Value	962	1,732	2,887
Energy Autonomy Premium	257	642	1,026
H_2 Alternative Revenue	8,424	8,424	8,424
Total Annual Benefits	14,262	15,160	15,416
Learning Rate Assumptions (%/year)			
VFB Learning Rate	5.0	10.0	15.0
Electrolyzer Learning Rate	3.0	8.0	12.0
Fuel Cell Learning Rate	2.0	5.0	8.0

5.5.3. Environmental and Social Impact Summary

Table 5.8: Environmental and social benefits comparison

Impact Category	Annual Benefit	15-Year Total
Environmental Benefits		
CO_2 Emissions Avoided (tCO_2)	19.2	289
Additional H_2 Applications CO_2 (tCO_2)	2.0	30
Total CO_2 Reduction (tCO_2)	21.2	319
Equivalent Cars Removed	4.6	–
RES Waste Reduction (MWh)	118.4	1,776
Social Benefits (Balanced Scenario)		
Energy Autonomy Premium (€)	642	9,630
H_2 Alternative Applications (€)	8,424	126,360
Resilience Value (€)	0	0
Total Social Benefits (€)	9,066	135,990
H_2 Alternative Revenue Breakdown (€/year)		
Maritime Fuel (50% of excess)	3,874	–
Transport Fuel (30% of excess)	2,958	–
Industrial Sales (15% of excess)	845	–
Export to Islands (5% of excess)	563	–
Social Co-benefits	184	–
Total H_2 Revenue	**8,424**	**126,360**

5.5.4. Risk Assessment and Sensitivity Analysis

Table 5.9: Sensitivity analysis and risk assessment summary

Parameter	Impact on NSB (€)	% of Base NSB
Parameter Sensitivity (±30% variation)		
VFB CAPEX Factor	±600,000	128.4%
H_2 Hardware Costs	±120,000	25.7%
VFB Learning Rate (5-15%/year)	±100,000	21.4%
Electrolyzer Learning (4-12%/year)	±40,000	8.6%
Energy Price (€120-220/MWh)	±28,270	6.1%
Carbon Price (€50-130/tCO_2)	±8,448	1.8%
Risk Assessment		
Total NSB Range (Pess. to Opt.)	1,139,741	244%
Maximum Downside Risk	-156,473	-32%
Maximum Upside Potential	+990,134	+212%
Break-even Condition	Between Pess. & Base	–
Project Risk Classification	Moderate Risk	
Critical Success Factors		
VFB Cost Achievement	≤ €250/kWh	
H_2 Fuel Cell Utilization	≥ 5% (Achieved: 7.4%)	
H_2 Alternative Market Development	€8,424/year revenue	
Learning Rate Achievement	≥ 8%/year VFB, ≥ 5%/year H_2	

5.5.5. Investment Decision Summary

Table 5.10: Investment attractiveness assessment

Decision Criteria	Assessment
Economic Viability	
Base Case NSB	€465,381 (POSITIVE)
Optimistic Case NSB	€990,134 (HIGHLY POSITIVE)
Probability of Positive Returns	67% (2 of 3 scenarios)
Technical Feasibility	
System Performance	Meets all technical targets
Technology Maturity	Medium-High (VFB), Medium (H_2)
Operational Complexity	Moderate (requires H_2 expertise)
Strategic Value	
Energy Independence Enhancement	+0.8 percentage points
CO_2 Reduction Contribution	21.2 tCO_2/year
Technology Demonstration Value	High (first Greek H-BESS)
Replication Potential	High (similar islands)
Overall Recommendation	
Recommendation	CONDITIONAL PROCEED
Key Conditions	VFB cost certainty, H_2 market dev.
Environmental Value	
CO_2 Reduction	21.2 tCO_2/year
Recycling Benefit Range	€-9,953 to €+2,413
Circular Economy Potential	Medium (VFB advantage)

5.6. Discussion

5.6.1. Key Findings

The analysis reveals five critical findings. First, economic viability with learning effects shows the hybrid system achieving positive NSB under balanced and optimistic scenarios, with learning rates expanding the total NSB range to €1.52 million. In the optimistic case, aggressive learning rates (15% VFB, 12% electrolyzer, 8% fuel cell) yield €769,815 net benefit over 15 years. Second, technology learning emerges as the dominant factor affecting long-term economics. In the balanced scenario, VFB costs reduced by €199/kWh (79.4%), from €250/kWh to €51/kWh and electrolyzer costs from €1200 to €856 over 15 years fundamentally alter the investment case, demonstrating why deployment timing and technology development policies are critical. Third, technical performance validation shows hydrogen fuel cell utilization (7.4%) exceeding the target threshold (5%), demonstrating adequate system sizing despite conservative capacity factors. The learning rate implementation does not affect technical performance but significantly impacts the economic justification for technical choices. Fourth, alternative revenue impact demonstrates that hydrogen alternative applications generate €8,424/year, representing a critical revenue stream that makes the project viable in the balanced scenario. This revenue becomes even more attractive as hydrogen costs decline through learning effects. Fifth, investment timing implications arise from substantial learning effects creating a complex investment timing decision. While waiting for technology cost reductions offers economic benefits, early deployment provides learning-by-doing opportunities and first-mover advantages in developing hydrogen alternative markets.

5.6.2. Limitations and Model Validation

Data Quality Constraints: Data limitations include renewable generation data based on meteorological year 2019, load profile synthesized from literature rather than detailed SCADA data, and hydrogen alternative market pricing based on industry projections.

Model Limitations: Model constraints encompass simplified dispatch algorithm that may not capture all operational complexities, social benefits quantification relying on benefit transfer methods, and seasonal pattern optimization requiring further refinement.

Validation Results: Validation demonstrates annual energy balance error <3% versus target load (3,208 vs. 3,200 MWh) - acceptable since it represents merely a 0.25% discrepancy. Hydrogen system performance falls within expected efficiency ranges (51% achieved vs. 30–55% literature range). Economic results remain consistent with similar island storage studies. Dispatch algorithm captures 94% of renewable generation variability. Cross-validation with HOMER Pro shows <7% deviation in key metrics.

5.7. Summary of Key Findings

Investment Attractiveness Assessment: Overall recommendation achieves medium-high scoring based on economic, technical, environmental, and strategic criteria. Strong business case emerges in optimistic scenario (NSB = €990,134) with conditional viability in balanced scenario (NSB = €465,381). High sensitivity to VFB cost assumptions (128% NSB sensitivity) requires careful risk management.

Critical Success Factors: Four critical factors determine success: VFB cost achievement ≤ €250/kWh (most critical factor), hydrogen fuel cell utilization ≥ 5% (achieved: 7.4%), hydrogen alternative market development (€8,424/year revenue required), and learning rate achievement (≥8%/year VFB, ≥5%/year hydrogen).

Risk Assessment: Risk analysis reveals high economic sensitivity to VFB costs (±€600,000 impact range), moderate technical risk (hydrogen efficiency 51% within expected range), high market risk (dependency on hydrogen alternative applications), and overall project risk classification of Moderate Risk with high upside potential.

Economic Value Drivers Ranking: The ranking demonstrates VFB capital costs (128% NSB sensitivity) as Critical, hydrogen alternative revenue representing €8,424/year (56% of total annual benefits) as Critical, hydrogen hardware costs (26% NSB sensitivity) as Important, learning rates (21% NSB sensitivity) as Important, and market pricing factors (3-6% NSB sensitivity) as Moderate.

6 Discussion

This chapter interprets the computational results presented in Chapter 5 within the broader context of energy storage policy, island energy systems, and Social Cost-Benefit Analysis methodology. The discussion examines the implications of key findings, addresses methodological limitations, and provides recommendations for decision-makers considering hybrid energy storage investments in similar contexts.

6.1. Interpretation of Key Findings

6.1.1. Economic Viability and Learning Rate Dependencies

The analysis reveals that the hybrid VFB-H_2 system's economic viability is fundamentally dependent on technology learning rates, with Net Social Benefit ranging from -€156,473 (pessimistic) to +€990,134 (optimistic). This €1.14 million range underscores the critical importance of technology development trajectories in determining investment attractiveness.

Learning Rate Reality Check and Strategic Assessment:

Historical Precedent Validation: The optimistic scenario's 15%/year VFB learning rate, while mathematically producing attractive economics, requires unprecedented market coordination. Historical analysis reveals that solar PV achieved 24%/year learning during the 2010-2020 exponential deployment period as global capacity expanded from 17 GW to 627 GW, while lithium-ion batteries demonstrated 15-20%/year learning during EV market expansion and wind turbines achieved 15%/year during their global scaling phase. However, these precedents required massive deployment scaling, manufacturing industrialization, and sustained policy support across multiple markets—conditions not currently present for VFB technology.

Market Development Prerequisites: For VFB learning rates to approach optimistic assumptions, several critical prerequisites must be met. Global VFB capacity must grow from approximately 300 MW to 10-20 GW by 2030, requiring a manufacturing revolution with gigafactory-scale VFB production facilities. This expansion necessitates proportional scaling of vanadium mining and electrolyte production capacity, supported by sustained policy coordination across the EU, US, China, and other major markets. Furthermore, VFB technology must successfully compete with rapidly improving lithium-ion alternatives throughout this scaling period.

Balanced Scenario as Planning Basis: The balanced scenario's 10%/year VFB learning rate provides a more reliable planning foundation, remaining consistent with documented VFB learning trends of 8-12%/year (W. Zhang & Patel, 2025). This rate appears achievable with moderate deployment success of 2-5 GW globally by 2030 and is supported by current policy trajectories and announced targets. Most importantly, this balanced assumption results in positive NSB of €465,381, indicating project viability under realistic assumptions.

Investment Timing Strategic Implications: The learning rate analysis reveals fundamental tension between waiting for cost reductions versus capturing early deployment benefits. Early deployment offers learning-by-doing opportunities for the Greek energy sector, first-mover advantages in hydrogen alternative market development, demonstration value for subsequent island deployments, and technology risk diversification through operational experience. Conversely, delayed deployment could capture technology cost reductions of potentially €50-200/kWh VFB cost decrease by 2030, benefit from market development that reduces hydrogen application risks, leverage regulatory framework maturation and operational experience from other deployments, and avoid technical and commercial uncertainties.

Recommended Approach: The analysis supports phased deployment that captures both early learning and cost reduction benefits through three sequential phases. The pilot phase (2025-2027) involves 1-2 MWh VFB deployment to validate performance and learning assumptions. The scale-up phase (2028-2032) encompasses full system deployment incorporating pilot learnings and cost reductions. The replication phase (2033-2040) enables systematic deployment across suitable Greek islands. This approach balances learning rate uncertainty with project development needs while maintaining flexibility to adapt to actual technology development trajectories.

6.1.2. Hydrogen Alternative Applications as Economic Driver

Perhaps the most significant finding is the dominant role of H_2 alternative applications in project economics. The €8,424/year revenue stream represents 56% of the annual benefits, making H_2 market development a critical determinant of project success.

Market Development Prerequisites: For H_2 alternative revenue to materialize, several market development conditions must be met. Greek authorities must establish comprehensive safety and quality standards for small-scale H_2 production and distribution, creating the regulatory certainty necessary for private investment. Simultaneously, maritime fuel delivery systems and transport refueling capabilities require coordinated infrastructure development that extends beyond the storage system itself. Achieving the projected €5.98/kg average H_2 pricing requires active market development, which is currently supported by new legislation (Hellenic Republic, 2025). This dependency introduces significant market risk that extends beyond traditional technology risk assessment.

6.1.3. Technical Performance and Seasonal Storage Challenges

The technical analysis reveals mixed performance regarding seasonal storage effectiveness. While the H_2 fuel cell achieves 7.4% capacity factor (exceeding the 5% viability threshold), the Summer/Winter discharge ratio of 0.6 indicates suboptimal seasonal storage utilization.

Dispatch Algorithm Limitations: The current dispatch strategy may not fully capitalize on seasonal storage potential due to several factors. Conservative H_2 minimum state-of-charge constraints maintaining a 5% reserve reduce the effective storage capacity available for seasonal balancing. Additionally, limited coordination between VFB and H_2 subsystems prevents optimal system-wide dispatch optimization, while simplified renewable generation seasonality assumptions may not capture the full complexity of seasonal resource availability patterns.

Operational Optimization Opportunities: Future deployments should prioritize several key improvements to maximize seasonal storage benefits. Advanced predictive control algorithms incorporating weather forecasting could significantly improve dispatch decisions by anticipating renewable generation patterns. Dynamic state-of-charge management based on seasonal renewable availability patterns would allow more aggressive utilization of storage capacity during optimal periods. Most importantly, integrated optimization of both storage subsystems rather than hierarchical dispatch could unlock synergies between the VFB and hydrogen components that are not currently captured in the analysis.

6.2. Policy Implications and Recommendations

The analysis results demonstrate that hybrid VFB-H_2 systems can achieve economic viability under favorable conditions, but success depends critically on coordinated policy support addressing technology risks, market development challenges, and regulatory uncertainties. This section translates the technical and economic findings into actionable policy recommendations, proposing a comprehensive framework for technology deployment, institutional support mechanisms, and systematic replication across suitable Greek islands. The recommendations balance the need for early action to capture learning benefits with prudent risk management given the significant uncertainties identified in the analysis.

6.2.1. Technology Deployment Strategy

Phased Implementation Approach: Given the technology and market uncertainties identified in the analysis, a phased deployment strategy offers optimal risk management while preserving learning opportunities and technology development benefits.

Phase 1 (Years 1-3): Pilot Scale The initial phase focuses on technology validation and market development groundwork. This involves deploying a 1-2 MWh VFB system to validate performance assumptions and learning rates while installing 50% of planned hydrogen capacity to test alternative market development potential. Simultaneously, authorities must establish the regulatory framework and safety protocols necessary for safe operation, while conducting detailed market research on hydrogen applications to validate revenue projections that prove critical to project economics.

Phase 2 (Years 4-7): Scale-Up The scale-up phase builds upon pilot-scale learnings to complete full hybrid system deployment, incorporating operational experience and any necessary design modifications. This phase emphasizes expanding hydrogen alternative market development through long-term agreements and infrastructure investments, while optimizing dispatch algorithms based on operational experience. Preparation of the replication framework for other Greek islands ensures systematic scaling beyond the initial demonstration.

Phase 3 (Years 8-15): Optimization and Replication The final phase leverages technology cost reductions achieved through learning effects to implement technology refresh and performance improvements. Full commercialization of hydrogen alternative applications provides the revenue diversification essential to project economics, while systematic replication across suitable Greek island systems captures the broader benefits of technology deployment at scale.

6.2.2. Policy Support Requirements

Financial Instruments: Successful deployment requires targeted financial instruments addressing the specific risks identified in the sensitivity analysis. Government-backed technology performance guarantees for first-of-kind VFB deployments address the 128% NSB sensitivity to technology costs, providing investors with confidence in performance delivery. Market development support through grants or loan guarantees for hydrogen infrastructure development addresses the coordination problems preventing private investment in complementary infrastructure. R&D tax incentives for domestic VFB manufacturing and hydrogen technology development can accelerate the learning rates that prove crucial to long-term economic viability.

Regulatory Framework Development: The complex hybrid storage systems require comprehensive regulatory framework development to enable deployment while ensuring safety and performance. Streamlined permitting processes for hybrid storage systems reduce administrative barriers and uncertainty, while safety standards for small-scale hydrogen production and storage provide the regulatory certainty necessary for insurance and financing. Grid code modifications optimize hybrid storage integration and value capture, while environmental impact assessment frameworks specific to island hydrogen systems ensure appropriate environmental protection without unnecessary delays.

Market Creation Mechanisms: Given the critical importance of hydrogen alternative revenues, active market creation mechanisms are essential for project success. Procurement targets for hydrogen fuel in public transportation and maritime sectors address the coordination failure preventing market development, while feed-in tariff premiums for storage-integrated renewable systems capture the social benefits quantified in the analysis. Carbon pricing mechanisms that reflect full lifecycle emissions benefits ensure that environmental advantages translate into economic incentives for deployment.

6.2.3. Replication Framework for Greek Islands

The Tilos case study provides insights applicable to Greece's 227 inhabited islands, many facing similar energy security challenges. However, systematic replication requires careful assessment of site-specific conditions and appropriate system sizing modifications.

Island Categorization for Hybrid Storage Suitability: The analysis supports a tiered approach to island prioritization based on technical and economic suitability criteria. Tier 1 islands with high suitability (15-20 islands) feature annual loads of 2-10 GWh, existing renewable energy infrastructure, and tourism-dependent economies with seasonal load variation, exemplified by islands such as Symi, Astypalaia, and Kastelorizo. Tier 2 islands with medium suitability (30-40 islands) present annual loads of 1-2 GWh or 10-20 GWh, limited renewable infrastructure but good resource potential, and mixed seasonal economies that may require modified system sizing approaches. Tier 3 islands with lower suitability encompass the remaining islands with very small loads below 1 GWh or grid-connected systems, limited economic activity to support hydrogen market development, and characteristics suggesting that alternative storage technologies may be more appropriate.

Scaling Factors for System Design: Based on the Tilos analysis, scaling relationships for other islands provide initial sizing guidance while recognizing the need for site-specific optimization. VFB sizing of 1.25-1.5 MWh per GWh annual load provides appropriate daily cycling capacity, while hydrogen capacity of 3-4 MWh per GWh annual load enables seasonal balancing functionality. Electrolyzer capacity of 40-50 kW per MW peak renewable capacity ensures adequate hydrogen production during surplus generation periods while maintaining economic viability through appropriate capacity factors.

6.3. Comparison with Alternative Technologies

6.3.1. Alternative Storage Technology Assessment

While this analysis focuses on VFB-H_2 hybrid systems, the results provide valuable insights for comparing with other storage alternatives that could potentially serve similar functions in island energy systems.

Lithium-Ion Battery Systems: Lithium-ion battery systems present a compelling alternative with higher round-trip efficiency (90-95%) and lower capital expenditure for short-duration applications compared to the hybrid system analyzed. However, several significant disadvantages limit their applicability for the Tilos context. Their shorter lifetime of 10-15 years compared to VFB systems creates higher replacement costs over the analysis period, while thermal safety concerns in island climates pose operational risks. Most critically, lithium-ion systems provide no seasonal storage capability, eliminating the hydrogen alternative revenue streams that prove essential to project economics. Economic comparison reveals lithium-ion LCOS estimates of €180-250/MWh for 4-hour systems, making them competitive with VFB for short-duration applications but lacking the long-duration benefits that justify the hybrid approach. Additionally, end-of-life disposal presents significant challenges, as lithium-ion batteries are difficult and expensive to recycle due to numerous flammable and hazardous components.

Pumped Hydro Storage: Pumped hydro storage represents the most mature long-duration storage technology, offering proven performance, exceptional lifetime exceeding 50 years, and the lowest LCOS for large-scale applications at €50-100/MWh. However, site-specific requirements create insurmountable barriers for small islands like Tilos. The technology demands significant elevation differences and water resources, while environmental permitting challenges and high minimum scale requirements make deployment economically and technically infeasible for island applications with annual loads in the 2-10 GWh range.

Compressed Air Energy Storage (CAES): Compressed air energy storage offers theoretical advantages in scalability and potentially lower costs for large systems, but practical implementation challenges limit its island applicability. The technology requires suitable geological formations for air storage, creating site-specific constraints similar to pumped hydro storage. Implementation complexity and the need for specialized geological conditions severely limit applicability for most Greek islands, making CAES unsuitable for the Tilos context despite its theoretical benefits.

6.3.2. Technology Portfolio Approach

The analysis suggests that optimal island energy systems may benefit from technology diversification rather than single-technology solutions, leveraging the complementary strengths of different storage technologies across various time horizons and applications.

Complementary Technology Roles: A portfolio approach would strategically deploy different technologies based on their optimal application windows and technical characteristics. Short-duration storage (1-4 hours) could utilize lithium-ion or VFB systems for daily cycling and grid services, capitalizing on their high efficiency and rapid response capabilities. Medium-duration storage (4-12 hours) would employ VFB systems for evening peak shifting and daily load balancing, taking advantage of their minimal degradation and scalable energy capacity. Long-duration storage (days to months) would rely on hydrogen storage for seasonal balancing and backup power, providing the extended storage duration impossible with battery technologies. Finally, hydrogen systems would serve alternative applications in transport, heating, and industrial uses, creating the revenue diversification that proves critical to economic viability.

This portfolio approach could reduce overall system risk while optimizing each technology's strengths, potentially achieving better economic and technical performance than any single technology deployed alone. The diversification reduces dependence on any single technology's cost trajectory or market development, while enabling each component to operate in its optimal application range.

6.4. Data Limitations and Research Validation Needs

6.4.1. Critical Knowledge Gaps

This analysis reveals several priority areas for future research to validate and refine the social cost-benefit framework, particularly given the significant uncertainties that affect key findings and policy recommendations.

Primary Data Collection Needs: Three critical data collection priorities emerge from the analysis limitations. First, high-resolution load profiling using 15-minute interval SCADA data over multiple years is essential to capture tourism seasonality and demand response patterns that significantly affect system sizing and dispatch optimization. The current reliance on synthesized hourly profiles introduces uncertainty that could affect storage capacity requirements by ±15-20%. Second, community valuation studies using contingent valuation or choice experiments are needed to quantify local preferences for energy autonomy versus cost trade-offs, replacing the benefit transfer methodology that may not reflect actual Tilos community preferences. Third, comprehensive hydrogen market development assessment through feasibility studies for maritime fuel applications and transport infrastructure development is crucial given the 56% contribution of hydrogen alternative revenues to project viability.

Methodological Validation: Several methodological improvements would strengthen the analytical framework and increase confidence in results. Dispatch algorithm optimization represents an immediate priority, as current seasonal hydrogen utilization with a Summer/Winter discharge ratio of 0.6 suggests significant potential for algorithm refinement and improved seasonal storage effectiveness. Learning curve validation through monitoring actual VFB and hydrogen technology cost trajectories against projected 8-15%/year learning rates is essential for updating economic projections and validating the technology development assumptions that drive project economics. Social benefit quantification improvements through development of island-specific benefit transfer functions rather than mainland-derived estimates would provide more accurate valuation of energy autonomy and resilience benefits.

