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THERMO-ECONOMIC MODELING OF HYDROGEN ENERGY INTEGRATION IN SMART FACTORIES

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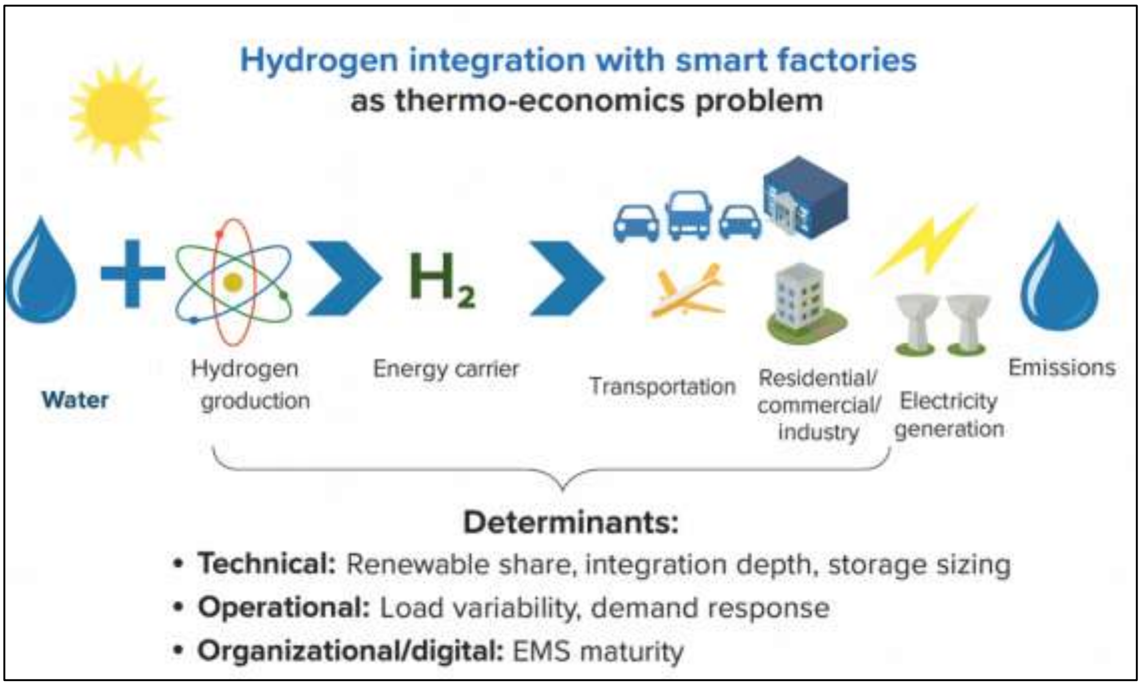
Abstract
Here we investigate when and how hydrogen integration improves thermo-economic performance in smart factories by synthesizing international evidence and analyzing a multi-case plant dataset; a systematic review of 46 peer-reviewed studies scoped the technology, operations, and exergy–cost foundations that informed the empirical model, and the problem addressed is the lack of plant-resolved, tariff-aware evidence linking digital maturity and integration depth to levelized cost outcomes; the purpose is to quantify the relationships among renewable share to electrolysis, integration depth across electrolyzer, storage, and fuel cell, storage-to-load ratio, load variability, demand-response participation, and energy-management maturity with plant-level key performance indicators including levelized cost of hydrogen, energy cost intensity, exergy efficiency, CO_2 intensity, and reliability; the design is quantitative, cross-sectional, and case-based; the sample comprises 120 cloud or enterprise cases with EMS or SCADA telemetry aligned to audited tariff and financial records; the analysis plan includes descriptive statistics, correlation matrices, and multiple regression with sector fixed effects, robust errors, and a pre-specified interaction term testing whether energy-management maturity amplifies the benefit of renewable share; headline findings show that higher renewable share is the strongest single predictor of lower unit cost, deeper integration raises exergetic efficiency and lowers emissions, storage exhibits diminishing cost returns beyond roughly work-shift duration, and digital maturity significantly strengthens the cost reductions associated with renewable alignment; implications for practice are to prioritize renewable-aligned electrolysis before oversizing storage, right-size duration to variability fingerprints, invest in EMS maturity and governance, and deploy fuel-cell CHP where thermal and electrical peaks coincide to decarbonize without compromising reliability.