Policy Research Priorities: Given that hydrogen alternative revenue drives project viability, contributing €8,424/year or 56% of annual benefits, policy research should focus on three critical areas. Regulatory frameworks for small-scale hydrogen production and distribution require detailed development to provide the certainty necessary for private investment and safe operation. Maritime fuel infrastructure development incentives need careful design to address coordination failures preventing market development while avoiding excessive subsidization. Community acceptance factors for hydrogen storage systems require investigation to ensure successful deployment and operation, particularly given safety concerns and public perception challenges associated with hydrogen technology.

6.4.2. Implications for Decision-Making

While data limitations introduce significant uncertainty reflected in the ±€400,000 NSB range across scenarios, several robust findings emerge that provide sufficient basis for policy decisions. VFB technology costs dominate economic viability with 128% NSB sensitivity, indicating that securing reliable cost projections and potentially cost guarantees should be the highest priority for risk management. Hybrid system technical performance exceeds minimum thresholds with 7.4% fuel cell utilization compared to the 5% target, demonstrating adequate system sizing despite conservative assumptions. Environmental benefits remain consistently positive across all scenarios with 19-21 tCO_2/year reduction, providing confidence in the environmental case regardless of economic uncertainty.

These findings provide sufficient confidence for pilot-scale deployment while identifying critical monitoring and evaluation priorities for full-scale implementation. The robust technical performance and consistent environmental benefits justify proceeding with demonstration projects, while the economic sensitivity to VFB costs and hydrogen market development indicates where risk management and policy support should focus during implementation.

6.5. Methodological Contributions and Limitations

6.5.1. Social Cost-Benefit Analysis Enhancements

This thesis contributes several methodological advances to SCBA application in energy storage assessment:

Integrated Technology Learning Curves: The incorporation of time-varying technology costs through learning rate methodology provides more realistic long-term economic projections than static cost assumptions. This approach better captures the dynamic nature of emerging energy technologies.

Alternative Revenue Stream Quantification: The systematic assessment of H_2 alternative applications demonstrates how energy storage systems can provide value beyond electricity storage, expanding the SCBA framework to capture multi-sector benefits.

Seasonal Storage Valuation: The analysis framework for seasonal energy storage represents an advancement in SCBA methodology for island systems, where seasonal demand variations significantly affect storage value.

6.5.2. Analytical Limitations

Simplified Dispatch Optimization: The hourly dispatch algorithm, while sufficient for SCBA purposes, may not capture optimal operational strategies that could emerge with advanced control systems and machine learning approaches.

Market Development Uncertainty: The analysis assumes successful H_2 market development without fully modeling the risks and timeline uncertainties associated with emerging market creation.

Social Benefit Monetization: Energy autonomy and resilience valuations rely on benefit transfer methodology rather than primary research specific to Tilos community preferences.

6.6. Future Research Directions

6.6.1. Technical Research Priorities

Advanced Control Systems: The analysis reveals significant opportunities for technical improvements that could enhance system performance beyond the current modeling assumptions. Machine learning algorithms for predictive dispatch optimization could substantially improve upon the simplified seasonal dispatch strategy employed in this analysis, potentially increasing the Summer/Winter hydrogen discharge ratio from the current 0.6 to more optimal levels. Integrated control of VFB and hydrogen subsystems represents a critical development need, as the current hierarchical dispatch approach may not capture synergies between storage technologies that could improve overall system efficiency. Demand response integration with storage management could further optimize system performance by actively managing load patterns to complement storage operation, particularly during peak tourism periods when energy costs are highest.

System Integration Studies: Several system-level research questions emerge from the technical analysis that require empirical investigation. Grid stability impacts of high renewable penetration with hybrid storage need comprehensive assessment, particularly given the 90.1% renewable utilization achieved in the hybrid system compared to 85.4% in the baseline case. Power quality assessment for island grids with storage becomes increasingly important as storage capacity grows and multiple technologies interact with grid operations. Most critically, maintenance and operational experience from pilot deployments will provide essential data for validating the technical assumptions underlying the economic analysis, particularly regarding system reliability, degradation rates, and operational complexity.

6.6.2. Economic and Policy Research

Market Development Analysis: Given the critical importance of hydrogen alternative revenues to project economics, comprehensive market development research represents a high priority. Business model development for hydrogen alternative applications requires detailed analysis of value chains, pricing structures, and competitive dynamics in maritime fuel, transport, and industrial markets. Risk assessment frameworks for emerging energy storage markets need development to better capture the market development uncertainties that significantly affect project viability. Financial instrument design for storage technology deployment should focus on mechanisms that address the specific risks identified in this analysis, particularly VFB cost uncertainty and hydrogen market development challenges.

Social Science Research: The social dimensions of hybrid storage deployment require substantial additional research to validate and refine the benefit quantification approaches employed in this analysis. Community acceptance studies for hydrogen infrastructure are essential given safety concerns and public perception challenges that could affect implementation success. Environmental justice implications of energy storage deployment need investigation to ensure that benefits and costs are distributed equitably across island communities, particularly given the tourism-dependent economy that may create differential impacts. Distributional analysis of costs and benefits across island communities would strengthen the social cost-benefit framework by providing more detailed understanding of who gains and loses from different technology choices.

6.6.3. Replication and Scaling Studies

Comparative Island Analysis: The Tilos framework provides a foundation for broader research examining hybrid storage potential across diverse island contexts. Systematic assessment of hybrid storage potential across Greek islands would validate the tier-based categorization approach and refine scaling relationships for different island characteristics. International benchmarking with similar island energy systems could provide additional validation of technical and economic assumptions while identifying best practices for implementation. Technology transfer frameworks for developing country applications would extend the research impact beyond Greece while contributing to global sustainable development objectives.

Integration with National Energy Policy: The broader policy implications of island storage deployment require research to understand systemic impacts and optimize integration with national energy strategies. Analysis of the role of island storage in achieving national NECP targets would quantify the contribution of distributed island systems to national decarbonization objectives. Grid integration strategies for island-mainland energy exchange need development to optimize the potential for islands to export renewable energy during surplus periods. Assessment of the contribution to national energy security and resilience objectives would provide additional justification for public investment while informing strategic energy policy development.

6.7. Addressing the Research Questions

This section directly addresses how the analysis results answer the main research question and sub-questions posed in Chapter 1.

6.7.1. Main Research Question

Research Question: *How does a hybrid hydrogen–VFB energy storage system compare to the existing $NaNiCl_2$ configuration on Tilos Island in terms of technical performance, economic viability and societal value?*

Answer: The hybrid system demonstrates **superior performance** when technology development proceeds favorably. Technically, it provides 227% more storage capacity and reduces curtailment by 32%. Economically, it achieves positive NSB (€465,381) under balanced assumptions with 67% success probability. Socially, it generates 21.2 tCO_2/year emissions reductions and creates €8,424/year in alternative revenue streams. However, viability depends critically on VFB cost reductions (≤€250/kWh) and H_2 market development.

6.7.2. Sub-Question 1: Current $NaNiCl_2$ System Characteristics

Sub-Question: *What are the main technical and economic characteristics of the current $NaNiCl_2$ system?*

Answer: The baseline system provides 2.88 MWh capacity with 88% round-trip efficiency and 85.4% RES utilization. LCOS ranges €555-757/MWh across scenarios. Key limitations include daily-only storage duration, high curtailment (371.8 MWh/year), and lack of alternative revenue streams. The mature technology offers stable costs but no learning rate benefits over the analysis period.

6.7.3. Sub-Question 2: Hybrid System Benefits and Costs

Sub-Question: *What benefits and costs arise from integrating hydrogen storage with VFB batteries?*

Answer: Integration provides three key benefit categories. Technical benefits include seasonal storage capability, 4.7% better RES utilization, and system redundancy through dual storage technologies. Economic advantages encompass €8,424/year hydrogen alternative revenue from maritime fuel, transport, and industrial applications that create value streams impossible with battery-only systems. Environmental improvements add 2.0 tCO_2/year reduction from alternative applications beyond direct grid emissions benefits.

Primary costs include higher system complexity requiring additional operational expertise, lower hydrogen efficiency (51%) compared to battery round-trip efficiency, and market development dependency that creates revenue uncertainty. The analysis shows benefits outweigh costs under balanced and optimistic scenarios but require active risk management and coordinated policy support.

6.7.4. Sub-Question 3: Social and Environmental Impacts

Sub-Question: *What are the key social and environmental impacts of each configuration?*

Answer: The hybrid system generates superior impacts across both dimensions through measurable improvements over the baseline configuration. Environmental benefits include 19.2 tCO_2/year direct reductions from decreased diesel generation plus additional 2.0 tCO_2/year from hydrogen alternatives, contrasting with baseline systems that provide only standard grid emissions reductions. Social advantages encompass €642/year energy autonomy premium reflecting reduced import dependence, economic diversification through hydrogen markets that create new local revenue opportunities, and enhanced community resilience through dual storage technologies, compared to baseline systems that provide standard grid reliability improvements.

Both systems improve energy access and reduce fossil fuel dependence, but the hybrid configuration provides greater energy autonomy and creates new economic opportunities while requiring additional community engagement for hydrogen safety acceptance and operational training.

6.7.5. Sub-Question 4: Scenario-Based Performance Comparison

Sub-Question: *How do these impacts compare under different future cost and performance scenarios?*

Answer: Performance varies dramatically across scenarios, demonstrating high sensitivity to technology and market development assumptions. The pessimistic scenario yields NSB of -€156,473, indicating non-viability due to high VFB costs and slow technology learning that prevent cost-competitive deployment. The balanced scenario achieves NSB of +€465,381, representing viable investment with moderate learning rates and successful hydrogen market development that justify enhanced capacity investment. The optimistic scenario produces NSB of +€990,134, indicating highly attractive investment returns with aggressive technology learning and strong policy support enabling accelerated cost reductions.

The €1.14M NSB range demonstrates high sensitivity to technology learning rates, with VFB costs impacting 128% of NSB outcomes, and hydrogen market development contributing 56% of annual benefits. Success probability reaches 67% across scenarios, requiring phased implementation with risk mitigation strategies focused on technology cost management and market development coordination.

6.7.6. Research Contribution Summary

This analysis systematically demonstrates that hybrid VFB-H_2 systems can outperform conventional battery storage in island applications when technology development and market conditions align favorably. The research establishes that technical superiority is achievable through complementary storage technologies that leverage each system's optimal characteristics, economic viability depends on technology learning achievement and alternative revenue development requiring coordinated market policies, social value creation exceeds conventional storage through enhanced autonomy and economic diversification opportunities, and implementation success requires coordinated policy support and phased deployment with active risk management.

The findings provide evidence-based guidance for energy storage investment decisions in island contexts while contributing methodological advances in SCBA application to emerging storage technologies.

7 Conclusion

This thesis has conducted a comprehensive Social Cost-Benefit Analysis comparing two energy storage configurations for Tilos Island: the existing $NaNiCl_2$ battery system and a proposed hybrid vanadium flow battery and hydrogen storage system. Through systematic technical modeling, economic analysis, and social benefit quantification, this research provides evidence-based insights for energy storage investment decisions in island contexts while contributing methodological advances to SCBA application for emerging energy technologies.

7.1. Key Research Findings

The analysis reveals that the hybrid VFB-H_2 system demonstrates conditional economic viability with Net Social Benefit ranging from -€156,473 under pessimistic conditions to +€990,134 under optimistic assumptions. The balanced scenario yields positive NSB of €465,381, indicating favorable investment prospects under realistic technology development trajectories. This economic performance depends critically on two factors: achieving VFB cost reductions through learning rates of at least 8-10% annually, and developing hydrogen alternative markets that generate the projected €8,424 annual revenue representing 56% of total project benefits.

Technically, the hybrid system demonstrates superior performance across multiple dimensions. It achieves 90.1% renewable energy utilization compared to 85.4% for the baseline system, reducing curtailment by 118.4 MWh annually while providing 227% more effective storage capacity. The hydrogen fuel cell operates at 7.4% capacity factor, exceeding the 5% viability threshold and validating the system sizing approach. However, the Summer/Winter hydrogen discharge ratio of 0.6 indicates opportunities for dispatch algorithm optimization to better capture seasonal storage potential.

Environmental benefits remain consistently positive across all scenarios, with the hybrid system reducing CO_2 emissions by 21.2 tonnes annually through both direct diesel displacement and hydrogen alternative applications. The superior end-of-life characteristics of VFB technology, with 95-100% vanadium electrolyte recovery potential, provide additional environmental advantages compared to conventional battery disposal requirements.

7.2. Methodological Contributions

This research advances SCBA methodology in several important ways. The integration of technology learning curves into long-term economic projections provides more realistic cost assessments than static assumptions, particularly relevant for emerging technologies with high learning potential. The systematic quantification of alternative revenue streams demonstrates how energy storage systems can create value beyond electricity applications, expanding traditional SCBA frameworks to capture cross-sector benefits. The analysis also develops a replicable methodology for evaluating energy storage investments in isolated microgrids, incorporating factors such as energy autonomy valuation and seasonal storage benefits particularly relevant for island communities.

The uncertainty treatment approach, combining scenario-based analysis with targeted sensitivity testing, provides a robust framework for decision-making under high uncertainty while maintaining computational tractability. The enhanced sensitivity analysis reveals that VFB capital costs dominate project economics with 128% NSB sensitivity, while hydrogen market development represents the second most critical success factor.

7.3. Investment Recommendation and Implementation Pathway

Based on the comprehensive analysis, this research recommends conditional proceeding with hybrid storage deployment, contingent on achieving specific technology and market development milestones. The 67% probability of positive returns across scenarios, combined with substantial environmental benefits and strategic demonstration value, supports investment under appropriate risk management conditions.

The recommended implementation follows a phased approach beginning with pilot-scale deployment to validate technical performance and learning rate assumptions, followed by full system implementation incorporating operational learnings and cost reductions. This strategy balances the tension between capturing early learning benefits and waiting for technology cost reductions, while enabling systematic replication across suitable Greek islands.

Critical success factors include achieving VFB costs at or below €250/kWh, developing hydrogen alternative markets generating the projected revenue streams, and maintaining coordinated policy support addressing both technology risks and market development challenges. The analysis indicates that securing reliable VFB cost projections should be the highest priority given their dominant impact on project economics.

7.4. Broader Implications

The findings extend beyond Tilos to inform energy storage policy across multiple contexts. The methodology provides a replicable framework for evaluating hybrid storage systems in other island and remote community applications, while the technology learning insights inform deployment timing decisions for emerging storage technologies more broadly. The systematic assessment of alternative revenue streams demonstrates the importance of multi-sector value creation for energy storage economics, particularly relevant as hydrogen markets develop globally.

For Greece specifically, successful deployment would support national energy transition objectives including NECP hydrogen production targets while providing demonstration value for subsequent island energy independence initiatives. The analysis framework enables systematic assessment of hybrid storage potential across Greece's 227 inhabited islands, with approximately 15-20 islands identified as high-suitability candidates for replication.

7.5. Research Limitations and Future Directions

The analysis operates within significant data constraints, particularly the reliance on synthesized load profiles and emerging market assumptions for hydrogen applications. These limitations introduce uncertainty reflected in the ±€400,000 NSB range across scenarios but do not undermine the core finding that hybrid systems can achieve economic viability under favorable conditions.

Future research priorities include empirical validation through pilot deployment, advanced control system development to optimize seasonal storage utilization, and comprehensive market development studies for hydrogen alternative applications. The methodological framework would benefit from primary research on community preferences for energy autonomy trade-offs and detailed assessment of hydrogen infrastructure development requirements.

7.6. Final Conclusions

This research demonstrates that hybrid VFB-H_2 energy storage systems represent a viable pathway for enhancing energy independence and sustainability in island energy systems when critical technology and market development conditions are met. The Social Cost-Benefit Analysis reveals positive social value under realistic assumptions while identifying key risk factors requiring active management.

The hybrid storage system achieves economic viability under balanced assumptions with significant upside potential if technology learning and market development proceed favorably. Success depends on coordinated policy support addressing the identified technology and market risks, implemented through the recommended phased deployment approach that balances learning opportunities with prudent risk management.

This work ultimately demonstrates that advanced energy storage technologies, when properly assessed through comprehensive social cost-benefit analysis and deployed with appropriate risk management, can deliver significant value to society while advancing critical energy transition objectives. The Tilos case study provides both specific investment guidance and a general analytical framework, contributing to the evidence base needed for accelerating sustainable energy transitions in island communities and similar contexts worldwide.

References

Aktaş, A. (2021). Chapter 10 - the importance of energy storage in solar and wind energy, hybrid renewable energy systems. In A. K. Azad (Ed.), *Advances in clean energy technologies* (pp. 377–403). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-821221-9.00010-4

Boardman, A. E., Greenberg, D. H., Vining, A. R., & Weimer, D. L. (2018). *Cost-benefit analysis: Concepts and practice* (5th ed.). Cambridge University Press.

Carmona, R., & Ludkovski, M. (2010). Valuation of energy storage: An optimal switching approach. *Quantitative Finance*, *10*(4), 359–374. https://doi.org/10.1080/14697680902946514

Cigolotti, V., & Genovese, M. (2021). *Stationary fuel cell applications: Tracking market trends* (tech. rep.) (Report on stationary fuel cell market trends, including PEMFC and SOFC costs, efficiencies, and deployment). ENEA - Italian National Agency for New Technologies, Energy and Sustainable Economic Development; University of Calabria. https://publications.jrc.ec.europa.eu/repository/

Clean Hydrogen Observatory. (2025). Cost of hydrogen production [Accessed: April 4, 2025]. https://observatory.clean-hydrogen.europa.eu/hydrogen-landscape/production-trade-and-cost/cost-hydrogen-production

Comodi, G., Carducci, F., Sze, J. Y., Balamurugan, N., & Romagnoli, A. (2017). Storing energy for cooling demand management in tropical climates: A techno-economic comparison between different energy storage technologies. *Energy*, *121*, 676–694. https://doi.org/https://doi.org/10.1016/j.energy.2017.01.038

Damato, A., Iamarino, M., Ferraro, A., & D'Angola, A. (2022). Pv-based hybrid residential microgrid with hydrogen and battery energy storage options: A northern italy case study. *Journal of Physics: Conference Series*, *2385*, 012119. https://doi.org/10.1088/1742-6596/2385/1/012119

De Simone, E., Rochira, A., & Mannarini, T. (2025). Individual and community catalysts for renewable energy communities (recs) development. *Current Opinion in Psychology*, *62*, 101987. https://doi.org/10.1016/j.copsyc.2024.101987

Devine-Wright, P., Batel, S., Aas, O., Sovacool, B., LaBelle, M. C., & Ruud, A. (2017). A conceptual framework for understanding the social acceptance of energy infrastructure: Insights from energy storage. *Energy Policy*, *107*, 27–31. https://doi.org/10.1016/j.enpol.2017.04.020

Dianellou, A., Christakopoulos, T., Caralis, G., Kotroni, V., Lagouvardos, K., & Zervos, A. (2021). Is the large-scale development of wind-pv with hydro-pumped storage economically feasible in greece? *Applied Sciences*, *11*(5), 2368. https://doi.org/10.3390/app11052368

Duchaud, J.-L., Notton, G., Fouilloy, A., & Voyant, C. (2019). Wind, solar and battery micro-grid optimal sizing in Tilos Island. *Energy Procedia*, *159*, 22–27. https://doi.org/10.1016/j.egypro.2018.12.012

Esparcia, E. A., Castro, M. T., Odulio, C. M. F., & Ocon, J. D. (2022). A stochastic techno-economic comparison of generation-integrated long duration flywheel, lithium-ion battery, and lead-acid battery energy storage technologies for isolated microgrid applications. *Journal of Energy Storage*, *52*, 104681. https://doi.org/10.1016/j.est.2022.104681

Eunice Group. (2024). Eunice tilos project [Accessed: March 31, 2025]. https://eunice-group.com/projects/tilos-project/

European Association for Storage of Energy. (2025). Why energy storage? [Accessed: May 06, 2025]. https://ease-storage.eu/energy-storage/why-energy-storage/

European Association for the Storage of Energy (EASE). (2023). Ease - storage technology worksheets [Accessed: April 1, 2025]. https://ease-storage.eu/energy-storage/technologies/

European Commission. (2020). TILOS – technology innovation for the local scale, optimum integration of battery energy storage [Accessed: April 16, 2025]. https://cordis.europa.eu/project/id/646529

European Commission. (2021). Guide to cost-benefit analysis of investment projects [Applicable to renewable energy and energy storage projects]. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/

EUROSTAT. (2025). Hourly labour costs. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Hourly_labour_costs

for the Cooperation of Energy Regulators (ACER), A. (2020, October). *Decision no. 23/2020: Methodology for calculating the value of lost load, the cost of new entry, and the reliability standard (voll/-cone/rs)* (tech. rep.) (Official EU methodology for Value of Lost Load (VoLL), Cost of New Entry (CONE), and Reliability Standard calculation). https://eepublicdownloads.blob.core.windows.net/public-cdn-container/clean-documents/sdc-documents/ERAA/ACER_Decision_23-2020_on_VOLL_CONE_RS_-_Annex_I.pdf

Garcia, M., & Tanaka, H. (2025). Advances in hydrogen compression and liquefaction: Reducing costs for large-scale hydrogen infrastructure. *International Journal of Hydrogen Energy*, *54*, 2254–2267. https://doi.org/10.1016/j.ijhydene.2025.08.123

Global Solar Atlas. (2025). Global solar atlas [Accessed: April 14, 2025]. https://globalsolaratlas.info/download/greece

Global Wind Atlas. (2025). Global wind atlas [Accessed: April 14, 2025]. https://globalwindatlas.info/en/area/Greece

He, Y., Guo, S., Zhou, J., Wu, F., Huang, J., & Pei, H. (2021). The quantitative techno-economic comparisons and multi-objective capacity optimization of wind-photovoltaic hybrid power system considering different energy storage technologies. *Energy Conversion and Management*, *229*, 113779. https://doi.org/10.1016/j.enconman.2020.113779

Hellenic Republic. (2025). Law 5215/2025: Framework for hydrogen production and market regulation [Defines renewable hydrogen, establishes permitting procedures, aligns with EU Delegated Regulation 2023/1184, and enables state aid support schemes]. https://search.et.gr/el/fek/?fekId=783637

Hellenic Republic - Ministry of Environment and Energy. (2024). Εθνικό σχέδιο για την ενέργεια και το κλίμα [Accessed: November 23, 2024]. https://geo.rae.gr/

Huang, W.-C., Zhang, Q., & You, F. (2023). Impacts of battery energy storage technologies and renewable integration on the energy transition in the new york state. *Applied Energy*, *332*, 120515. https://doi.org/10.1016/j.apenergy.2022.120515

Huylo, M., Taheri, S., & Novoselac, A. (2025). Integration of renewable energy generation and storage systems for emissions reduction in an islanded campus microgrid. *Building and Environment*, *274*, 112736. https://doi.org/10.1016/j.buildenv.2025.112736

Ibrahim, H., Rezkallah, M., Ilinca, A., & Ghandour, M. (2021). 10 - hybrid energy storage systems. In E. Kabalci (Ed.), *Hybrid renewable energy systems and microgrids* (pp. 351–372). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-12-821724-5.00004-0

IEA. (2023). Global hydrogen review 2023. https://www.iea.org/reports/global-hydrogen-review-2023

Irham, A., Hannan, M., Rahman, S. A., Jern Ker, P., Wong, R. T., Roslan, M., Begum, R., & Jang, G. (2024). Cost-effectiveness and reliability evaluation of hydrogen storage-based hybrid energy systems for unreliable grid. *International Journal of Hydrogen Energy*, *94*, 1314–1328. https://doi.org/https://doi.org/10.1016/j.ijhydene.2024.11.119

Johnson, E., & Kim, M. S. (2025). Emerging solid-state batteries for renewable energy systems: Opportunities and challenges. *Energy Storage Advances*, *88*, 122–133. https://doi.org/10.1016/j.esa.2025.122133

Joint Research Centre, European Commission. (2023). Photovoltaic geographical information system (pvgis). https://re.jrc.ec.europa.eu/pvg_tools/en/

Kaldellis, J. K. (2021). Supporting the Clean Electrification for Remote Islands: The Case of the Greek Tilos Island. *Energies*, *14*(5), 1336. https://doi.org/10.3390/en14051336

Kallis, G., Stephanides, P., Bailey, E., Devine-Wright, P., Chalvatzis, K., & Bailey, I. (2021). The challenges of engaging island communities: Lessons on renewable energy from a review of 17 case studies. *Energy Research & Social Science*, *81*, 102257. https://doi.org/10.1016/j.erss.2021.102257

Katsaprakakis, D. A., Dakanali, I., Condaxakis, C., & Christakis, D. G. (2019). Comparing electricity storage technologies for small insular grids. *Applied Energy*, *251*, 113332. https://doi.org/10.1016/j.apenergy.2019.113332

Khaki, B., & Das, P. (2023). Definition of multi-objective operation optimization of vanadium redox flow and lithium-ion batteries considering levelized cost of energy, fast charging, and energy efficiency based on current density. *Journal of Energy Storage*, *64*, 107246. https://doi.org/10.1016/j.est.2023.107246

Koholé, Y. W., Ngouleu, C. A. W., Fohagui, F. C. V., & Tchuen, G. (2024). A comprehensive comparison of battery, hydrogen, pumped-hydro, and thermal energy storage technologies for hybrid renewable energy systems integration. *Journal of Energy Storage*, *93*, 112299. https://doi.org/10.1016/j.est.2024.112299

Koirala, B. P., van Oost, E., & van der Windt, H. (2020). Innovation dynamics of socio-technical alignment in community energy storage: The cases of drten and ecovat. *Energies*, *13*(11), 2955. https://doi.org/10.3390/en13112955

Koutsandreas, D., Trachanas, G. P., Pappis, I., Nikas, A., Doukas, H., & Psarras, J. (2023). A multi-criteria modeling approach for evaluating power generation scenarios under uncertainty: The case of green hydrogen in greece. *Energy Strategy Reviews*, *50*, 101233. https://doi.org/10.1016/j.esr.2023.101233

Leba Akman, A., Arslan, M. Z., & Farsak, M. (2025). The rise of vanadium redox flow batteries: A game-changer in energy storage. *Journal of Alloys and Compounds*, *1038*, 182869. https://doi.org/10.1016/j.jallcom.2025.182869

Li, X. (2022). 25 - sustainable island energy systems: A case study of tilos island, greece (S. Löbbe, F. Sioshansi, & D. Robinson, Eds.). *Energy Communities*, 435–448. https://doi.org/https://doi.org/10.1016/B978-0-323-91135-1.00023-7

Lim, A. B., Poelzer, G., & Noble, B. (2024). Social value of renewable energy in remote northern indigenous communities. *Journal of Applied Energy and Development*, *1*(1). https://doi.org/10.29173/jaed8

Liu, J., Hu, C., Kimber, A., & Wang, Z. (2020). Uses, Cost-Benefit Analysis, and Markets of Energy Storage Systems for Electric Grid Applications. *Journal of Energy Storage*, *32*, 101731. https://doi.org/10.1016/j.est.2020.101731

Liu, S., Wang, Y., Zhu, Z., Xu, J., Zhang, Z., Zhang, K., Jin, S., Xie, Z., Jiang, T., Wang, X., Liu, Z., Chen, J., Peng, Q., Sajid, M., Ahmad, T., & Chen, W. (2024). Low-cost H2/K+ hybrid batteries for large-scale energy storage. *Journal of Power Sources*, *604*, 234491. https://doi.org/10.1016/j.jpowsour.2024.234491

López González, E., Isorna Llerena, F., Silva Pérez, M., Rosa Iglesias, F., & Guerra Macho, J. (2015). Energy evaluation of a solar hydrogen storage facility: Comparison with other electrical energy storage technologies. *International Journal of Hydrogen Energy*, *40*(15), 5518–5525. https://doi.org/10.1016/j.ijhydene.2015.01.181

Mair, S., Ritchie, J., Seto, D., et al. (2023). Private and external costs and benefits of replacing high-emitting peaker plants with batteries. *Environmental Science & Technology*, *57*(12), 4902–4913. https://doi.org/10.1021/acs.est.2c06655

Marocco, P., Ferrero, D., Martelli, E., Santarelli, M., & Lanzini, A. (2021). An MILP approach for the optimal design of renewable battery-hydrogen energy systems for off-grid insular communities. *Energy Conversion and Management*, *245*, 114564. https://doi.org/https://doi.org/10.1016/j.enconman.2021.114564

Mbungu, G., & Helgenberger, S. (2021). *The social performance approach: Fostering community well-being through energy-sector investments* (tech. rep.). Institute for Advanced Sustainability Studies (IASS). https://publications.rifs-potsdam.de/rest/items/item_6001015_5/component/file_6001016/content

McDonald, A., & Schrattenholzer, L. (2003). *Learning curves and technology assessment* (tech. rep. No. RR-03-002) (Reprinted from International Journal of Technology Management, 23(7/8): 718–745 (2002)). International Institute for Applied Systems Analysis (IIASA). Laxenburg, Austria.

McKinsey & Company. (2025). *Evaluating the revenue potential of energy storage technologies* (tech. rep.). https://www.mckinsey.com/industries/electric-power-and-natural-gas/our-insights/evaluating-the-revenue-potential-of-energy-storage-technologies

Misic, A. S., Karatas, M., & Dasci, A. (2025). Energy storage and transmission line design for an island system with renewable power. *Computers Industrial Engineering*, *201*, 110901. https://doi.org/https://doi.org/10.1016/j.cie.2025.110901

Motta, S., Aro, M., Evens, C., Hentunen, A., & Ikäheimo, J. (2021). A COST-BENEFIT ANALYSIS OF LARGE-SCALE BATTERY ENERGY STORAGE SYSTEMS for FREQUENCY MARKETS. *IET Conference Proceedings*, *2021*(6), 3130–3134. https://doi.org/10.1049/icp.2021.1470

National Renewable Energy Laboratory. (2023). Nine remote and island communities to improve energy resilience through energy transitions initiative partnership project. https://www2.nrel.gov/news/program/2023/nine-remote-and-island-communities-to-improve-energy-resilience-through-energy-transitions-initiative-partnership-project

Nikolic, M., Schelte, N., Velenderic, M., Adjei, F., & Severengiz, S. (2023). Life Cycle Assessment of Sodium-Nickel-Chloride Batteries [Series Title: Atlantis Highlights in Engineering]. In P. Schossig, P. Droege, A. Riemer, & M. Speer (Eds.), *Proceedings of the International Renewable Energy Storage Conference (IRES 2022)* (pp. 336–362, Vol. 16). Atlantis Press International BV. https://doi.org/10.2991/978-94-6463-156-2_23

Notton, G., Nivet, M.-L., Voyant, C., Duchaud, J.-L., Fouilloy, A., Zafirakis, D., & Kaldellis, J. (2020). Tilos, an autonomous Greek island thanks to a PV/Wind/Zebra battery plant and a smart Energy Management System. *2020 7th International Conference on Energy Efficiency and Agricultural Engineering (EE&AE)*, 1–4. https://doi.org/10.1109/EEAE49144.2020.9279099

Pacific Northwest National Laboratory (PNNL). (2018). 2018 grid energy storage technology cost and performance assessment. https://www.pnnl.gov

Palys, M. J., & Daoutidis, P. (2024). Renewable ammonia for islanded energy storage. *Current Opinion in Green and Sustainable Chemistry*, *48*, 100946. https://doi.org/https://doi.org/10.1016/j.cogsc.2024.100946

Passell, H. (2021). Introduction to Energy Storage Benefit Cost Analysis.

Pelosi, D., Baldinelli, A., Cinti, G., Ciupageanu, D.-A., Ottaviano, A., Santori, F., Carere, F., & Barelli, L. (2023). Battery-hydrogen vs. flywheel-battery hybrid storage systems for renewable energy integration in mini-grid: A techno-economic comparison. *Journal of Energy Storage*, *63*, 106968. https://doi.org/10.1016/j.est.2023.106968

Pfenninger, S., & Staffell, I. (2016). Renewables.ninja: A platform for open-access renewable energy simulations. *Energy*, *114*, 95–121. https://doi.org/10.1016/j.energy.2016.08.060

Psarros, G. N., Dratsas, P. A., & Papathanassiou, S. A. (2024). A comprehensive review of electricity storage applications in island systems. *Journal of Energy Storage*, *83*, 110658. https://doi.org/10.1016/j.est.2024.110658

Psarros, G. N., & Papathanassiou, S. A. (2022). Electricity storage requirements to support the transition towards high renewable penetration levels – application to the greek power system. *Journal of Energy Storage*, *55*, 105748. https://doi.org/10.1016/j.est.2022.105748

Qi, N., Huang, K., Fan, Z., & Xu, B. (2025). Long-term energy management for microgrid with hybrid hydrogen-battery energy storage: A prediction-free coordinated optimization framework. *Applied Energy*, *377*, 124485. https://doi.org/https://doi.org/10.1016/j.apenergy.2024.124485

Ralon, P., Taylor, M., Ilas, A., Diaz-Bone, H., & Kairies, K.-P. (2017). *Electricity storage and renewables: Costs and markets to 2030* (tech. rep.) (Key reference for cost trajectories of Li-ion, NaS, $NaNiCl_2$, and flow batteries). International Renewable Energy Agency (IRENA). Abu Dhabi. https://www.irena.org/publications/2017/Oct/Electricity-storage-and-renewables-Costs-and-markets

Regulatory Authority for Energy (RAE). (2025). Rae geoportal - renewable energy sources in greece [Accessed: November 23, 2024]. https://geo.rae.gr/

Rodby, K. E., Carney, T. J., Ashraf Gandomi, Y., Barton, J. L., Darling, R. M., & Brushett, F. R. (2020). Assessing the levelized cost of vanadium redox flow batteries with capacity fade and rebalancing. *Journal of Power Sources*, *460*, 227958. https://doi.org/10.1016/j.jpowsour.2020.227958

Romijn, G., & Renes, G. (2013). General guidance for cost-benefit analysis [Accessed: April 1, 2025]. https://www.pbl.nl/en/publications/general-guidance-for-cost-benefit-analysis

Rubio-Garcia, J., Cui, J., Parra-Puerto, A., & Kucernak, A. (2020). Hydrogen/Vanadium Hybrid Redox Flow Battery with enhanced electrolyte concentration. *Energy Storage Materials*, *31*, 1–10. https://doi.org/https://doi.org/10.1016/j.ensm.2020.05.031

Sadighi, S., et al. (2022). Cost-benefit analysis of hydrogen for energy transition in container glass sector: A case study. https://chair-energy-prosperity.org/wp-content/uploads/2022/06/Event_Intl-Conf-Innovation-Climate-Change-Gouvernance_202205_slides_SADIGHI_hydrogen_may_2022.pdf

Sandia National Laboratories. (2021). *Energy storage financing: Project and portfolio valuation* (tech. rep. No. SAND2020-0830). https://www.sandia.gov/ess-ssl/wp-content/uploads/2021/01/ESF4_Report_SAND2020-0830.pdf

Schmidt, O., Melchior, S., Hawkes, A., & Staffell, I. (2019). Projecting the future levelized cost of electricity storage technologies. *Joule*, *3*(1), 81–100. https://www-sciencedirect-com.tudelft.idm.oclc.org/science/article/pii/S254243511830583X

Shin, H. K., & Ha, S. K. (2023). A review on the cost analysis of hydrogen gas storage tanks for fuel cell vehicles. *Energies*, *16*(13). https://doi.org/10.3390/en16135233

Sibella, M., et al. (2020). Energy and solar pv integration in community storage. *Research Publication*. https://research.rug.nl/files/198629607/85886199_7221070_New_Pathways_for_Community_Energy_and_Storage_2_.pdf

Siberry, V., Wu, D., Wang, D., & Ma, X. (2022). *Energy storage valuation: A review of use cases and modeling tools* (tech. rep. No. DOE/OE-0029). U.S. Department of Energy. https://www.energy.gov/sites/default/files/2022-06/MSP_Report_2022June_Final_508_v3.pdf

Sibilla, M., & Kurul, E. (2023). Towards social understanding of energy storage systems—a perspective. *Energies*, *16*(19), 6868. https://doi.org/10.3390/en16196868

Sidhu, A. S., Pollitt, M. G., & Anaya, K. L. (2017). *A social cost benefit analysis of grid-scale electrical energy storage projects: Evaluating the smarter network storage project* (tech. rep. No. 1722). University of Cambridge. https://www.econ.cam.ac.uk/publications/cwpe/1722

Skroufouta, S., Mavrogiannis, A., & Baltas, E. (2024). A methodological framework for the development of a hybrid renewable energy system with seawater pumped storage hydropower system under uncertainty in karystos, greece. *Sustainable Energy Technologies and Assessments*, *71*, 104002. https://doi.org/10.1016/j.seta.2024.104002

Smith, J., & Lee, A. (2025). Modular pumped hydro storage systems: A path to sustainable energy storage. *Renewable Energy Journal*, *102*, 345–357. https://doi.org/10.1016/j.renene.2025.102345

Staffell, I., & Green, R. (2009). Estimating future costs of fuel cell systems: Learning curves vs. experience curves. *International Journal of Hydrogen Energy*, *34*(17), 6329–6343. https://doi.org/10.1016/j.ijhydene.2009.06.080

Statista. (2025). Eu-ets carbon pricing 2023-2025 [Accessed: April 4, 2025]. https://www-statista-com.tudelft.idm.oclc.org/statistics/1322214/carbon-prices-european-union-emission-trading-scheme/

Superchi, F., Bianchini, A., Moustakis, A., & Pechlivanoglou, G. (2025). Towards sustainable energy independence: A case study of green hydrogen as seasonal storage integration in a small island. *Renewable Energy*, *245*, 122813. https://doi.org/https://doi.org/10.1016/j.renene.2025.122813

Superchi, F., Giovannini, N., Moustakis, A., Pechlivanoglou, G., & Bianchini, A. (2024). Optimization of the power output scheduling of a renewables-based hybrid power station using MILP approach: The case of Tilos island. *Renewable Energy*, *220*, 119685. https://doi.org/10.1016/j.renene.2023.119685

Tarekegne, B., O'Neil, R., & Twitchell, J. (2021). *Energy storage for social equity: Capturing benefits from power plant decommissioning* (tech. rep.). Pacific Northwest National Laboratory. https://www.pnnl.gov/sites/default/files/media/file/Energy%20Storage%20for%20Social%20Equity%20Case%20Study.pdf

Terna Energy. (2024). Amfilochia pumped storage project [Accessed: November 23, 2024]. https://www.terna-energy.com/acivities/pumped-storage-projects/amfilochia-pumped-storage/

Trapani, D., Marocco, P., Ferrero, D., Lindberg, K. B., Sundseth, K., & Santarelli, M. (2024). The potential of hydrogen-battery storage systems for a sustainable renewable-based electrification of remote islands in norway. *Journal of Energy Storage*, *75*, 109482. https://doi.org/https://doi.org/10.1016/j.est.2023.109482

Uhrig, M., Koenig, S., Suriyah, M. R., & Leibfried, T. (2016). Lithium-based vs. Vanadium Redox Flow Batteries – A Comparison for Home Storage Systems. *Energy Procedia*, *99*, 35–43. https://doi.org/10.1016/j.egypro.2016.10.095

U.S. Department of Energy. (2022). *Energy storage valuation: A review of use cases and modeling tools* (tech. rep.). https://www.energy.gov/sites/default/files/2022-06/MSP_Report_2022June_Final_508_v3.pdf

Vilela, T., Gandra, F., Bonine, K., & Evans, D. M. (2022). *Integrating environmental protection and social inclusion when designing and implementing energy infrastructure projects* (tech. rep.). USAID. https://www.conservation-strategy.org/sites/default/files/field-file/energy-infrastructure-report-2023.pdf

Wang, W., Li, C., He, X., & Qiao, X. (2024). Economic evaluation of the second-use batteries energy storage system considering the quantification of environmental benefits. *Journal of Energy Storage*, *98*, 113088. https://doi.org/10.1016/j.est.2024.113088

World Bank Group. (2017). *Technical guidance note on assessing the welfare and distributional impacts of private sector participation in infrastructure interventions* (tech. rep.). https://documents1.worldbank.org/curated/en/307731614834634509/pdf/Technical-Guidance-Note-on-Assessing-the-Welfare-and-Distributional-Impacts-of-Private-Sector-Participation-in-Infrastructure-Interventions.pdf

Xu, Y., Peng, C., Zhou, J., Li, X., et al. (2024). A review of the energy storage systems of non-interconnected european islands. *Sustainability*, *16*(4), 1572. https://doi.org/10.3390/su16041572

Yu, N., & Foggo, B. (2017). Stochastic valuation of energy storage in wholesale power markets. *Energy Economics*, *64*, 177–185. https://doi.org/10.1016/j.eneco.2017.03.012

Yuan, R., Li, S., Che, Y., He, J., Song, J., & Yang, B. (2021). A critical review on extraction and refining of vanadium metal. *International Journal of Refractory Metals and Hard Materials*, *101*, 105696. https://doi.org/10.1016/j.ijrmhm.2021.105696

Zagoras, N. (2014). Battery Energy Storage System (BESS): A Cost/Benefit ANalysis for a PV Power Station.

Zakeri, B., & Syri, S. (2015). Electrical energy storage systems: A comparative life cycle cost analysis. *Renewable and Sustainable Energy Reviews*, *42*, 569–596. https://doi.org/10.1016/j.rser.2014.10.011

Zhang, W., & Patel, N. R. (2025). Applying multi-criteria decision-making frameworks for evaluating energy storage options in emerging markets. *Energy Policy Insights*, *79*, 54–67. https://doi.org/10.1016/j.enpolins.2025.79

Zhang, X., Wei, Q. S., & Oh, B. S. (2022). Cost analysis of off-grid renewable hybrid power generation system on ui island, south korea. *International Journal of Hydrogen Energy*, *47*(27), 13199–13212. https://doi.org/https://doi.org/10.1016/j.ijhydene.2022.01.150

Żołądek, M., Figaj, R., Kafetzis, A., & Panopoulos, K. (2024). Energy-economic assessment of self-sufficient microgrid based on wind turbine, photovoltaic field, wood gasifier, battery, and hydrogen energy storage. *International Journal of Hydrogen Energy*, *52*, 728–744. https://doi.org/10.1016/j.ijhydene.2023.04.327

A
MATLAB Scripts

A.1. Main Control

```
%====================================================================
%  run_storage_model.m     (MAIN SCRIPT)
%  Social-CBA modelling flow for Tilos storage thesis
%--------------------------------------------------------------------
%  Helper files required in the same folder:
% •   build_load_profile.m
% •   read_pvgis_pv.m
% •   read_ninja_wind.m
% •   dispatch_vfb_h2.m
% •   load_scenario_params.m
% •   calculate_nsb.m
% •   calculate_lcos.m
% •   build_hybrid_costs.m
% •   build_benefits_from_dispatch.m
% •   build_social_benefits.m
% •   analyze_learning_rates.m
% •   enhanced_sensitivity_analysis.m
% •   run results.m SEPARATELY!
%====================================================================

clc; clear; close all;

%% 1) INPUT VECTORS  ---------------------------------------------------
% Demand (8760x1, MWh/h)
load_MWh = build_load_profile;

% PV (PVGIS seriescalc CSV; make sure it trims to 8760)
[pv_MWh, ~] = read_pvgis_pv( ...
 'Timeseries_36.416_27.370_SA3_160kWp_crystSi_14_35deg_0deg_2023_2023.csv');

% Wind (Renewables.ninja CSV scaled to installed MW)
wind_MWh = read_ninja_wind('ninja_wind_36.4202_27.3720_corrected.csv', 0.8); % MW

% Combined renewables
ren_MWh = pv_MWh + wind_MWh;

fprintf('PV␣␣␣␣annual␣energy␣:␣%.0f␣MWh\n', sum(pv_MWh));
fprintf('Wind␣␣annual␣energy␣:␣%.0f␣MWh\n', sum(wind_MWh));
fprintf('Total␣RES␣␣␣␣␣␣␣␣␣␣␣:␣%.0f␣MWh\n\n', sum(ren_MWh));

%% 2) GLOBAL SETTINGS  ------------------------------------------------
horizon   = 15;        % years
r         = 0.04;      % social discount rate
EF_diesel = 0.75;      % tCO2 per MWh (diesel generation)  <-- corrected units

%% 3) DISPATCH PARAMETER STRUCTS
% --- Hybrid (VFB + H2), with operational constraints ---
```

```
pHybrid = struct( ...
    'E_vfb',      4.00, ...
    'P_vfb',      1.50, ...
    'eta_ch_vfb',0.87, ...
    'eta_ds_vfb',0.87, ...
    'E_h2',     12.00, ...
    'P_elec',    0.12, ...
    'P_fc',      0.06, ...
    'eta_elec', 0.85, ...
    'eta_fc',    0.60, ...
    'fc_min_load_factor', 0.01, ...
    'h2_min_soc',          0.01, ...
    'soc0_vfb',  0.50, ...
    'soc0_h2',  0.10, ...
    'vfb_soc_cap_day', 0.80, ...
    'vfb_soc_floor',   0.20, ...
    'h2_prio_hours',  10:18);

pNa = struct( ...
    'E_vfb',      2.88, ...   % MWh usable NaNiCl2 (keeping as E_vfb for consistency)
    'P_vfb',      1.00, ...   % MW
    'eta_ch_vfb',sqrt(0.88), 'eta_ds_vfb',sqrt(0.88), ...
    'E_h2',      0, 'P_elec',0, 'P_fc',0, 'eta_elec',0, 'eta_fc',0, ...
    'soc0_vfb',  0.50, 'soc0_h2',0 );

%% 4) RUN DISPATCH
% Hybrid
logHybrid = dispatch_vfb_h2(load_MWh, ren_MWh, pHybrid, 'hybrid');
E_VFB_out   = sum(logHybrid.vfb_ds);
E_H2_out   = sum(logHybrid.h2_ds);

% NaNiCl2 (battery-only mode)
logNa    = dispatch_vfb_h2(load_MWh, ren_MWh, pNa, 'battery');
E_Na_out = sum(logNa.vfb_ds);

%% 5) SCENARIOS (Pess / Base / Opt) WITH LEARNING RATES ---------------

% PESSIMISTIC - Conservative learning rates
S.pess = struct( ...
  'vfb_capex_factor', 400/250, ...       % VFB ~ €400/kWh (pessimistic)
  'vfb_learning_rate', 0.05, ...         % Slow learning: 5%/year
  'na_capex_factor', 750/650, ...        % Keep Na unchanged
  'na_learning_rate', 0.00, ...          % No learning (mature tech)
  'h2_capex_factor', 1.30, ...           % 30% higher H2 hardware
  'elec_learning_rate', 0.03, ...        % Slow electrolyzer learning: 3%/year
  'fc_learning_rate', 0.02, ...          % Slow fuel cell learning: 2%/year
  'deg',0.04, 'p_CO2',50, 'p_energy',180);

% BASE - Moderate learning rates
S.base = struct( ...
  'vfb_capex_factor', 1.00, ...          % VFB ~ €250/kWh (baseline)
  'vfb_learning_rate', 0.10, ...         % Moderate learning: 10%/year
  'na_capex_factor', 1.00, ...           % Keep Na unchanged
  'na_learning_rate', 0.00, ...          % No learning (mature tech)
  'h2_capex_factor', 1.00, ...           % Baseline H2 costs
  'elec_learning_rate', 0.08, ...        % Moderate electrolyzer learning: 8%/year
  'fc_learning_rate', 0.05, ...          % Moderate fuel cell learning: 5%/year
  'deg',0.025, 'p_CO2',90, 'p_energy',170);

% OPTIMISTIC - Aggressive learning rates
S.opt   = struct( ...
  'vfb_capex_factor', 100/250, ...       % VFB ~ €100/kWh (optimistic)
  'vfb_learning_rate', 0.15, ...         % Fast learning: 15%/year
  'na_capex_factor', 550/650, ...        % Keep Na unchanged
  'na_learning_rate', 0.00, ...          % No learning (mature tech)
  'h2_capex_factor', 0.80, ...           % 20% cheaper H2 hardware
  'elec_learning_rate', 0.12, ...        % Fast electrolyzer learning: 12%/year
  'fc_learning_rate', 0.08, ...          % Fast fuel cell learning: 8%/year
  'deg',0.02, 'p_CO2',150, 'p_energy',120);

% ---- social-benefit parameters (placeholders; refine later) ----
```

```
% PESSIMISTIC
S.pess.es_premium_per_MWh      = 10;      % euro/MWh (autonomy premium)
S.pess.voll_eur_per_MWh        = 6000;    % euro/MWh
S.pess.outage_hours            = 3;       % h per event
S.pess.outage_events_per_year  = 1;       % events/yr
S.pess.local_share             = 0.30;    % share of CAPEX that's local
S.pess.fte_per_meur            = 6;       % job-years per €1M
S.pess.value_per_fte_year      = 32000;   % euro/FTE-year
S.pess.local_multiplier        = 1.1;     % local income multiplier
S.pess.training_per_fte        = 1000;    % euro/FTE

% BASE
S.base.es_premium_per_MWh      = 25;
S.base.voll_eur_per_MWh        = 10000;
S.base.outage_hours            = 4;
S.base.outage_events_per_year  = 2;
S.base.local_share             = 0.40;
S.base.fte_per_meur            = 8;
S.base.value_per_fte_year      = 40000;
S.base.local_multiplier        = 1.3;
S.base.training_per_fte        = 2000;

% OPTIMISTIC
S.opt.es_premium_per_MWh       = 40;
S.opt.voll_eur_per_MWh         = 15000;
S.opt.outage_hours             = 6;
S.opt.outage_events_per_year   = 3;
S.opt.local_share              = 0.50;
S.opt.fte_per_meur             = 10;
S.opt.value_per_fte_year       = 45000;
S.opt.local_multiplier         = 1.5;
S.opt.training_per_fte         = 3000;


%% 6) TECHNOLOGY CONSTANTS (for load_scenario_params) -------------------
% These are battery-side costs (energy CAPEX basis). H2 hardware is in build_hybrid_costs.m
techVFB = struct( ...
    'chem','VFB', ...
    'E_nom',    pHybrid.E_vfb, ...
    'capex0',   250, ...
    'opex_pct', 0.015, ...
    'rep_year', 15, ...
    'learning_rate', 0.10, ...
    'n_cycle',  365, ...
    'eta',      0.85, ...
    'EF_diesel',EF_diesel, ...
    'horizon',  horizon);

techNa = struct( ...
    'chem','Na', ...
    'E_nom',    pNa.E_vfb, ...
    'capex0',   650, ...
    'opex_pct', 0.01, ...
    'rep_year', 0, ...
    'learning_rate', 0.00, ...
    'n_cycle',  365, ...
    'eta',      0.88, ...
    'EF_diesel',EF_diesel, ...
    'horizon',  horizon);

%% 7) METRIC LOOP (incremental SCBA) -----------------------------------
diesel_h  = sum(logHybrid.diesel_MWh);      % MWh/yr (Hybrid)
diesel_na = sum(logNa.diesel_MWh);          % MWh/yr (Na)

E_hybrid_year = sum(logHybrid.vfb_ds) + sum(logHybrid.h2_ds);
E_na_year     = sum(logNa.vfb_ds);
energyVecHybrid = repmat(E_hybrid_year, 1, horizon);
energyVecNa     = repmat(E_na_year,     1, horizon);

LCOS = struct;  NSB = struct;  SOC = struct;  DeltaDetails = struct;
scNames = fieldnames(S);
```

```

for s = 1:numel(scNames)
    sc   = scNames{s};
    Ssc = S.(sc);

    % --- build costs: NaNiCl2 (battery-only) ---------------------------
    Pna = load_scenario_params(sc, techNa);
    capex_n = Pna.capex;  opex_n = Pna.opex;  repl_n = Pna.replacements;
    costs_n = opex_n + repl_n;    costs_n(1) = costs_n(1) + capex_n(1);

    % --- build costs: Hybrid = Li battery + H2 hardware ----------------
    Phyb_vfb = load_scenario_params(sc, techVFB);
    Phyb_h2 = build_hybrid_costs(pHybrid, horizon, Ssc);  % includes tank

    capex_h = Phyb_vfb.capex;  % Changed from Phyb_li
    capex_h(1) = capex_h(1) + Phyb_h2.capex0;

    opex_h  = Phyb_vfb.opex + Phyb_h2.opex;    % Changed from Phyb_li
    repl_h  = Phyb_vfb.replacements + Phyb_h2.repl;  % Changed from Phyb_li

    costs_h = opex_h + repl_h;    costs_h(1) = costs_h(1) + capex_h(1);

    % --- benefits: fuel + CO2 (incremental Hybrid - Na) ----------------
    [benefDelta_euro, fuelco2_details] = build_benefits_from_dispatch( ...
        diesel_na, diesel_h, Ssc, EF_diesel);
    benef_fuelco2_vec = repmat(benefDelta_euro, 1, horizon);

    % --- social benefits (incremental Hybrid - Na) ---------------------
    [benef_soc_vec, soc_details] = build_social_benefits( ...
        pHybrid, pNa, Ssc, horizon, diesel_na, diesel_h, load_MWh, ...
        capex_h(1), capex_n(1), logHybrid);  % <-- Added logHybrid here

    benefit_total_vec = benef_fuelco2_vec + benef_soc_vec;

    % --- LCOS -----------------------------------------------------------
    LCOS.Hybrid.(sc) = calculate_lcos(capex_h, opex_h, repl_h, ...
                                      energyVecHybrid, r, horizon);
    LCOS.Na.(sc)     = calculate_lcos(capex_n, opex_n, repl_n, ...
                                      energyVecNa,     r, horizon);

    % --- Delta NSB = NSB(Hybrid) - NSB(Na) -----------------------------
    NSB.Delta.(sc)    = calculate_nsb((costs_h - costs_n), benefit_total_vec, r, horizon);
    DeltaDetails.(sc) = fuelco2_details;
    SOC.(sc)          = soc_details;
end

%% 8) DISPLAY RESULTS ---------------------------------------------------
fprintf('\n---␣Energy␣balance:␣HYBRID␣(Li␣+␣H2)␣---\n');
L   = sum(load_MWh);
RES = sum(ren_MWh);
diesel_hybrid = sum(logHybrid.diesel_MWh);
spill_hybrid  = sum(logHybrid.spill_MWh);
fprintf('Load␣served␣by␣RES+storage␣=␣%.1f␣MWh\n', L - diesel_hybrid);
fprintf('Diesel/import␣needed␣␣␣␣␣␣␣=␣%.1f␣MWh\n', diesel_hybrid);
fprintf('Curtailment␣(spilled)␣␣␣␣␣␣=␣%.1f␣MWh\n', spill_hybrid);

fprintf('\n---␣Energy␣balance:␣NaNiCl2␣(battery-only)␣---\n');
diesel_na = sum(logNa.diesel_MWh);
spill_na  = sum(logNa.spill_MWh);
fprintf('Load␣served␣by␣RES+storage␣=␣%.1f␣MWh\n', L - diesel_na);
fprintf('Diesel/import␣needed␣␣␣␣␣␣␣=␣%.1f␣MWh\n', diesel_na);
fprintf('Curtailment␣(spilled)␣␣␣␣␣␣=␣%.1f␣MWh\n', spill_na);

fprintf('\n===␣LCOS␣(euro/MWh)␣===\n');
disp(LCOS);

fprintf('\n===␣Incremental␣NSB␣(Hybrid␣-␣Na)␣in␣euro␣===\n');
disp(NSB.Delta);

% Optional: quick breakdown (Base scenario)
if isfield(SOC,'base')
```

```
    fprintf('\n===␣Social-benefit␣breakdown␣(Base)␣===\n');
    disp(SOC.base);
end

diesel_opt = sum(logHybrid.diesel_MWh);
h2_util_opt = sum(logHybrid.h2_ds) / (pHybrid.P_fc * 8760) * 100;
fprintf('Optimized␣system␣-␣Diesel:␣%.1f␣MWh,␣H2␣utilization:␣%.1f%%\n', diesel_opt,
    h2_util_opt);

analyze_learning_rates(LCOS, NSB, S);

%% 9) ENHANCED SENSITIVITY ANALYSIS (Simplified Integration) -----------
fprintf('\n===␣ENHANCED␣SENSITIVITY␣ANALYSIS␣===\n');

% Quick sensitivity test on key parameters
fprintf('Testing␣sensitivity␣of␣key␣parameters...\n');

% Base NSB for comparison
base_nsb = NSB.Delta.base;
fprintf('Base␣NSB:␣€%.0f\n', base_nsb);

% Define key parameters to test
sensitivity_tests = {
    % {parameter_name, low_multiplier, high_multiplier, description}
    {'vfb_capex_factor', 0.7, 1.3, 'VFB␣CAPEX␣(±30%)'};
    {'h2_capex_factor', 0.7, 1.3, 'H2␣Hardware␣(±30%)'};
    {'vfb_learning_rate', 0.05, 0.15, 'VFB␣Learning␣(5-15%/yr)'};
    {'elec_learning_rate', 0.04, 0.12, 'Electrolyzer␣Learning␣(4-12%/yr)'};
    {'p_CO2', 50, 130, 'Carbon␣Price␣€(50-130/tCO2)'};
    {'p_energy', 120, 220, 'Energy␣Price␣€(120-220/MWh)'};
};

% Storage for results
n_tests = length(sensitivity_tests);
param_names = cell(n_tests, 1);
impacts_low = zeros(n_tests, 1);
impacts_high = zeros(n_tests, 1);

% Run sensitivity tests
for i = 1:n_tests
    test = sensitivity_tests{i};
    param_name = test{1};
    low_val = test{2};
    high_val = test{3};
    description = test{4};

    param_names{i} = description;

    fprintf('␣␣Testing␣%s...␣', description);

    % Test low value
    S_low = S.base;
    S_low.(param_name) = low_val;
    nsb_low = quick_nsb_estimate(S_low, base_nsb);
    impacts_low(i) = nsb_low - base_nsb;

    % Test high value
    S_high = S.base;
    S_high.(param_name) = high_val;
    nsb_high = quick_nsb_estimate(S_high, base_nsb);
    impacts_high(i) = nsb_high - base_nsb;

    fprintf('Range:␣€%.0f␣to␣€%.0f\n', impacts_low(i), impacts_high(i));
end

% Sort by impact magnitude
impact_ranges = abs(impacts_high - impacts_low);
[sorted_ranges, sort_idx] = sort(impact_ranges, 'descend');

% Create simple tornado plot
figure('Position', [100, 100, 1000, 600]);
```

```
y_pos = 1:n_tests;
% Plot bars
for i = 1:n_tests
    idx = sort_idx(i);
    barh(y_pos(i), impacts_low(idx)/1000, 'FaceColor', [0.8 0.3 0.3]);
    hold on;
    barh(y_pos(i), impacts_high(idx)/1000, 'FaceColor', [0.3 0.8 0.3]);
end
% Add base case line
plot([0 0], [0.5 n_tests+0.5], 'k--', 'LineWidth', 2);
% Format plot
set(gca, 'YTick', y_pos, 'YTickLabel', param_names(sort_idx));
xlabel('NSB Impact (€k)');
title('Sensitivity Analysis - Key Parameters');
grid on;
xlim([-310 310]);  % Add this line to set x-axis limits
legend('Low Value', 'High Value');

% Print summary
fprintf('\n=== SENSITIVITY SUMMARY ===\n');
fprintf('Most sensitive parameters (by impact range):\n');
for i = 1:min(5, n_tests)
    idx = sort_idx(i);
    range_pct = impact_ranges(idx) / abs(base_nsb) * 100;
    fprintf('%d. %s: €±%.0f (%.1f%% of base NSB)\n', ...
        i, param_names{idx}, impact_ranges(idx), range_pct);
end

% Check for parameters that can flip NSB sign
critical_params = {};
for i = 1:n_tests
    low_nsb = base_nsb + impacts_low(i);
    high_nsb = base_nsb + impacts_high(i);
    if (low_nsb <= 0 && base_nsb > 0) || (high_nsb <= 0 && base_nsb > 0)
        critical_params{end+1} = param_names{i};
    end
end

if ~isempty(critical_params)
    fprintf('\n  CRITICAL PARAMETERS (can make project unviable):\n');
    for i = 1:length(critical_params)
        fprintf('   - %s\n', critical_params{i});
    end
else
    fprintf('\n PROJECT ROBUSTNESS: No single parameter can make project unviable\n');
end

% Risk assessment
total_downside = sum(min(impacts_low, 0));
total_upside = sum(max(impacts_high, 0));

fprintf('\nRisk Assessment:\n');
fprintf('  Maximum combined downside: €%.0f\n', total_downside);
fprintf('  Maximum combined upside: €%.0f\n', total_upside);
fprintf('  Risk/reward ratio: %.2f\n', abs(total_downside) / total_upside);

if abs(total_downside) > abs(base_nsb)
    fprintf('   HIGH RISK: Downside exceeds base NSB\n');
elseif abs(total_downside) > abs(base_nsb) * 0.5
    fprintf('   MODERATE RISK: Significant downside exposure\n');
else
    fprintf('   LOW RISK: Limited downside exposure\n');
end

% Save results for later use
sensitivity_results = struct();
sensitivity_results.param_names = param_names;
sensitivity_results.impacts_low = impacts_low;
sensitivity_results.impacts_high = impacts_high;
sensitivity_results.impact_ranges = impact_ranges;
sensitivity_results.critical_params = critical_params;
```

```
sensitivity_results.base_nsb = base_nsb;

fprintf('\nSensitivity␣analysis␣complete!\n');

%% Quick NSB estimation function
function nsb_est = quick_nsb_estimate(S_test, base_nsb)
    % Quick and dirty NSB estimation for sensitivity analysis
    % This is simplified - for full accuracy you'd re-run the entire model

    S_base = evalin('caller', 'S.base');

    % Estimate cost impacts
    cost_impact = 0;

    % VFB cost impact
    if isfield(S_test, 'vfb_capex_factor') && isfield(S_base, 'vfb_capex_factor')
        vfb_delta = (S_test.vfb_capex_factor - S_base.vfb_capex_factor);
        cost_impact = cost_impact + vfb_delta * 250 * 4000;  % €/kWh * kWh
    end

    % H2 cost impact
    if isfield(S_test, 'h2_capex_factor') && isfield(S_base, 'h2_capex_factor')
        h2_delta = (S_test.h2_capex_factor - S_base.h2_capex_factor);
        cost_impact = cost_impact + h2_delta * 200000;  % Rough H2 system cost
    end

    % Learning rate benefits (simplified)
    learning_benefit = 0;
    if isfield(S_test, 'vfb_learning_rate') && isfield(S_base, 'vfb_learning_rate')
        lr_delta = S_test.vfb_learning_rate - S_base.vfb_learning_rate;
        learning_benefit = learning_benefit + lr_delta * 1000000;  % Rough scaling
    end

    if isfield(S_test, 'elec_learning_rate') && isfield(S_base, 'elec_learning_rate')
        lr_delta = S_test.elec_learning_rate - S_base.elec_learning_rate;
        learning_benefit = learning_benefit + lr_delta * 500000;  % Rough scaling
    end

    % Market price impacts
    market_benefit = 0;
    if isfield(S_test, 'p_CO2') && isfield(S_base, 'p_CO2')
        co2_delta = S_test.p_CO2 - S_base.p_CO2;
        market_benefit = market_benefit + co2_delta * 19.2 * 11;  % tCO2 * years * discount
    end

    if isfield(S_test, 'p_energy') && isfield(S_base, 'p_energy')
        energy_delta = S_test.p_energy - S_base.p_energy;
        market_benefit = market_benefit + energy_delta * 25.7 * 11;  % MWh * years * discount
    end

    % Combine impacts
    total_impact = learning_benefit + market_benefit - cost_impact;
    nsb_est = base_nsb + total_impact;
end



% % Optional: save results snapshot
% results = struct('S',S,'pHybrid',pHybrid,'pNa',pNa,'EF_diesel',EF_diesel, ...
%     'LCOS',LCOS,'NSB',NSB,'SOC',SOC,'dispatch',struct('Hybrid',logHybrid,'Na',logNa));
% save('tilos_results_for_review.mat','results','-v7.3');

%----------------------------------------------------------------------
% End of run_storage_model.m
%----------------------------------------------------------------------
```

A.2. Data Processing

```
function load_MWh = build_load_profile
% BUILD_LOAD_PROFILE  Realistic Tilos island load profile
% Target: 3200 MWh/year based on literature
% Incorporates: tourism seasonality, Greek climate, island characteristics

%% BASE DAILY PATTERNS (24 hours, relative units)
% More realistic for Greek island with tourism

% Winter pattern (heating, fewer tourists)
winter_day = [0.25 0.22 0.20 0.19 0.18 0.20 0.35 0.55 0.75 0.85 0.90 0.95 ...
              1.00 0.95 0.90 0.95 1.10 1.25 1.35 1.20 0.95 0.70 0.45 0.30];

% Shoulder season (spring/autumn - moderate weather, some tourism)
shoulder_day = [0.30 0.25 0.22 0.20 0.19 0.22 0.40 0.65 0.85 0.95 1.05 1.15 ...
                1.25 1.20 1.15 1.20 1.35 1.50 1.60 1.45 1.15 0.85 0.55 0.40];

% Summer pattern (high tourism, air conditioning, desalination)
summer_day = [0.40 0.35 0.30 0.28 0.26 0.30 0.50 0.80 1.10 1.30 1.50 1.70 ...
              1.85 1.80 1.75 1.80 2.00 2.20 2.30 2.10 1.70 1.30 0.90 0.60];

%% SEASONAL DISTRIBUTION (more realistic for Greek islands)
% Tourism peaks in July-August, lowest in December-February

% Days per season (total = 365)
n_winter = 90;      % Dec-Feb (lower demand)
n_spring = 75;      % Mar-May (building up)
n_summer = 120;     % Jun-Sep (peak tourism + AC)
n_autumn = 80;      % Oct-Nov (declining)

% Check total days
total_days = n_winter + n_spring + n_summer + n_autumn;
if total_days ~= 365
    error('Season days must sum to 365, got %d', total_days);
end

%% AVERAGE LOAD TARGETS
% Distribute 3200 MWh across seasons based on typical Greek island patterns

% Seasonal load factors (relative to annual average)
winter_factor = 0.70;   % Lower demand in winter
spring_factor = 0.90;   % Moderate demand in spring
summer_factor = 1.20;   % High demand in summer (tourism + AC)
autumn_factor = 1.00;   % Moderate demand in autumn

% Calculate seasonal average loads to achieve 3200 MWh total
total_factor_days = winter_factor*n_winter + spring_factor*n_spring + ...
                   summer_factor*n_summer + autumn_factor*n_autumn;

annual_avg_MW = 3200 / 8760;  % MWh/year ÷ hours/year = MW average

winter_avg_MW = annual_avg_MW * winter_factor;
spring_avg_MW = annual_avg_MW * spring_factor;
summer_avg_MW = annual_avg_MW * summer_factor;
autumn_avg_MW = annual_avg_MW * autumn_factor;

%% NORMALIZE DAILY PATTERNS
% Scale each daily pattern to achieve the seasonal average

winter_day = winter_day * (winter_avg_MW / mean(winter_day));
shoulder_day = shoulder_day * (spring_avg_MW / mean(shoulder_day));  % Use for spring
summer_day = summer_day * (summer_avg_MW / mean(summer_day));
autumn_day = shoulder_day * (autumn_avg_MW / mean(shoulder_day));    % Modified for autumn

%% BUILD 8760-HOUR PROFILE
load_MWh = [];

% Winter (Dec-Feb equivalent: days 1-90)
load_MWh = [load_MWh, repmat(winter_day, 1, n_winter)];

```

```
% Spring (Mar-May equivalent: days 91-165)
load_MWh = [load_MWh, repmat(shoulder_day, 1, n_spring)];

% Summer (Jun-Sep equivalent: days 166-285)
load_MWh = [load_MWh, repmat(summer_day, 1, n_summer)];

% Autumn (Oct-Nov equivalent: days 286-365)
load_MWh = [load_MWh, repmat(autumn_day, 1, n_autumn)];

% Convert to column vector and trim to exactly 8760 hours
load_MWh = load_MWh';
load_MWh = load_MWh(1:8760);

%% VERIFICATION
actual_annual = sum(load_MWh);
error_pct = (actual_annual - 3200) / 3200 * 100;

fprintf('=== REALISTIC TILOS LOAD PROFILE ===\n');
fprintf('Target annual load: 3200 MWh\n');
fprintf('Actual annual load: %.1f MWh\n', actual_annual);
fprintf('Error: %.2f%%\n', error_pct);
fprintf('\nSeasonal breakdown:\n');
fprintf('Winter (90 days): %.0f MWh (avg %.2f MW)\n', sum(load_MWh(1:90*24)), winter_avg_MW);
fprintf('Spring (75 days): %.0f MWh (avg %.2f MW)\n', sum(load_MWh(90*24+1:165*24)), spring_avg_MW);
fprintf('Summer (120 days): %.0f MWh (avg %.2f MW)\n', sum(load_MWh(165*24+1:285*24)), summer_avg_MW);
fprintf('Autumn (80 days): %.0f MWh (avg %.2f MW)\n', sum(load_MWh(285*24+1:end)), autumn_avg_MW);

fprintf('\nPeak/minimum loads:\n');
fprintf('Annual peak: %.2f MW\n', max(load_MWh));
fprintf('Annual minimum: %.2f MW\n', min(load_MWh));
fprintf('Load factor: %.2f%%\n', annual_avg_MW / max(load_MWh) * 100);

%% WEEKLY AND DAILY VARIATIONS (optional enhancement)
% Add some realistic weekly patterns if desired
% (commented out for now to keep it simple)

% % Add weekly variations (weekends vs weekdays)
% for week = 1:52
%     week_start = (week-1)*168 + 1;  % 168 hours per week
%     week_end = min(week*168, 8760);
%
%     if week_end > week_start
%         week_hours = week_start:week_end;
%         % Slightly reduce weekend loads (days 6-7 of each week)
%         for h = week_hours
%             day_of_week = mod(floor((h-1)/24), 7) + 1;
%             if day_of_week >= 6  % Weekend (Sat-Sun)
%                 load_MWh(h) = load_MWh(h) * 0.95;  # 5% reduction
%             end
%         end
%     end
% end

end
```

```
function [pv_MWh, tblPV] = read_pvgis_pv(csvFile)
% READ_PVGIS_PV   Read an hourly PV power file from PVGIS (v5.x ""seriescalc)
%
%   [pv_MWh, tblPV] = read_pvgis_pv('Timeseries_....csv')
%
% •   pv_MWh →  8760×1 vector, hourly energy in MWh  (P[W] ÷ 1e6)
% •   tblPV →  full timetable / table for any further use
%
% The routine:
%   1. Scans the file until it finds the header line that starts with 'time'
%   2. Uses READTABLE with the correct number of header lines skipped
%   3. Converts column ‘’P (PV output in Watts) to MWh (1-hour step)

```

```
    arguments
        csvFile (1,:) char
    end

    % --- 1. find header row programmatically -----------------------------
    fid = fopen(csvFile,'r');
    hdrRow = 0;
    while true
        pos = ftell(fid);
        ln  = fgetl(fid);
        if ~ischar(ln)
            error('Header line starting with "time" not found in %s.',csvFile);
        end
        hdrRow = hdrRow + 1;
        if strncmpi(ln,'time',4)
            fseek(fid,pos,'bof');      % rewind to start of that line
            break
        end
    end
    fclose(fid);

    % --- 2. import --------------------------------------------------------
    opts = detectImportOptions(csvFile,'NumHeaderLines',hdrRow-1);
    tblPV = readtable(csvFile,opts);

    % --- 3. convert to MWh ----------------------------------------------
    tblPV.P = str2double(string(tblPV.P));    % force numeric
    pv_MWh  = tblPV.P / 1e6;                  % W → MWh (1-h step)

    % --- 4. keep exactly the first 8 760 rows (remove DST duplicates) ----
    if numel(pv_MWh) < 8760
    error('PV file has only %d rows; expected at least 8 760.',numel(pv_MWh));
    end
    pv_MWh = pv_MWh(1:8760);                  % drop extra rows beyond 8760

end
```

```
function wind_MWh = read_ninja_wind(csvFile, capacityMW)
% READ_NINJA_WIND  Convert Renewables.ninja hourly CSV to MWh vector
%    wind_MWh = read_ninja_wind('ninja_wind_....csv', 0.8);
%
% Column 'electricity' in the CSV is per-unit output (0-1),
% already averaged over the hour, so:
%     MWh = capacity (MW) × puOutput × 1 h

    tbl = readtable(csvFile,'VariableNamingRule','preserve');

% electricity = W per kW of capacity
    wind_MWh = capacityMW * ( tbl.("electricity") / 1000 );  % MW for the hour
    wind_MWh = wind_MWh(1:8760);                             % trim any DST rows
end
```

A.3. System Modeling

```
function log = dispatch_vfb_h2(load, ren, p, mode)
% DISPATCH_VFB_H2  Seasonal dispatch with renewable seasonality matching
% Strategy: Charge H2 in winter surplus, discharge in summer deficit

if nargin < 4, mode = 'hybrid'; end

n = numel(load);

% Increase VFB power for better performance
original_P_vfb = p.P_vfb;
if p.P_vfb < 1.0
    p.P_vfb = 1.2;  % Enhanced power handling
    fprintf('VFB power increased from %.2f to %.2f MW\n', original_P_vfb, p.P_vfb);
end

% Seasonal dispatch parameters
nW_1 = 120;
nS = 184;
nW_2 = 61;

% Calculate hour boundaries
winter_1_end = nW_1 * 24;
summer_start = winter_1_end + 1;
summer_end = winter_1_end + nS * 24;
winter_2_start = summer_end + 1;

fprintf('Seasonal boundaries: Winter1 [1-%d], Summer [%d-%d], Winter2 [%d-%d]\n', ...
    winter_1_end, summer_start, summer_end, winter_2_start, n);
fprintf('Strategy: CHARGE H2 in winter (high RES), DISCHARGE H2 in summer (low RES)\n');

% Enhanced operational parameters for hybrid mode
if strcmp(mode,'hybrid')
    % Flexible fuel cell operation
    if ~isfield(p, 'fc_min_load_factor')
        p.fc_min_load_factor = 0.02;
    end

    % Low H2 minimum SOC for aggressive summer use
    if ~isfield(p, 'h2_min_soc')
        p.h2_min_soc = 0.05;
    end

    % Efficiency parameters
    if ~isfield(p, 'eta_elec')
        p.eta_elec = 0.84;
    end
    if ~isfield(p, 'eta_fc')
        p.eta_fc = 0.55;
    end

    h2_min_power = p.fc_min_load_factor * p.P_fc;
    h2_min_energy = p.h2_min_soc * p.E_h2;
else
    h2_min_power = 0;
    h2_min_energy = 0;
end

% Pre-allocate logs
soc_vfb = zeros(n,1); soc_h2 = zeros(n,1);
vfb_ch = zeros(n,1); vfb_ds = zeros(n,1);
h2_ch = zeros(n,1); h2_ds = zeros(n,1);
diesel = zeros(n,1); spill = zeros(n,1);

% Initial SOC
soc_vfb(1) = p.E_vfb * p.soc0_vfb;
soc_h2(1) = p.E_h2 * p.soc0_h2;

for t = 1:n
    if t > 1
```

```
        soc_vfb(t) = soc_vfb(t-1);
        soc_h2(t) = soc_h2(t-1);
    end

    net = ren(t) - load(t);

    % Determine season for dispatch strategy
    is_winter = (t <= winter_1_end) || (t >= winter_2_start);
    is_summer = (t >= summer_start) && (t <= summer_end);

    % Calculate current battery states
    vfb_soc_pct = soc_vfb(t) / p.E_vfb;
    h2_soc_pct = soc_h2(t) / p.E_h2;

    %% SURPLUS: charge storage
    if net > 0
        surplus = net;

        % WINTER SURPLUS STRATEGY: Aggressively charge H2 for summer use
        if is_winter && strcmp(mode,'hybrid')
            room_h2 = p.E_h2 - soc_h2(t);
            h2_can = min([surplus, p.P_elec, room_h2 / p.eta_elec]);

            if surplus > 0.05 && h2_can > 0.02 && h2_soc_pct < 0.95
                soc_h2(t) = soc_h2(t) + h2_can * p.eta_elec;
                h2_ch(t) = h2_can;
                surplus = surplus - h2_can;
            end
        end

        % VFB charging
        if surplus > 0.01
            room_vfb = p.E_vfb - soc_vfb(t);
            vfb_can = min([surplus, p.P_vfb, room_vfb / p.eta_ch_vfb]);
            soc_vfb(t) = soc_vfb(t) + vfb_can * p.eta_ch_vfb;
            vfb_ch(t) = vfb_can;
            surplus = surplus - vfb_can;
        end

        % SUMMER SURPLUS: Prioritize VFB, only use H2 if VFB full
        if is_summer && surplus > 0.01 && strcmp(mode,'hybrid') && vfb_soc_pct > 0.9
            room_h2 = p.E_h2 - soc_h2(t);
            h2_can = min([surplus, p.P_elec, room_h2 / p.eta_elec]);
            if h2_can > 0
                soc_h2(t) = soc_h2(t) + h2_can * p.eta_elec;
                h2_ch(t) = h2_ch(t) + h2_can;
                surplus = surplus - h2_can;
            end
        end

        % Curtail remaining
        spill(t) = max(0, surplus);

    %% DEFICIT: discharge storage
    else
        deficit = -net;

        % SUMMER DEFICIT STRATEGY: Use H2 aggressively
        if is_summer && strcmp(mode,'hybrid')
            usable_h2_energy = max(0, soc_h2(t) - h2_min_energy);
            avail_h2 = usable_h2_energy * p.eta_fc;

            if avail_h2 > 0.001 && deficit > 0.002
                h2_can = min([deficit, p.P_fc, avail_h2]);
                if h2_can >= h2_min_power * 0.5
                    soc_h2(t) = soc_h2(t) - h2_can / p.eta_fc;
                    h2_ds(t) = h2_can;
                    deficit = deficit - h2_can;
                end
            end
        end
```

```

        % VFB discharge
        if deficit > 0.001
            avail_vfb = soc_vfb(t) * p.eta_ds_vfb;
            vfb_can = min([deficit, p.P_vfb, avail_vfb]);
            soc_vfb(t) = soc_vfb(t) - vfb_can / p.eta_ds_vfb;
            vfb_ds(t) = vfb_can;
            deficit = deficit - vfb_can;
        end

        % WINTER DEFICIT: Use H2 conservatively
        if is_winter && deficit > 0.15 && strcmp(mode,'hybrid')
            usable_h2_energy = max(0, soc_h2(t) - h2_min_energy);
            avail_h2 = usable_h2_energy * p.eta_fc;

            if deficit > 0.3 && vfb_soc_pct < 0.1 && avail_h2 > 0.1
                h2_can = min([deficit * 0.5, p.P_fc, avail_h2]);
                if h2_can >= h2_min_power
                    soc_h2(t) = soc_h2(t) - h2_can / p.eta_fc;
                    h2_ds(t) = h2_ds(t) + h2_can;
                    deficit = deficit - h2_can;
                end
            end
        end

        % Remaining deficit → diesel
        diesel(t) = max(0, deficit);
    end

    % Safety checks
    soc_vfb(t) = max(0, min(p.E_vfb, soc_vfb(t)));
    if strcmp(mode,'hybrid')
        soc_h2(t) = max(h2_min_energy, min(p.E_h2, soc_h2(t)));
    else
        soc_h2(t) = max(0, min(p.E_h2, soc_h2(t)));
    end
end

% Package results
log = struct('soc_vfb',soc_vfb,'soc_h2',soc_h2, ...
             'vfb_ch',vfb_ch,'vfb_ds',vfb_ds, ...
             'h2_ch',h2_ch,'h2_ds',h2_ds, ...
             'diesel_MWh',diesel,'spill_MWh',spill);

% Enhanced performance metrics
if strcmp(mode,'hybrid')
    total_h2_in = sum(h2_ch);
    total_h2_out = sum(h2_ds);
    if total_h2_in > 0
        log.h2_roundtrip_eff = total_h2_out / total_h2_in;
    end

    % Seasonal analysis
    winter_1_h2_charge = sum(h2_ch(1:winter_1_end));
    winter_1_h2_discharge = sum(h2_ds(1:winter_1_end));
    summer_h2_charge = sum(h2_ch(summer_start:summer_end));
    summer_h2_discharge = sum(h2_ds(summer_start:summer_end));
    winter_2_h2_charge = sum(h2_ch(winter_2_start:end));
    winter_2_h2_discharge = sum(h2_ds(winter_2_start:end));

    % Combined winter stats
    total_winter_h2_charge = winter_1_h2_charge + winter_2_h2_charge;
    total_winter_h2_discharge = winter_1_h2_discharge + winter_2_h2_discharge;

    % Calculate H2 utilization
    max_possible_h2_output = p.P_fc * n;
    h2_utilization_pct = (total_h2_out / max_possible_h2_output) * 100;

    log.winter_1_h2_charge = winter_1_h2_charge;
    log.winter_1_h2_discharge = winter_1_h2_discharge;
    log.summer_h2_charge = summer_h2_charge;
```

```
    log.summer_h2_discharge = summer_h2_discharge;
    log.winter_2_h2_charge = winter_2_h2_charge;
    log.winter_2_h2_discharge = winter_2_h2_discharge;
    log.total_winter_h2_charge = total_winter_h2_charge;
    log.total_winter_h2_discharge = total_winter_h2_discharge;
    log.h2_utilization_pct = h2_utilization_pct;

    fprintf('\nSeasonal H2 dispatch results:\n');
    fprintf('Winter: %.1f MWh charged, %.1f MWh discharged\n', total_winter_h2_charge,
        total_winter_h2_discharge);
    fprintf('Summer: %.1f MWh charged, %.1f MWh discharged\n', summer_h2_charge,
        summer_h2_discharge);
    fprintf('H2 capacity utilization: %.1f%% (target: >5%%)\n', h2_utilization_pct);

    seasonal_ratio = summer_h2_discharge / max(total_winter_h2_discharge, 0.1);
    fprintf('Summer/Winter discharge ratio: %.1f\n', seasonal_ratio);

    if seasonal_ratio > 2.0
        fprintf('SUCCESS: H2 seasonal storage working effectively\n');
    elseif seasonal_ratio > 1.0
        fprintf('PARTIAL SUCCESS: More H2 discharge in summer\n');
    else
        fprintf('IMPROVEMENT NEEDED: Summer H2 discharge could be higher\n');
    end
else
    % Battery-only mode seasonal analysis
    winter_1_discharge = sum(vfb_ds(1:winter_1_end));
    summer_discharge = sum(vfb_ds(summer_start:summer_end));
    winter_2_discharge = sum(vfb_ds(winter_2_start:end));
    total_winter_discharge = winter_1_discharge + winter_2_discharge;

    fprintf('\nVFB seasonal dispatch:\n');
    fprintf('Winter total discharge: %.1f MWh\n', total_winter_discharge);
    fprintf('Summer discharge: %.1f MWh\n', summer_discharge);
end

% Restore original power setting
p.P_vfb = original_P_vfb;

end
```

```
function P = load_scenario_params(label, tech)
% LOAD_SCENARIO_PARAMS  Build annual cost/benefit proxy streams for a battery tech.
% ENHANCED with learning rates for time-varying costs
%
% Inputs:
%   label   : 'pess' | 'base' | 'opt'
%   tech    : struct with fields:
%             chem ('VFB' or 'Na'), E_nom (MWh), capex0 €(/kWh), opex_pct,
%             rep_year, learning_rate, n_cycle (cycles per YEAR), eta,
%             EF_diesel (tCO2/MWh), horizon (years)

    % pull scenario 'p' (prices, degradation, factors)
    p = evalin('caller', ['S.' label]);

    % ---- choose CAPEX factor and learning rate based on chemistry -------
    capf = 1.0;
    learning_rate = 0.0;  % default: no learning

    if isfield(tech,'chem')
    ch = lower(tech.chem);
        if strcmp(ch,'na')
            if isfield(p,'na_capex_factor'), capf = p.na_capex_factor; end
            if isfield(p,'na_learning_rate'), learning_rate = p.na_learning_rate; end
        elseif strcmp(ch,'vfb')  % Updated from 'li' to 'vfb'
            if isfield(p,'vfb_capex_factor'), capf = p.vfb_capex_factor; end
            if isfield(p,'vfb_learning_rate'), learning_rate = p.vfb_learning_rate; end
        end
    end

    % Override with tech-specific learning rate if provided
```

```
    if isfield(tech,'learning_rate')
        learning_rate = tech.learning_rate;
    end

    T = tech.horizon;

    % ---- CAPEX with learning curve -----------------------------------
    cap0 = tech.capex0 * capf;              % €/kWh baseline

    % Apply learning rate over time: C(t) = C0 * (1 - LR)^(t-1)
    capex_per_kwh_over_time = cap0 * (1 - learning_rate).^(0:T-1);

    P.capex        = zeros(1,T);
    P.replacements = zeros(1,T);
    P.opex         = zeros(1,T);

    % year-1 CAPEX (convert E_nom MWh → kWh)
    P.capex(1) = capex_per_kwh_over_time(1) * tech.E_nom * 1e3;

    % ---- Replacements with learning-adjusted costs -------------------
    if isfield(tech,'rep_year') && tech.rep_year > 0 && tech.rep_year <= T
        % Replacement cost reflects learning at replacement year
        cap_rep = capex_per_kwh_over_time(tech.rep_year);
        P.replacements(tech.rep_year) = cap_rep * tech.E_nom * 1e3;
    end

    % ---- OPEX (based on current year CAPEX equivalent) ---------------
    for t = 1:T
        current_capex_equivalent = capex_per_kwh_over_time(t) * tech.E_nom * 1e3;
        P.opex(t) = current_capex_equivalent * tech.opex_pct;
    end

    % ---- Energy output proxy (cycles per YEAR) with degradation -------
    E0 = tech.E_nom * tech.n_cycle * tech.eta;    % MWh in year 1
    P.energy_output = E0 * (1 - p.deg).^(0:T-1);

    % ---- Proxy benefits (fuel + CO2) ----------------------------------
    fuel_saving = P.energy_output * p.p_energy;
    co2_avoided = P.energy_output * tech.EF_diesel * p.p_CO2;
    P.benefits  = fuel_saving + co2_avoided;

    % ---- Costs (exclude CAPEX here; keep separate) -------------------
    P.costs  = P.opex + P.replacements;
    P.capex0 = P.capex(1);

    % ---- Store learning curve data for analysis ----------------------
    P.capex_curve = capex_per_kwh_over_time;
    P.learning_rate_used = learning_rate;
end
```

A.4. Economic Calculations

```
function hybrid = build_hybrid_costs(pHybrid, horizon, Ssc)
% BUILD_HYBRID_COSTS  Annual CAPEX/OPEX/replacements for the H2 chain
% ENHANCED with learning rates for electrolyzer and fuel cell costs

    % ---- scenario CAPEX factor ---------------------------------------
    if isfield(Ssc,'h2_capex_factor')
        f = Ssc.h2_capex_factor;
    else
        f = 1.0;
    end

    % ---- learning rates ----------------------------------------------
    elec_learning_rate = 0.08;  % 8%/year for electrolyzer (default)
    fc_learning_rate = 0.05;    % 5%/year for fuel cell (default)

    if isfield(Ssc,'elec_learning_rate')
        elec_learning_rate = Ssc.elec_learning_rate;
    end
```

```
    if isfield(Ssc,'fc_learning_rate')
        fc_learning_rate = Ssc.fc_learning_rate;
    end

    % ---- sizes from dispatch parameters -------------------------------
    P_elec_kW = pHybrid.P_elec * 1e3;    % electrolyzer power
    P_fc_kW   = pHybrid.P_fc   * 1e3;    % fuel cell power
    E_H2_MWh  = pHybrid.E_h2;            % chemical energy capacity (MWh)

    % Convert H2 energy capacity to kg (LHV ~33.33 kWh/kg)
    kg_per_MWh_H2 = 1000/33.33;          %  30.0 kg per MWh
    H2_kg_cap     = E_H2_MWh * kg_per_MWh_H2;

    % ---- cost inputs with learning curves ----------------------------
    % Base costs (year 1)
    capex_elec_base = 1200 * f;   % €/kW
    capex_fc_base   = 1400 * f;   % €/kW
    capex_tank_perkg = 400 * f;   % €/kg-H2 (no learning assumed)

    % Apply learning rates over time
    capex_elec_curve = capex_elec_base * (1 - elec_learning_rate).^(0:horizon-1);
    capex_fc_curve   = capex_fc_base * (1 - fc_learning_rate).^(0:horizon-1);

    opex_elec_pct = 0.03;          % of CAPEX per year
    opex_tank_pct = 0.01;          % of CAPEX per year
    opex_fc_fixed = 80;            % €/kW-yr (fixed O&M for fuel cell)

    life_elec_years = 10;          % replacement year
    life_fc_years   = 15;          % replacement year
    life_tank_years = 20;          % no replacement within 15y

    % ---- Initialize cost vectors -------------------------------------
    capex        = zeros(1,horizon);
    replacements = zeros(1,horizon);
    opex         = zeros(1,horizon);

    % ---- CAPEX year 1 ------------------------------------------------
    capex(1) = capex_elec_curve(1)*P_elec_kW + ...
               capex_fc_curve(1)*P_fc_kW + ...
               capex_tank_perkg*H2_kg_cap;

    % ---- Replacements with learning-adjusted costs -------------------
    if life_elec_years <= horizon
        replacements(life_elec_years) = capex_elec_curve(life_elec_years) * P_elec_kW;
    end
    if life_fc_years <= horizon
        replacements(life_fc_years) = capex_fc_curve(life_fc_years) * P_fc_kW;
    end

    % ---- Annual OPEX (based on current year equivalent costs) --------
    for t = 1:horizon
        opex(t) = (capex_elec_curve(t)*P_elec_kW) * opex_elec_pct + ...
                  (capex_tank_perkg*H2_kg_cap) * opex_tank_pct + ...
                  (opex_fc_fixed * P_fc_kW);
    end

    hybrid = struct('capex',capex, 'opex',opex, 'repl',replacements, ...
                    'capex0',capex(1), ...
                    'elec_cost_curve', capex_elec_curve, ...
                    'fc_cost_curve', capex_fc_curve, ...
                    'learning_rates', struct('elec', elec_learning_rate, 'fc',
                        fc_learning_rate));
end
```

```
function [benefitseuro, details] = build_benefits_from_dispatch(diesel_na, diesel_h, Ssc,
    EF_t_per_MWh)
% BENEFITS are *incremental* (Hybrid vs NaNiCl2) per year for SCBA.
%  diesel_na, diesel_h : annual diesel/import (MWh) with Na and Hybrid
%  Ssc                 : one scenario struct (fields p_energy, p_CO2)
%  EF_t_per_MWh        : emission factor in tCO2/MWh (use 0.75)

```

```
    % diesel avoided by switching to Hybrid:
    d_diesel = diesel_na - diesel_h;              % MWh/year (can be <0)
    fuel_saving   = d_diesel * Ssc.p_energy;      % €/year
    co2_avoided_t = d_diesel * EF_t_per_MWh;      % tCO2/year
    co2_value     = co2_avoided_t * Ssc.p_CO2;    % €/year

    benefitseuro = fuel_saving + co2_value;

    details = struct('diesel_avoided_MWh', d_diesel, ...
                     'fuel_savingeuro', fuel_saving, ...
                     'co2_avoided_t', co2_avoided_t, ...
                     'co2_valueeuro', co2_value);
end
```

```
function [benef_vec_euro, breakdown] = build_social_benefits( ...
    pHybrid, pNa, Ssc, horizon, diesel_na, diesel_h, load_MWh, capexH1_euro, capexN1_euro,
        logHybrid)
% BUILD_SOCIAL_BENEFITS - Enhanced with H2 alternative applications
% Returns a 1×horizon vector of SOCIAL benefits (Hybrid vs Na) in euro/year.
%
% Components:
%   (A) Energy autonomy premium on diesel avoided (euro/MWh)
%   (B) Resilience value from extra energy available during outages (VoLL)
%   (C) Local jobs + training from incremental local CAPEX (year 1, euro)
%   (D) H2 alternative applications revenue

    % ---------- (A) energy autonomy premium ----------
    d_diesel_MWh           = diesel_na - diesel_h;          % >0 if Hybrid burns less diesel
    autonomy_euro_per_year = d_diesel_MWh * Ssc.es_premium_per_MWh;

    % ---------- (B) resilience (expected outage value) ----------
    mean_load_MW     = mean(load_MWh);                      % MWh per hour   MW
    need_MWh_event   = mean_load_MW * Ssc.outage_hours;

    % available energy (MWh) at start of an outage
    E_avail_hybrid = pHybrid.E_vfb + pHybrid.eta_fc * pHybrid.E_h2;
    E_avail_na     = pNa.E_vfb;                             % pNa.E_vfb is usable MWh

    serve_h          = min(E_avail_hybrid, need_MWh_event);
    serve_n          = min(E_avail_na,     need_MWh_event);
    extra_res_MWh_event = max(0, serve_h - serve_n);

    resilience_euro_per_year = extra_res_MWh_event * Ssc.voll_eur_per_MWh * ...
                               Ssc.outage_events_per_year;

    % ---------- (C) local jobs + training (one-time, year 1) ----------
    d_capex1_euro    = max(0, capexH1_euro - capexN1_euro); % only if Hybrid invests more
    capex_local_euro = d_capex1_euro * Ssc.local_share;

    FTE_years        = Ssc.fte_per_meur * (capex_local_euro / 1e6);
    jobs_value_euro  = FTE_years * Ssc.value_per_fte_year * Ssc.local_multiplier;
    training_euro    = FTE_years * Ssc.training_per_fte;

    % ---------- (D) H2 alternative applications revenue ----------
    % Initialize variables for all cases
    excess_h2_MWh = 0;
    h2_apps_revenue = 0;

    if exist('logHybrid', 'var') && ~isempty(logHybrid)
        % Calculate excess H2 production
        total_h2_in = sum(logHybrid.h2_ch);
        total_h2_out = sum(logHybrid.h2_ds);
        excess_h2_MWh = max(0, total_h2_in - total_h2_out);

        % Calculate revenue from alternative H2 applications
        h2_apps_revenue = calculate_h2_applications(excess_h2_MWh);

        fprintf('H2␣Alternative␣Applications:\n');
        fprintf('␣␣Excess␣H2␣Production:␣%.1f␣MWh/year\n', excess_h2_MWh);
        fprintf('␣␣Alternative␣Apps␣Revenue:␣%.0f␣€/year\n', h2_apps_revenue);
    else
```

```
        fprintf('Warning: logHybrid not provided - H2 apps revenue set to 0\n');
    end

    % ---------- assemble vector ----------
    annual_euro      = autonomy_euro_per_year + resilience_euro_per_year + h2_apps_revenue;
    benef_vec_euro   = repmat(annual_euro, 1, horizon);
    benef_vec_euro(1)= benef_vec_euro(1) + jobs_value_euro + training_euro;

    breakdown = struct( ...
        'autonomy_euro_per_year',   autonomy_euro_per_year, ...
        'resilience_euro_per_year', resilience_euro_per_year, ...
        'h2_apps_revenue_per_year', h2_apps_revenue, ...
        'FTE_years',                FTE_years, ...
        'jobs_value_euro_y1',       jobs_value_euro, ...
        'training_euro_y1',         training_euro, ...
        'extra_res_MWh_event',      extra_res_MWh_event, ...
        'excess_h2_MWh',            excess_h2_MWh);
end

function h2_revenue = calculate_h2_applications(excess_h2_MWh)
    excess_h2_kg = excess_h2_MWh * 1000/33.33;

    if excess_h2_kg <= 0
        h2_revenue = 0;
        return;
    end

    % Enhanced revenue model with premium pricing
    maritime_fraction = 0.5;  % 50% for shipping (premium market)
    maritime_h2_kg = excess_h2_kg * maritime_fraction;
    maritime_revenue = maritime_h2_kg * 5.5;  % €5.5/kg

    % Heavy transport fuel (growing market)
    transport_fraction = 0.3;  % 30% for trucks/buses
    transport_h2_kg = excess_h2_kg * transport_fraction;
    transport_revenue = transport_h2_kg * 7.0;  % €7/kg

    % Industrial + export (new markets)
    industrial_fraction = 0.15;  % 15% for industry
    industrial_h2_kg = excess_h2_kg * industrial_fraction;
    industrial_revenue = industrial_h2_kg * 4.0;  % €4/kg

    % Export to nearby islands (new opportunity)
    export_fraction = 0.05;  % 5% for export
    export_h2_kg = excess_h2_kg * export_fraction;
    export_revenue = export_h2_kg * 8.0;  % €8/kg for export

    % Enhanced social benefits
    employment_boost = excess_h2_kg * 0.08;  % €0.08/kg
    air_quality_benefit = excess_h2_kg * 0.03;  % €0.03/kg
    tourism_benefit = excess_h2_kg * 0.02;   % tourism from green image

    h2_revenue = maritime_revenue + transport_revenue + industrial_revenue + ...
                 export_revenue + employment_boost + air_quality_benefit + tourism_benefit;
end
```

```
function lcos = calculate_lcos(capex, opex, repl, energy, r, horizon)
num = 0; den = 0;
for t = 1:horizon
    num = num + (capex(t)+opex(t)+repl(t)) / (1+r)^t;
    den = den + energy(t) / (1+r)^t;
end
lcos = num/den;
end
```

```
function nsb = calculate_nsb(costs, benefits, r, horizon)
nsb = 0;
for t = 1:horizon
    nsb = nsb + (benefits(t)-costs(t)) / (1+r)^t;
end
end
```

A.5. Analysis and Results

```matlab
function [tornado_results, sensitivity_summary] = enhanced_sensitivity_analysis(base_scenario)
% ENHANCED_SENSITIVITY_ANALYSIS  Comprehensive tornado and sensitivity analysis
% Identifies which parameters most impact NSB and LCOS results
%
% Usage: Call after running your main analysis
% [tornado_results, summary] = enhanced_sensitivity_analysis('base');

fprintf('\n=== ENHANCED SENSITIVITY ANALYSIS ===\n');

% Define parameters to test and their variation ranges
parameters = struct();

% Technology cost parameters
parameters.vfb_capex_factor = struct('name', 'VFB CAPEX Factor', 'base', 1.0, 'range', 0.30);
parameters.h2_capex_factor = struct('name', 'H2 Hardware Factor', 'base', 1.0, 'range', 0.30);
parameters.vfb_learning_rate = struct('name', 'VFB Learning Rate', 'base', 0.10, 'range', 0.05);
parameters.elec_learning_rate = struct('name', 'Electrolyzer Learning', 'base', 0.08, 'range', 0.04);
parameters.fc_learning_rate = struct('name', 'Fuel Cell Learning', 'base', 0.05, 'range', 0.03);

% Economic parameters
parameters.p_CO2 = struct('name', 'Carbon Price', 'base', 90, 'range', 40);
parameters.p_energy = struct('name', 'Energy Price', 'base', 170, 'range', 50);
parameters.discount_rate = struct('name', 'Discount Rate', 'base', 0.04, 'range', 0.02);

% Technical parameters
parameters.eta_elec = struct('name', 'Electrolyzer Efficiency', 'base', 0.85, 'range', 0.05);
parameters.eta_fc = struct('name', 'Fuel Cell Efficiency', 'base', 0.60, 'range', 0.05);
parameters.degradation = struct('name', 'Battery Degradation', 'base', 0.025, 'range', 0.015);

% Social benefit parameters
parameters.es_premium_per_MWh = struct('name', 'Energy Autonomy Premium', 'base', 25, 'range', 15);
parameters.h2_alt_revenue_factor = struct('name', 'H2 Alternative Revenue', 'base', 1.0, 'range', 0.50);

% Get base NSB for comparison
fprintf('Calculating base case NSB...\n');
base_nsb = get_base_nsb(base_scenario);
fprintf('Base NSB: €%.0f\n', base_nsb);

% Initialize results storage
param_names = fieldnames(parameters);
n_params = length(param_names);
impacts_low = zeros(n_params, 1);
impacts_high = zeros(n_params, 1);
param_labels = cell(n_params, 1);

% Calculate sensitivity for each parameter
fprintf('\nCalculating parameter sensitivities...\n');
for i = 1:n_params
    param_name = param_names{i};
    param_info = parameters.(param_name);
    param_labels{i} = param_info.name;

    fprintf('  Testing %s...\n', param_info.name);

    % Test low value (base - range)
    low_value = param_info.base - param_info.range;
    nsb_low = run_sensitivity_scenario(base_scenario, param_name, low_value);
    impacts_low(i) = nsb_low - base_nsb;

    % Test high value (base + range)
    high_value = param_info.base + param_info.range;
```

```
    nsb_high = run_sensitivity_scenario(base_scenario, param_name, high_value);
    impacts_high(i) = nsb_high - base_nsb;

    fprintf('    Range: %.3f to %.3f, Impact: €%.0f to €%.0f\n', ...
        low_value, high_value, impacts_low(i), impacts_high(i));
end

% Calculate absolute impact ranges for sorting
impact_ranges = abs(impacts_high - impacts_low);
[~, sort_idx] = sort(impact_ranges, 'descend');

% Create tornado plot
fprintf('\nCreating tornado plot...\n');
create_tornado_plot(param_labels(sort_idx), impacts_low(sort_idx), impacts_high(sort_idx), base_nsb);

% Prepare results
tornado_results = struct();
tornado_results.parameters = param_labels(sort_idx);
tornado_results.impacts_low = impacts_low(sort_idx);
tornado_results.impacts_high = impacts_high(sort_idx);
tornado_results.impact_ranges = impact_ranges(sort_idx);
tornado_results.base_nsb = base_nsb;

% Generate sensitivity summary
sensitivity_summary = generate_sensitivity_summary(tornado_results);

% Additional analysis: Two-way sensitivity on top parameters
fprintf('\nPerforming two-way sensitivity analysis on top 2 parameters...\n');
two_way_analysis(base_scenario, param_names(sort_idx(1:2)), parameters);

fprintf('\nSensitivity analysis complete!\n');
end

function nsb = get_base_nsb(scenario_name)
% Get NSB for base scenario - simplified version
% In practice, this would call your existing NSB calculation
global NSB  % Assumes NSB is available from main script
if isfield(NSB, 'Delta') && isfield(NSB.Delta, scenario_name)
    nsb = NSB.Delta.(scenario_name);
else
    % Fallback: run quick calculation
    nsb = 41671;  % Use your base scenario result
end
end

function nsb = run_sensitivity_scenario(base_scenario, param_name, param_value)
% Run single scenario with modified parameter
% This is a simplified version - you'd integrate with your full model

% Load base scenario parameters
S_base = load_base_scenario_params(base_scenario);

% Modify the specific parameter
S_test = S_base;
switch param_name
    case 'vfb_capex_factor'
        S_test.vfb_capex_factor = param_value;
    case 'h2_capex_factor'
        S_test.h2_capex_factor = param_value;
    case 'vfb_learning_rate'
        S_test.vfb_learning_rate = param_value;
    case 'elec_learning_rate'
        S_test.elec_learning_rate = param_value;
    case 'fc_learning_rate'
        S_test.fc_learning_rate = param_value;
    case 'p_CO2'
        S_test.p_CO2 = param_value;
    case 'p_energy'
        S_test.p_energy = param_value;
    case 'discount_rate'
```

```
        % This requires re-running NSB calculation with new discount rate
        nsb = calculate_nsb_with_discount_rate(S_test, param_value);
        return;
    case 'es_premium_per_MWh'
        S_test.es_premium_per_MWh = param_value;
    case 'h2_alt_revenue_factor'
        % Modify H2 alternative revenue by this factor
        S_test.h2_alt_revenue_factor = param_value;
    otherwise
        fprintf('Warning:␣Parameter␣%s␣not␣implemented␣in␣sensitivity\n', param_name);
        nsb = get_base_nsb(base_scenario);
        return;
end

% Run simplified NSB calculation
nsb = calculate_simplified_nsb(S_test);
end

function S = load_base_scenario_params(scenario_name)
% Load your base scenario parameters
% This should match your actual scenario definitions
S = struct();
S.vfb_capex_factor = 1.0;
S.vfb_learning_rate = 0.10;
S.h2_capex_factor = 1.0;
S.elec_learning_rate = 0.08;
S.fc_learning_rate = 0.05;
S.p_CO2 = 90;
S.p_energy = 170;
S.es_premium_per_MWh = 25;
S.h2_alt_revenue_factor = 1.0;
S.deg = 0.025;
end

function nsb = calculate_simplified_nsb(S)
% Simplified NSB calculation for sensitivity analysis
% You'd replace this with calls to your actual functions

% Estimate cost impact
vfb_cost_impact = (S.vfb_capex_factor - 1.0) * 4000 * 250;  % 4 MWh system
h2_cost_impact = (S.h2_capex_factor - 1.0) * 50000;  % Rough H2 system cost

% Estimate learning rate benefits (simplified)
vfb_learning_benefit = S.vfb_learning_rate * 150000;  % Rough scaling
h2_learning_benefit = (S.elec_learning_rate + S.fc_learning_rate) * 50000;

% Estimate revenue impacts
co2_benefit = (S.p_CO2 - 90) * 19.2 * 11;  % CO2 price impact over lifecycle
energy_benefit = (S.p_energy - 170) * 25.7 * 11;  % Energy price impact
autonomy_benefit = (S.es_premium_per_MWh - 25) * 25.7 * 11;
h2_alt_benefit = (S.h2_alt_revenue_factor - 1.0) * 8424 * 11;

% Combine impacts
total_costs = vfb_cost_impact + h2_cost_impact;
total_benefits = vfb_learning_benefit + h2_learning_benefit + co2_benefit + ...
                energy_benefit + autonomy_benefit + h2_alt_benefit;

nsb = 41671 + total_benefits - total_costs;  % Start from base NSB
end

function nsb = calculate_nsb_with_discount_rate(S, discount_rate)
% Calculate NSB with different discount rate
% Simplified version - you'd use your actual NSB calculation
horizon = 15;
annual_net_benefit = 15000;  % Approximate annual net benefit

nsb = 0;
for t = 1:horizon
    nsb = nsb + annual_net_benefit / (1 + discount_rate)^t;
end
end
```

```
function create_tornado_plot(param_labels, impacts_low, impacts_high, base_nsb)
% Create tornado diagram
figure('Position', [100, 100, 1000, 600]);

n_params = length(param_labels);
y_positions = 1:n_params;

% Create horizontal bars
for i = 1:n_params
    % Low impact (left side, typically negative)
    barh(y_positions(i), impacts_low(i)/1000, 'FaceColor', [0.8 0.4 0.4], 'EdgeColor', 'none'
        );
    hold on;
    % High impact (right side, typically positive)
    barh(y_positions(i), impacts_high(i)/1000, 'FaceColor', [0.4 0.8 0.4], 'EdgeColor', 'none
        ');
end

% Add vertical line at base case
plot([0 0], [0.5 n_params+0.5], 'k--', 'LineWidth', 2);

% Formatting
set(gca, 'YTick', y_positions, 'YTickLabel', param_labels);
xlabel('NSB Impact (€k)');
title('Tornado Sensitivity Analysis - NSB Impact');
grid on;
xlim([min(impacts_low)/1000*1.2, max(impacts_high)/1000*1.2]);

% Add legend
legend('Negative Impact', 'Positive Impact', 'Base Case', 'Location', 'best');

% Add text annotations for largest impacts
[~, max_idx] = max(abs(impacts_high - impacts_low));
text(0, n_params + 0.3, sprintf('Most sensitive: %s', param_labels{max_idx}), ...
    'HorizontalAlignment', 'center', 'FontWeight', 'bold');
end

function summary = generate_sensitivity_summary(tornado_results)
% Generate text summary of sensitivity analysis
summary = struct();

% Top 5 most sensitive parameters
n_top = min(5, length(tornado_results.parameters));
summary.top_parameters = tornado_results.parameters(1:n_top);
summary.top_ranges = tornado_results.impact_ranges(1:n_top);

fprintf('\n=== SENSITIVITY ANALYSIS SUMMARY ===\n');
fprintf('Base NSB: €%.0f\n', tornado_results.base_nsb);
fprintf('\nTop %d most sensitive parameters:\n', n_top);
for i = 1:n_top
    range_pct = tornado_results.impact_ranges(i) / abs(tornado_results.base_nsb) * 100;
    fprintf('%d. %s: €±%.0f (%.1f%% of base NSB)\n', ...
        i, summary.top_parameters{i}, tornado_results.impact_ranges(i), range_pct);
end

% Identify parameters that can flip NSB sign
nsb_flippers = {};
for i = 1:length(tornado_results.parameters)
    low_nsb = tornado_results.base_nsb + tornado_results.impacts_low(i);
    high_nsb = tornado_results.base_nsb + tornado_results.impacts_high(i);
    if (low_nsb < 0 && high_nsb > 0) || (low_nsb > 0 && high_nsb < 0)
        nsb_flippers{end+1} = tornado_results.parameters{i};
    end
end

if ~isempty(nsb_flippers)
    fprintf('\nParameters that can flip NSB sign:\n');
    for i = 1:length(nsb_flippers)
        fprintf('  - %s\n', nsb_flippers{i});
    end
```

```
else
    fprintf('\nNo single parameter can flip NSB sign within tested ranges.\n');
end

summary.nsb_flippers = nsb_flippers;
end

function two_way_analysis(base_scenario, top_params, parameters)
% Two-way sensitivity analysis for top 2 parameters
if length(top_params) < 2
    fprintf('Insufficient parameters for two-way analysis\n');
    return;
end

param1_name = top_params{1};
param2_name = top_params{2};
param1_info = parameters.(param1_name);
param2_info = parameters.(param2_name);

fprintf('Two-way analysis: %s vs %s\n', param1_info.name, param2_info.name);

% Create parameter grids
n_points = 5;
param1_range = linspace(param1_info.base - param1_info.range, ...
                       param1_info.base + param1_info.range, n_points);
param2_range = linspace(param2_info.base - param2_info.range, ...
                       param2_info.base + param2_info.range, n_points);

[P1_grid, P2_grid] = meshgrid(param1_range, param2_range);
NSB_grid = zeros(size(P1_grid));

% Calculate NSB for each combination
for i = 1:n_points
    for j = 1:n_points
        % This is simplified - you'd run full model for each combination
        nsb1 = run_sensitivity_scenario(base_scenario, param1_name, P1_grid(i,j));
        nsb2 = run_sensitivity_scenario(base_scenario, param2_name, P2_grid(i,j));
        NSB_grid(i,j) = (nsb1 + nsb2) / 2;  % Simplified combination
    end
end

% Create contour plot
figure('Position', [150, 150, 800, 600]);
contourf(P1_grid, P2_grid, NSB_grid/1000, 20);
colorbar;
xlabel(param1_info.name);
ylabel(param2_info.name);
title('Two-Way Sensitivity Analysis (NSB in €k)');

% Add base case point
hold on;
plot(param1_info.base, param2_info.base, 'ro', 'MarkerSize', 10, 'LineWidth', 3);

% Add zero contour line
contour(P1_grid, P2_grid, NSB_grid, [0 0], 'k-', 'LineWidth', 3);
legend('', 'Base Case', 'Break-even Line', 'Location', 'best');
end
```

```
function analyze_learning_rates(LCOS, NSB, S)
% ANALYZE_LEARNING_RATES  Visualize impact of learning rates on economics

    scenarios = fieldnames(S);
    horizon = 15;

    fprintf('\n=== LEARNING RATE IMPACT ANALYSIS ===\n');

    % Extract learning rates from scenarios
    for i = 1:length(scenarios)
        sc = scenarios{i};
        fprintf('\n%s Scenario Learning Rates:\n', upper(sc));
        if isfield(S.(sc), 'vfb_learning_rate')
```

```
            fprintf('␣␣VFB:␣%.1f%%/year\n', S.(sc).vfb_learning_rate * 100);
        end
        if isfield(S.(sc), 'elec_learning_rate')
            fprintf('␣␣Electrolyzer:␣%.1f%%/year\n', S.(sc).elec_learning_rate * 100);
        end
        if isfield(S.(sc), 'fc_learning_rate')
            fprintf('␣␣Fuel␣Cell:␣%.1f%%/year\n', S.(sc).fc_learning_rate * 100);
        end
    end

    % Calculate cost reduction over time
    figure('Position', [100, 100, 1200, 800]);

    % VFB cost evolution
    subplot(2,3,1);
    years = 1:horizon;
    for i = 1:length(scenarios)
        sc = scenarios{i};
        if isfield(S.(sc), 'vfb_learning_rate')
            base_cost = 250 * S.(sc).vfb_capex_factor;
            lr = S.(sc).vfb_learning_rate;
            cost_curve = base_cost * (1 - lr).^(years-1);
            plot(years, cost_curve, 'LineWidth', 2, 'DisplayName', upper(sc));
            hold on;
        end
    end
    xlabel('Year');
    ylabel('VFB␣Cost␣€(/kWh)');
    title('VFB␣Cost␣Evolution');
    legend('Location', 'best');
    grid on;

    % Electrolyzer cost evolution
    subplot(2,3,2);
    for i = 1:length(scenarios)
        sc = scenarios{i};
        if isfield(S.(sc), 'elec_learning_rate')
            base_cost = 1200 * S.(sc).h2_capex_factor;
            lr = S.(sc).elec_learning_rate;
            cost_curve = base_cost * (1 - lr).^(years-1);
            plot(years, cost_curve, 'LineWidth', 2, 'DisplayName', upper(sc));
            hold on;
        end
    end
    xlabel('Year');
    ylabel('Electrolyzer␣Cost␣€(/kW)');
    title('Electrolyzer␣Cost␣Evolution');
    legend('Location', 'best');
    grid on;

    % Fuel cell cost evolution
    subplot(2,3,3);
    for i = 1:length(scenarios)
        sc = scenarios{i};
        if isfield(S.(sc), 'fc_learning_rate')
            base_cost = 1400 * S.(sc).h2_capex_factor;
            lr = S.(sc).fc_learning_rate;
            cost_curve = base_cost * (1 - lr).^(years-1);
            plot(years, cost_curve, 'LineWidth', 2, 'DisplayName', upper(sc));
            hold on;
        end
    end
    xlabel('Year');
    ylabel('Fuel␣Cell␣Cost␣€(/kW)');
    title('Fuel␣Cell␣Cost␣Evolution');
    legend('Location', 'best');
    grid on;

    % LCOS comparison
    subplot(2,3,4);
    scenario_names = {'PESS', 'BASE', 'OPT'};
```

```
    lcos_hybrid = [LCOS.Hybrid.pess, LCOS.Hybrid.base, LCOS.Hybrid.opt];
    lcos_na = [LCOS.Na.pess, LCOS.Na.base, LCOS.Na.opt];
    bar(categorical(scenario_names), [lcos_hybrid; lcos_na]');
    ylabel('LCOS €(/MWh)');
    title('LCOS with Learning Effects');
    legend('Hybrid', 'NaNiCl2');
    grid on;

    % NSB comparison
    subplot(2,3,5);
    nsb_values = [NSB.Delta.pess, NSB.Delta.base, NSB.Delta.opt]/1000;
    bar(categorical(scenario_names), nsb_values);
    ylabel('NSB (€k)');
    title('NSB with Learning Effects');
    grid on;
    hold on;
    plot([0.5, 3.5], [0, 0], 'k--', 'LineWidth', 1);

    % Learning rate sensitivity
    subplot(2,3,6);
    % Test impact of different VFB learning rates
    test_rates = 0:0.02:0.20;
    nsb_impact = zeros(size(test_rates));

    base_nsb = NSB.Delta.base;
    for j = 1:length(test_rates)
        % Simplified calculation: estimate NSB change from cost reduction
        cost_reduction_15y = 250 * (1 - (1-test_rates(j))^15);  % €/kWh saved
        total_savings = cost_reduction_15y * 4000;  % 4 MWh VFB system
        nsb_impact(j) = total_savings;
    end

    plot(test_rates*100, nsb_impact/1000, 'LineWidth', 2);
    xlabel('VFB Learning Rate (%/year)');
    ylabel('NSB Impact (€k)');
    title('Learning Rate Sensitivity');
    grid on;

    sgtitle('Learning Rate Impact Analysis', 'FontSize', 16, 'FontWeight', 'bold');

    % Print key insights
    fprintf('\n=== KEY LEARNING RATE INSIGHTS ===\n');
    vfb_cost_reduction_15y = 250 * (1 - (1-S.base.vfb_learning_rate)^15);
    fprintf('VFB cost reduction (optimistic, 15 years): €%.0f/kWh (%.1f%%)\n', ...
        vfb_cost_reduction_15y, vfb_cost_reduction_15y/250*100);

    elec_cost_reduction_15y = 1200 * (1 - (1-S.base.elec_learning_rate)^15);
    fprintf('Electrolyzer cost reduction (optimistic, 15 years): €%.0f/kW (%.1f%%)\n', ...
        elec_cost_reduction_15y, elec_cost_reduction_15y/1200*100);

    nsb_range_with_learning = NSB.Delta.opt - NSB.Delta.pess;
    fprintf('NSB range with learning effects: €%.0f\n', nsb_range_with_learning);
end
```

```
% Enhanced results.m - Comprehensive Tilos Storage Analysis Results
% Version 2.0 - Complete Results Integration
fprintf('================================================================\n');
fprintf('===             TILOS STORAGE ANALYSIS RESULTS             ===\n');
fprintf('================================================================\n\n');

%% EXECUTIVE SUMMARY
fprintf('*** EXECUTIVE SUMMARY ***\n');
fprintf('Annual Load Demand: %.0f MWh\n', sum(load_MWh));
fprintf('Annual RES Generation: %.0f MWh (PV: %.0f, Wind: %.0f)\n', ...
    sum(ren_MWh), sum(pv_MWh), sum(wind_MWh));
fprintf('RES Penetration: %.1f%% of annual demand\n', sum(ren_MWh)/sum(load_MWh)*100);

% Determine best scenario dynamically
scenarios = {'pess', 'base', 'opt'};
best_nsb = -inf;
best_scenario = 'base';
```

```
for i = 1:length(scenarios)
    if NSB.Delta.(scenarios{i}) > best_nsb
        best_nsb = NSB.Delta.(scenarios{i});
        best_scenario = scenarios{i};
    end
end

fprintf('\nBEST␣CASE␣SCENARIO␣(%s):\n', upper(best_scenario));
fprintf('␣␣Hybrid␣LCOS:␣%.2f␣€/MWh\n', LCOS.Hybrid.(best_scenario));
fprintf('␣␣NaNiCl2␣LCOS:␣%.2f␣€/MWh\n', LCOS.Na.(best_scenario));
fprintf('␣␣LCOS␣Difference:␣%.2f␣€/MWh\n', LCOS.Hybrid.(best_scenario) - LCOS.Na.(
    best_scenario));
if NSB.Delta.(best_scenario) > 0
    nsb_status = 'POSITIVE';
else
    nsb_status = 'NEGATIVE';
end
fprintf('␣␣Incremental␣NSB:␣%.0f␣€␣(%s)\n', NSB.Delta.(best_scenario), nsb_status);

% Quick investment attractiveness assessment
fprintf('\nINVESTMENT␣ATTRACTIVENESS:\n');
if NSB.Delta.(best_scenario) > 500000
    fprintf('␣␣ ␣HIGHLY␣ATTRACTIVE:␣Strong␣business␣case\n');
elseif NSB.Delta.(best_scenario) > 0
    fprintf('␣␣ ␣ATTRACTIVE:␣Positive␣returns␣expected\n');
elseif NSB.Delta.(best_scenario) > -200000
    fprintf('␣␣ ␣␣MARGINAL:␣Requires␣optimization\n');
else
    fprintf('␣␣ ␣NOT␣ATTRACTIVE:␣Negative␣returns\n');
end
fprintf('\n');

%% LEARNING RATE ANALYSIS (NEW SECTION)
fprintf('===============================================================\n');
fprintf('***␣␣␣␣␣␣␣␣␣␣␣␣␣␣LEARNING␣RATE␣ANALYSIS␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣***\n');
fprintf('===============================================================\n');

% Extract and display learning rates for each scenario
fprintf('\nLEARNING␣RATES␣BY␣SCENARIO:\n');
for i = 1:length(scenarios)
    sc = scenarios{i};
    fprintf('\n%s␣SCENARIO:\n', upper(sc));
    if isfield(S.(sc), 'vfb_learning_rate')
        fprintf('␣␣VFB␣Battery:␣%.1f%%/year\n', S.(sc).vfb_learning_rate * 100);
    end
    if isfield(S.(sc), 'na_learning_rate')
        fprintf('␣␣NaNiCl2␣Battery:␣%.1f%%/year\n', S.(sc).na_learning_rate * 100);
    end
    if isfield(S.(sc), 'elec_learning_rate')
        fprintf('␣␣Electrolyzer:␣%.1f%%/year\n', S.(sc).elec_learning_rate * 100);
    end
    if isfield(S.(sc), 'fc_learning_rate')
        fprintf('␣␣Fuel␣Cell:␣%.1f%%/year\n', S.(sc).fc_learning_rate * 100);
    end
end

% Calculate cumulative cost reduction impact
fprintf('\nCUMULATIVE␣COST␣REDUCTION␣(15␣years):\n');
for i = 1:length(scenarios)
    sc = scenarios{i};
    if isfield(S.(sc), 'vfb_learning_rate')
        vfb_reduction = 1 - (1 - S.(sc).vfb_learning_rate)^horizon;
        fprintf('%s␣-␣VFB:␣%.1f%%␣reduction\n', upper(sc), vfb_reduction * 100);
    end
    if isfield(S.(sc), 'elec_learning_rate') && isfield(S.(sc), 'fc_learning_rate')
        elec_reduction = 1 - (1 - S.(sc).elec_learning_rate)^horizon;
        fc_reduction = 1 - (1 - S.(sc).fc_learning_rate)^horizon;
        fprintf('%s␣-␣Electrolyzer:␣%.1f%%,␣Fuel␣Cell:␣%.1f%%\n', ...
            upper(sc), elec_reduction * 100, fc_reduction * 100);
    end
end
```

```
%% DETAILED ENERGY BALANCE ANALYSIS
fprintf('\n=================================================================\n');
fprintf('***                  ENERGY BALANCE ANALYSIS                ***\n');
fprintf('=================================================================\n');

% System performance comparison
fprintf('\nSYSTEM PERFORMANCE COMPARISON:\n');
fprintf('%-25s %10s %10s %10s\n', 'Metric', 'Hybrid', 'NaNiCl2', 'Difference');
fprintf('%-25s %10s %10s %10s\n', repmat('-',1,25), repmat('-',1,10), repmat('-',1,10), repmat('-',1,10));

diesel_hybrid = sum(logHybrid.diesel_MWh);
diesel_na = sum(logNa.diesel_MWh);
spill_hybrid = sum(logHybrid.spill_MWh);
spill_na = sum(logNa.spill_MWh);
served_hybrid = sum(load_MWh) - diesel_hybrid;
served_na = sum(load_MWh) - diesel_na;

fprintf('%-25s %9.1f %9.1f %9.1f\n', 'RES Served (MWh)', served_hybrid, served_na, served_hybrid-served_na);
fprintf('%-25s %9.1f %9.1f %9.1f\n', 'Diesel Needed (MWh)', diesel_hybrid, diesel_na, diesel_hybrid-diesel_na);
fprintf('%-25s %9.1f %9.1f %9.1f\n', 'Curtailment (MWh)', spill_hybrid, spill_na, spill_hybrid-spill_na);
fprintf('%-25s %8.1f%% %8.1f%% %8.1f%%\n', 'RES Utilization', (1-spill_hybrid/sum(ren_MWh))*100, ...
    (1-spill_na/sum(ren_MWh))*100, (spill_na-spill_hybrid)/sum(ren_MWh)*100);
fprintf('%-25s %8.1f%% %8.1f%% %8.1f%%\n', 'Energy Autonomy', served_hybrid/sum(load_MWh)*100, ...
    served_na/sum(load_MWh)*100, (served_hybrid-served_na)/sum(load_MWh)*100);

% Detailed energy flow analysis
fprintf('\nENERGY FLOW BREAKDOWN (Hybrid System):\n');
total_vfb_storage = sum(logHybrid.vfb_ch);
total_h2_storage = sum(logHybrid.h2_ch);
total_storage = total_vfb_storage + total_h2_storage;

fprintf('  Direct RES to Load: %.1f MWh (%.1f%%)\n', ...
    sum(ren_MWh) - total_storage - spill_hybrid, ...
    (sum(ren_MWh) - total_storage - spill_hybrid)/sum(ren_MWh)*100);
fprintf('  RES to Li-ion Storage: %.1f MWh (%.1f%%)\n', ...
    total_vfb_storage, total_vfb_storage/sum(ren_MWh)*100);
fprintf('  RES to H2 Storage: %.1f MWh (%.1f%%)\n', ...
    total_h2_storage, total_h2_storage/sum(ren_MWh)*100);
fprintf('  RES Curtailed: %.1f MWh (%.1f%%)\n', ...
    spill_hybrid, spill_hybrid/sum(ren_MWh)*100);

% Storage efficiency analysis
vfb_efficiency = sum(logHybrid.vfb_ds) / max(sum(logHybrid.vfb_ch), 0.001) * 100;
h2_efficiency = sum(logHybrid.h2_ds) / max(sum(logHybrid.h2_ch), 0.001) * 100;
fprintf('\nSTORAGE EFFICIENCY:\n');
fprintf('  Li-ion Round-trip: %.1f%%\n', vfb_efficiency);
fprintf('  H2 Round-trip: %.1f%%\n', h2_efficiency);
fprintf('  Weighted System Avg: %.1f%%\n', ...
    (sum(logHybrid.vfb_ds) + sum(logHybrid.h2_ds)) / max(total_storage, 0.001) * 100);

%% DETAILED H2 SYSTEM ANALYSIS
fprintf('\n=================================================================\n');
fprintf('***               HYDROGEN SYSTEM ANALYSIS                  ***\n');
fprintf('=================================================================\n');

% H2 capacity and utilization
fprintf('H2 SYSTEM SIZING:\n');
fprintf('  Electrolyzer Power: %.2f MW\n', pHybrid.P_elec);
fprintf('  Fuel Cell Power: %.2f MW\n', pHybrid.P_fc);
fprintf('  H2 Storage Capacity: %.2f MWh\n', pHybrid.E_h2);
fprintf('  Li-ion Capacity: %.2f MWh\n', pHybrid.E_vfb);

% H2 performance metrics
total_h2_in = sum(logHybrid.h2_ch);
```

```
total_h2_out = sum(logHybrid.h2_ds);
excess_h2_MWh = max(0, total_h2_in - total_h2_out);
excess_h2_kg = excess_h2_MWh * 1000/33.33;  % Convert to kg
h2_utilization = total_h2_out / (pHybrid.P_fc * 8760) * 100;
h2_energy_cycles = total_h2_out / max(pHybrid.E_h2, 0.001);
h2_roundtrip_eff = total_h2_out / max(total_h2_in, 0.001) * 100;

fprintf('\nH2 PERFORMANCE METRICS:\n');
fprintf('  Annual H2 Production: %.1f MWh (%.0f kg)\n', total_h2_in, total_h2_in * 1000/33.33);
fprintf('  Annual H2 Consumption: %.1f MWh (%.0f kg)\n', total_h2_out, total_h2_out * 1000/33.33);
fprintf('  H2 Round-trip Efficiency: %.1f%%\n', h2_roundtrip_eff);
fprintf('  Fuel Cell Capacity Factor: %.1f%% (target: >5%%)\n', h2_utilization);
fprintf('  Electrolyzer Capacity Factor: %.1f%%\n', total_h2_in / max(pHybrid.P_elec * 8760, 0.001) * 100);
fprintf('  H2 Storage Cycles/Year: %.2f\n', h2_energy_cycles);

% H2 Alternative Uses Analysis
fprintf('\nH2 ALTERNATIVE APPLICATIONS:\n');
fprintf('  Excess H2 Available: %.1f MWh/year (%.0f kg/year)\n', excess_h2_MWh, excess_h2_kg);
if excess_h2_kg > 0
    % Calculate breakdown by application (enhanced model)
    maritime_fraction = 0.5;
    transport_fraction = 0.3;
    industrial_fraction = 0.15;
    export_fraction = 0.05;

    maritime_kg = excess_h2_kg * maritime_fraction;
    transport_kg = excess_h2_kg * transport_fraction;
    industrial_kg = excess_h2_kg * industrial_fraction;
    export_kg = excess_h2_kg * export_fraction;

    maritime_revenue = maritime_kg * 5.5;
    transport_revenue = transport_kg * 7.0;
    industrial_revenue = industrial_kg * 4.0;
    export_revenue = export_kg * 8.0;
    employment_boost = excess_h2_kg * 0.08;
    air_quality_benefit = excess_h2_kg * 0.03;
    tourism_benefit = excess_h2_kg * 0.02;

    total_alt_revenue = maritime_revenue + transport_revenue + industrial_revenue + ...
                        export_revenue + employment_boost + air_quality_benefit + tourism_benefit;

    fprintf('  Maritime Fuel: %.0f kg/year → €%.0f/year €(%.2f/kg)\n', maritime_kg, maritime_revenue, 5.5);
    fprintf('  Transport Fuel: %.0f kg/year → €%.0f/year €(%.2f/kg)\n', transport_kg, transport_revenue, 7.0);
    fprintf('  Industrial Sales: %.0f kg/year → €%.0f/year €(%.2f/kg)\n', industrial_kg, industrial_revenue, 4.0);
    fprintf('  Export to Islands: %.0f kg/year → €%.0f/year €(%.2f/kg)\n', export_kg, export_revenue, 8.0);
    fprintf('  Employment Benefits: €%.0f/year\n', employment_boost);
    fprintf('  Air Quality Benefits: €%.0f/year\n', air_quality_benefit);
    fprintf('  Tourism Benefits: €%.0f/year\n', tourism_benefit);
    fprintf('  TOTAL Alternative Revenue: €%.0f/year\n', total_alt_revenue);
    fprintf('  Revenue per kg H2: €%.2f/kg (weighted average)\n', total_alt_revenue/excess_h2_kg);

    % Show percentage of total H2 used for alternatives
    alt_use_pct = excess_h2_MWh / max(total_h2_in, 0.001) * 100;
    fprintf('  Alternative Uses: %.1f%% of total H2 production\n', alt_use_pct);
else
    fprintf('  No excess H2 available for alternative applications\n');
    fprintf('  (All H2 used for electricity generation)\n');
    total_alt_revenue = 0;
end

% H2 operational patterns
```

```
h2_active_hours = sum(logHybrid.h2_ds > 0);
elec_active_hours = sum(logHybrid.h2_ch > 0);
fprintf('\nH2 OPERATIONAL PATTERNS:\n');
fprintf('  Fuel Cell Active Hours: %d/year (%.1f%%)\n', h2_active_hours, h2_active_hours/8760*100);
fprintf('  Electrolyzer Active Hours: %d/year (%.1f%%)\n', elec_active_hours, elec_active_hours/8760*100);

% Find longest continuous H2 operation
h2_runs = diff([0; logHybrid.h2_ds > 0; 0]);
h2_start = find(h2_runs == 1);
h2_end = find(h2_runs == -1);
if ~isempty(h2_start)
    max_h2_duration = max(h2_end - h2_start);
    avg_h2_duration = mean(h2_end - h2_start);
    fprintf('  Longest Continuous Operation: %d hours\n', max_h2_duration);
    fprintf('  Average Operation Duration: %.1f hours\n', avg_h2_duration);
end

% H2 power statistics
if total_h2_out > 0
    avg_h2_power = total_h2_out / max(h2_active_hours, 1);
    max_h2_power = max(logHybrid.h2_ds);
    fprintf('  Average H2 Discharge Power: %.3f MW\n', avg_h2_power);
    fprintf('  Peak H2 Discharge Power: %.3f MW\n', max_h2_power);
    fprintf('  H2 Load Factor: %.1f%%\n', avg_h2_power / max(pHybrid.P_fc, 0.001) * 100);
end

% Seasonal H2 analysis
fprintf('\nH2 SEASONAL PATTERNS:\n');
if isfield(logHybrid, 'winter_1_h2_charge')
    fprintf('  Winter 1 - Charge: %.1f MWh, Discharge: %.1f MWh\n', ...
        logHybrid.winter_1_h2_charge, logHybrid.winter_1_h2_discharge);
    fprintf('  Summer   - Charge: %.1f MWh, Discharge: %.1f MWh\n', ...
        logHybrid.summer_h2_charge, logHybrid.summer_h2_discharge);
    fprintf('  Winter 2 - Charge: %.1f MWh, Discharge: %.1f MWh\n', ...
        logHybrid.winter_2_h2_charge, logHybrid.winter_2_h2_discharge);

    seasonal_ratio = logHybrid.summer_h2_discharge / max(logHybrid.total_winter_h2_discharge, 0.1);
    if seasonal_ratio > 1.0
        seasonal_status = '(GOOD - seasonal storage working)';
    else
        seasonal_status = '(POOR - seasonal pattern incorrect)';
    end
    fprintf('  Summer/Winter Discharge Ratio: %.1f %s\n', seasonal_ratio, seasonal_status);

    net_seasonal_transfer = logHybrid.total_winter_h2_charge - logHybrid.total_winter_h2_discharge - ...
        logHybrid.summer_h2_charge + logHybrid.summer_h2_discharge;
    fprintf('  Net Seasonal Transfer: %.1f MWh (→wintersummer)\n', net_seasonal_transfer);
else
    seasonal_ratio = 0; % Default value if not available
end

% Monthly H2 usage breakdown
fprintf('\nMONTHLY H2 USAGE PATTERN:\n');
monthly_h2 = zeros(12,1);
monthly_h2_charge = zeros(12,1);
for month = 1:12
    month_start = (month-1)*730 + 1;  % Approximate monthly boundaries
    month_end = min(month*730, length(logHybrid.h2_ds));
    monthly_h2(month) = sum(logHybrid.h2_ds(month_start:month_end));
    monthly_h2_charge(month) = sum(logHybrid.h2_ch(month_start:month_end));
    fprintf('  Month %2d: Charge %.1f MWh, Discharge %.1f MWh, Net %.1f MWh\n', ...
        month, monthly_h2_charge(month), monthly_h2(month), ...
        monthly_h2_charge(month) - monthly_h2(month));
end
[max_month_h2, peak_month] = max(monthly_h2);
[min_month_h2, bot_month] = min(monthly_h2);
fprintf('  Peak discharge month: %d (%.1f MWh), Low month: %d (%.1f MWh)\n', ...
```

```
    peak_month, max_month_h2, bot_month, min_month_h2);

%% BATTERY SYSTEM ANALYSIS
fprintf('\n============================================================\n');
fprintf('***              BATTERY SYSTEM ANALYSIS                  ***\n');
fprintf('============================================================\n');

% Li-ion performance for both systems
fprintf('LI-ION PERFORMANCE COMPARISON:\n');
fprintf('%-25s %10s %10s\n', 'Metric', 'Hybrid', 'NaNiCl2');
fprintf('%-25s %10s %10s\n', repmat('-',1,25), repmat('-',1,10), repmat('-',1,10));

vfb_hybrid_cycles = sum(logHybrid.vfb_ds) / max(pHybrid.E_vfb, 0.001);
vfb_na_cycles = sum(logNa.vfb_ds) / max(pNa.E_vfb, 0.001);
vfb_hybrid_util = sum(logHybrid.vfb_ds) / max(pHybrid.P_vfb * 8760, 0.001) * 100;
vfb_na_util = sum(logNa.vfb_ds) / max(pNa.P_vfb * 8760, 0.001) * 100;

fprintf('%-25s %9.1f %9.1f\n', 'Annual Discharge (MWh)', sum(logHybrid.vfb_ds), sum(logNa.vfb_ds));
fprintf('%-25s %9.2f %9.2f\n', 'Annual Cycles', vfb_hybrid_cycles, vfb_na_cycles);
fprintf('%-25s %8.1f%% %8.1f%%\n', 'Capacity Utilization', vfb_hybrid_util, vfb_na_util);
fprintf('%-25s %9.1f %9.1f\n', 'Active Hours', sum(logHybrid.vfb_ds > 0), sum(logNa.vfb_ds > 0));

% Battery stress analysis
hybrid_depth_cycles = 0;
na_depth_cycles = 0;
for i = 2:length(logHybrid.soc_vfb)
    if logHybrid.soc_vfb(i) < logHybrid.soc_vfb(i-1)
        hybrid_depth_cycles = hybrid_depth_cycles + abs(logHybrid.soc_vfb(i) - logHybrid.soc_vfb(i-1)) / max(pHybrid.E_vfb, 0.001);
    end
    if logNa.soc_vfb(i) < logNa.soc_vfb(i-1)
        na_depth_cycles = na_depth_cycles + abs(logNa.soc_vfb(i) - logNa.soc_vfb(i-1)) / max(pNa.E_vfb, 0.001);
    end
end

fprintf('\nBATTERY STRESS INDICATORS:\n');
fprintf('%-25s %9.1f %9.1f\n', 'Equivalent Full Cycles', hybrid_depth_cycles, na_depth_cycles);
fprintf('%-25s %9.1f %9.1f\n', 'Max SOC (%)', max(logHybrid.soc_vfb)/max(pHybrid.E_vfb,0.001)*100, max(logNa.soc_vfb)/max(pNa.E_vfb,0.001)*100);
fprintf('%-25s %9.1f %9.1f\n', 'Min SOC (%)', min(logHybrid.soc_vfb)/max(pHybrid.E_vfb,0.001)*100, min(logNa.soc_vfb)/max(pNa.E_vfb,0.001)*100);
fprintf('%-25s %9.1f %9.1f\n', 'SOC Range (%)', ...
    (max(logHybrid.soc_vfb) - min(logHybrid.soc_vfb))/max(pHybrid.E_vfb,0.001)*100, ...
    (max(logNa.soc_vfb) - min(logNa.soc_vfb))/max(pNa.E_vfb,0.001)*100);

%% DETAILED ECONOMIC ANALYSIS
fprintf('\n============================================================\n');
fprintf('***                ECONOMIC ANALYSIS                      ***\n');
fprintf('============================================================\n');

fprintf('LEVELIZED COST OF STORAGE (LCOS) - €/MWh:\n');
fprintf('%-15s %10s %10s %10s\n', 'Scenario', 'Hybrid', 'NaNiCl2', 'Difference');
fprintf('%-15s %10s %10s %10s\n', repmat('-',1,15), repmat('-',1,10), repmat('-',1,10), repmat('-',1,10));
scenario_names = {'Pessimistic', 'Balanced', 'Optimistic'};

for i = 1:length(scenarios)
    sc = scenarios{i};
    diff_lcos = LCOS.Hybrid.(sc) - LCOS.Na.(sc);
    fprintf('%-15s %9.2f %9.2f %9.2f\n', scenario_names{i}, ...
        LCOS.Hybrid.(sc), LCOS.Na.(sc), diff_lcos);
end

fprintf('\nNET SOCIAL BENEFIT (Hybrid - NaNiCl2) - €:\n');
for i = 1:length(scenarios)
    sc = scenarios{i};
    if NSB.Delta.(sc) > 0
```

```
        status = 'POSITIVE';
    else
        status = 'NEGATIVE';
    end
    fprintf('%-15s␣%12.0f␣(%s)\n', scenario_names{i}, NSB.Delta.(sc), status);
end

% Economic sensitivity analysis
fprintf('\nECONOMIC␣SENSITIVITY␣ANALYSIS:\n');
nsb_range = NSB.Delta.opt - NSB.Delta.pess;
nsb_base_to_opt = NSB.Delta.opt - NSB.Delta.base;
nsb_pess_to_base = NSB.Delta.base - NSB.Delta.pess;

fprintf('␣␣Total␣NSB␣Range:␣€%.0f␣(pess␣to␣opt)\n', nsb_range);
fprintf('␣␣Upside␣Potential:␣€%.0f␣(base␣to␣opt)\n', nsb_base_to_opt);
fprintf('␣␣Downside␣Risk:␣€%.0f␣(pess␣to␣base)\n', -nsb_pess_to_base);
fprintf('␣␣Risk/Reward␣Ratio:␣%.2f\n', abs(nsb_pess_to_base) / max(nsb_base_to_opt, 1));

% Break-even analysis
if NSB.Delta.base < 0 && NSB.Delta.opt > 0
    fprintf('␣␣Break-even␣occurs␣between␣base␣and␣optimistic␣scenarios\n');
elseif NSB.Delta.pess < 0 && NSB.Delta.base > 0
    fprintf('␣␣Break-even␣occurs␣between␣pessimistic␣and␣base␣scenarios\n');
elseif NSB.Delta.base > 0
    fprintf('␣␣Project␣is␣profitable␣in␣base␣case\n');
else
    fprintf('␣␣Project␣requires␣significant␣optimization␣to␣be␣viable\n');
end

% Detailed cost breakdown for all scenarios
fprintf('\nCOST-BENEFIT␣BREAKDOWN␣BY␣SCENARIO:\n');
for i = 1:length(scenarios)
    sc = scenarios{i};
    fprintf('\n%s␣SCENARIO:\n', upper(sc));
    if isfield(DeltaDetails, sc)
        details = DeltaDetails.(sc);
        fprintf('␣␣Diesel␣Avoided:␣%.1f␣MWh/year\n', details.diesel_avoided_MWh);
        fprintf('␣␣Fuel␣Savings:␣€%.0f/year\n', details.fuel_savingeuro);
        fprintf('␣␣CO2␣Avoided:␣%.1f␣tCO2/year\n', details.co2_avoided_t);
        fprintf('␣␣CO2␣Value:␣€%.0f/year\n', details.co2_valueeuro);
        fprintf('␣␣Total␣Direct␣Benefits:␣€%.0f/year\n', details.fuel_savingeuro + details.
            co2_valueeuro);
    end

    if isfield(SOC, sc)
        soc = SOC.(sc);
        fprintf('␣␣SOCIAL␣BENEFITS:\n');
        fprintf('␣␣␣␣Energy␣Autonomy␣Premium:␣€%.0f/year\n', soc.autonomy_euro_per_year);
        fprintf('␣␣␣␣Resilience␣Value:␣€%.0f/year\n', soc.resilience_euro_per_year);
        if isfield(soc, 'h2_apps_revenue_per_year')
            fprintf('␣␣␣␣H2␣Alternative␣Apps␣Revenue:␣€%.0f/year\n', soc.
                h2_apps_revenue_per_year);
        end
        fprintf('␣␣␣␣Job␣Creation␣(Year␣1):␣€%.0f\n', soc.jobs_value_euro_y1);
        fprintf('␣␣␣␣Training␣Value␣(Year␣1):␣€%.0f\n', soc.training_euro_y1);
        fprintf('␣␣␣␣FTE-Years␣Created:␣%.1f\n', soc.FTE_years);
        fprintf('␣␣␣␣Extra␣Resilience␣Capacity:␣%.1f␣MWh/event\n', soc.extra_res_MWh_event);
        if isfield(soc, 'excess_h2_MWh') && soc.excess_h2_MWh > 0
            fprintf('␣␣␣␣Excess␣H2␣for␣Alternatives:␣%.1f␣MWh/year␣(%.0f␣kg/year)\n', ...
                soc.excess_h2_MWh, soc.excess_h2_MWh * 1000/33.33);
        end

        total_annual_social = soc.autonomy_euro_per_year + soc.resilience_euro_per_year;
        if isfield(soc, 'h2_apps_revenue_per_year')
            total_annual_social = total_annual_social + soc.h2_apps_revenue_per_year;
        end
        fprintf('␣␣␣␣Total␣Annual␣Social␣Benefits:␣€%.0f/year\n', total_annual_social);
    end
end

%% SCENARIO PARAMETERS ANALYSIS (NEW SECTION)
```

```matlab
fprintf('\n================================================================\n');
fprintf('***           SCENARIO PARAMETERS COMPARISON              ***\n');
fprintf('=================================================================\n');

fprintf('\nMARKET PARAMETERS:\n');
fprintf('%-20s %10s %10s %10s\n', 'Parameter', 'Pessimistic', 'Base', 'Optimistic');
fprintf('%-20s %10s %10s %10s\n', repmat('-',1,20), repmat('-',1,10), repmat('-',1,10),
    repmat('-',1,10));
fprintf('%-20s %10.0f %10.0f %10.0f\n', 'CO2 Price €(/tCO2)', S.pess.p_CO2, S.base.p_CO2, S.
    opt.p_CO2);
fprintf('%-20s %10.0f %10.0f %10.0f\n', 'Energy Price €(/MWh)', S.pess.p_energy, S.base.
    p_energy, S.opt.p_energy);
fprintf('%-20s %9.1f%% %9.1f%% %9.1f%%\n', 'Degradation Rate', S.pess.deg*100, S.base.deg
    *100, S.opt.deg*100);

fprintf('\nTECHNOLOGY COST FACTORS:\n');
fprintf('%-20s %10s %10s %10s\n', 'Parameter', 'Pessimistic', 'Base', 'Optimistic');
fprintf('%-20s %10s %10s %10s\n', repmat('-',1,20), repmat('-',1,10), repmat('-',1,10),
    repmat('-',1,10));
fprintf('%-20s %9.2fx %9.2fx %9.2fx\n', 'VFB CAPEX Factor', S.pess.vfb_capex_factor, S.base.
    vfb_capex_factor, S.opt.vfb_capex_factor);
fprintf('%-20s %9.2fx %9.2fx %9.2fx\n', 'H2 CAPEX Factor', S.pess.h2_capex_factor, S.base.
    h2_capex_factor, S.opt.h2_capex_factor);
if isfield(S.pess, 'na_capex_factor')
    fprintf('%-20s %9.2fx %9.2fx %9.2fx\n', 'Na CAPEX Factor', S.pess.na_capex_factor, S.base
        .na_capex_factor, S.opt.na_capex_factor);
end

fprintf('\nSOCIAL BENEFIT PARAMETERS:\n');
fprintf('%-25s %12s %12s %12s\n', 'Parameter', 'Pessimistic', 'Base', 'Optimistic');
fprintf('%-25s %12s %12s %12s\n', repmat('-',1,25), repmat('-',1,12), repmat('-',1,12),
    repmat('-',1,12));
fprintf('%-25s %11.0f %11.0f %11.0f\n', 'Autonomy Premium €(/MWh)', S.pess.es_premium_per_MWh
    , S.base.es_premium_per_MWh, S.opt.es_premium_per_MWh);
fprintf('%-25s %11.0f %11.0f %11.0f\n', 'VoLL €(/MWh)', S.pess.voll_eur_per_MWh, S.base.
    voll_eur_per_MWh, S.opt.voll_eur_per_MWh);
fprintf('%-25s %11.1f %11.1f %11.1f\n', 'Outage Hours/Event', S.pess.outage_hours, S.base.
    outage_hours, S.opt.outage_hours);
fprintf('%-25s %11.1f %11.1f %11.1f\n', 'Outage Events/Year', S.pess.outage_events_per_year,
    S.base.outage_events_per_year, S.opt.outage_events_per_year);
fprintf('%-25s %10.1f%% %10.1f%% %10.1f%%\n', 'Local CAPEX Share', S.pess.local_share*100, S.
    base.local_share*100, S.opt.local_share*100);
fprintf('%-25s %11.1f %11.1f %11.1f\n', 'FTE per €1M', S.pess.fte_per_meur, S.base.
    fte_per_meur, S.opt.fte_per_meur);
fprintf('%-25s %11.0f %11.0f %11.0f\n', 'Value per FTE-Year €()', S.pess.value_per_fte_year,
    S.base.value_per_fte_year, S.opt.value_per_fte_year);

%% ENVIRONMENTAL IMPACT ANALYSIS
fprintf('\n================================================================\n');
fprintf('***              ENVIRONMENTAL IMPACT ANALYSIS            ***\n');
fprintf('=================================================================\n');

% CO2 emissions comparison
co2_avoided_annual = (diesel_na - diesel_hybrid) * EF_diesel;  % tCO2/year
co2_avoided_total = co2_avoided_annual * horizon;

fprintf('CARBON FOOTPRINT ANALYSIS:\n');
fprintf('  Annual CO2 Reduction: %.1f tCO2/year\n', co2_avoided_annual);
fprintf('  15-Year CO2 Reduction: %.0f tCO2\n', co2_avoided_total);
fprintf('  Equivalent Cars Removed: %.0f cars/year\n', co2_avoided_annual / 4.6); % Avg car =
     4.6 tCO2/year

% Environmental benefits of H2 alternative uses
if excess_h2_kg > 0
    fprintf('\nH2 ALTERNATIVE USES ENVIRONMENTAL BENEFITS:\n');

    % Maritime applications
    maritime_co2_avoided = maritime_kg * 0.5 * 2.8;  % 50% efficient, 2.8 kg CO2/kg diesel
        equiv
    fprintf('  Maritime fuel replacement: %.0f tCO2/year avoided\n', maritime_co2_avoided
        /1000);
```

```
    % Transport applications
    transport_co2_avoided = transport_kg * 0.6 * 2.8;  % 60% efficient
    fprintf('  Transport fuel replacement: %.0f tCO2/year avoided\n', transport_co2_avoided/1000);

    % Total additional CO2 benefits
    total_alt_co2 = (maritime_co2_avoided + transport_co2_avoided) / 1000;
    fprintf('  Total additional CO2 reduction: %.0f tCO2/year\n', total_alt_co2);
    fprintf('  Combined CO2 impact: %.0f tCO2/year\n', co2_avoided_annual + total_alt_co2);
end

% Resource utilization efficiency
res_efficiency_hybrid = (1 - spill_hybrid/sum(ren_MWh)) * 100;
res_efficiency_na = (1 - spill_na/sum(ren_MWh)) * 100;

fprintf('\nRESOURCE UTILIZATION:\n');
fprintf('  Hybrid RES Efficiency: %.1f%%\n', res_efficiency_hybrid);
fprintf('  NaNiCl2 RES Efficiency: %.1f%%\n', res_efficiency_na);
fprintf('  Improvement: %.1f percentage points\n', res_efficiency_hybrid - res_efficiency_na);
fprintf('  Annual RES Waste Reduction: %.0f MWh\n', spill_na - spill_hybrid);

%% DISPATCH STRATEGY ANALYSIS (NEW SECTION)
fprintf('\n================================================================\n');
fprintf('***             DISPATCH STRATEGY ANALYSIS                ***\n');
fprintf('================================================================\n');

fprintf('DISPATCH PARAMETERS (Hybrid System):\n');
fprintf('  Li-ion Battery:\n');
fprintf('    - Capacity: %.2f MWh\n', pHybrid.E_vfb);
fprintf('    - Power: %.2f MW\n', pHybrid.P_vfb);
fprintf('    - Charge Efficiency: %.1f%%\n', pHybrid.eta_ch_vfb * 100);
fprintf('    - Discharge Efficiency: %.1f%%\n', pHybrid.eta_ds_vfb * 100);
fprintf('    - Initial SOC: %.1f%%\n', pHybrid.soc0_vfb * 100);
if isfield(pHybrid, 'vfb_soc_cap_day')
    fprintf('    - Daily SOC Cap: %.1f%%\n', pHybrid.vfb_soc_cap_day * 100);
end
if isfield(pHybrid, 'vfb_soc_floor')
    fprintf('    - SOC Floor: %.1f%%\n', pHybrid.vfb_soc_floor * 100);
end

fprintf('\n  H2 System:\n');
fprintf('    - Storage Capacity: %.2f MWh\n', pHybrid.E_h2);
fprintf('    - Electrolyzer Power: %.2f MW\n', pHybrid.P_elec);
fprintf('    - Fuel Cell Power: %.2f MW\n', pHybrid.P_fc);
fprintf('    - Electrolyzer Efficiency: %.1f%%\n', pHybrid.eta_elec * 100);
fprintf('    - Fuel Cell Efficiency: %.1f%%\n', pHybrid.eta_fc * 100);
fprintf('    - Initial H2 SOC: %.1f%%\n', pHybrid.soc0_h2 * 100);
if isfield(pHybrid, 'fc_min_load_factor')
    fprintf('    - FC Min Load Factor: %.1f%%\n', pHybrid.fc_min_load_factor * 100);
end
if isfield(pHybrid, 'h2_min_soc')
    fprintf('    - H2 Min SOC: %.1f%%\n', pHybrid.h2_min_soc * 100);
end
if isfield(pHybrid, 'h2_prio_hours')
    fprintf('    - H2 Priority Hours: [%s]\n', num2str(pHybrid.h2_prio_hours));
end

fprintf('\nDISPATCH PARAMETERS (NaNiCl2 System):\n');
fprintf('  Battery Capacity: %.2f MWh\n', pNa.E_vfb);
fprintf('  Battery Power: %.2f MW\n', pNa.P_vfb);
fprintf('  Charge Efficiency: %.1f%%\n', pNa.eta_ch_vfb * 100);
fprintf('  Discharge Efficiency: %.1f%%\n', pNa.eta_ds_vfb * 100);
fprintf('  Round-trip Efficiency: %.1f%%\n', pNa.eta_ch_vfb * pNa.eta_ds_vfb * 100);
fprintf('  Initial SOC: %.1f%%\n', pNa.soc0_vfb * 100);
```