Keywords
Smart Factory, Hydrogen, Thermo-Economics, Exergy, Levelized Cost Of Hydrogen, Energy Management Systems, Industry 4.0

INTRODUCTION

Hydrogen is an energy carrier that can be produced, stored, and reconverted to electricity and heat, enabling sector coupling across power, heat, transport, and industry. In thermo-economic terms, plant-level decisions about hydrogen hinge on technical performance (efficiency, availability, degradation) *and* costs over the life cycle, typically summarized as the levelized cost of hydrogen (LCOH), alongside second-law (exergy) indicators that locate where useful work potential is destroyed within components and flows. Exergy analysis formalizes these ideas by quantifying irreversibilities at the component and system levels and, when combined with costing ("exergoeconomics"), links thermodynamic losses directly to economic losses an especially useful lens for factory settings where production schedules, tariffs, and equipment interactions jointly determine energy cost intensity (Gahleitner, 2013; Lasi et al., 2014).

Figure 1: Thermo-Economic Integration of Hydrogen Systems in Smart Factories



On the technology side, modern hydrogen pathways in factories typically combine on-site renewables, grid electricity, and water electrolysis (alkaline, PEM, or SOEC), optional hydrogen storage, and end-use via fuel cells or direct combustion/processing, often integrated with heat recovery and digital energy management systems. Contemporary syntheses characterize water electrolysis as commercially ready and improving, while noting stack and balance-of-plant costs, efficiency, lifetime, and operational strategies as dominant LCOH drivers (Ursúa et al., 2012). Thermo-economic modeling, therefore, must attend to both first- and second-law performance; tariff, utilization, and duty-cycle effects; and plant digitalization maturity (EMS/SCADA, cyber-physical systems), which shapes load following, curtailment mitigation, and self-consumption. At the international level, studies show that declining renewable costs, improved electrolyzer performance, and flexible operation can place renewable hydrogen within competitive ranges for certain uses and locations, reframing hydrogen from a niche chemical input to a cross-sector asset in smart manufacturing. Within smart-factory contexts where sensing, connectivity, and analytics coordinate machines and energy assets hydrogen integration requires modeling frameworks that co-optimize thermodynamics and economics under real tariffs and constraints, rather than idealized average conditions (ISO, 2011).

Manufacturing accounts for a large fraction of final energy use and electricity consumption worldwide, and factories increasingly deploy energy management systems (EMS) under ISO 50001 programs to cut energy cost and intensity. In this environment, hydrogen offers a route to electrify or decarbonize high-temperature heat, provide backup/ancillary services via fuel cells, and buffer variable renewables through power-to-hydrogen-to-power or process routes. Reviews underline hydrogen's roles across geographies in mobility depots, chemical sites, metals processing, and distributed generation with techno-economic viability dependent on local resource quality, electricity price structures, and utilization. In energy-intensive industries, demand-side management and flexible scheduling can synchronize electrolysis with low-price, low-carbon hours, lowering effective LCOH and total energy cost intensity; this literature highlights substantive flexibility in sectors like steel, chemicals, pulp and paper, and cement where continuous or batch operations can be time-shifted within quality constraints (Bunse et al., 2011; Paulus & Borggrefe, 2011). Thermo-economically, the international picture shows that component-level irreversibilities and interactions matter: advanced exergy/exergoeconomic methods separate endogenous losses (in a component) from exogenous ones (imposed by the rest of the system), focusing improvement efforts where they yield the largest economic benefit an approach applicable to electrolyzers, compressors, storage, and fuel cells under factory duty cycles. Meanwhile, system reviews of energy storage technologies situate hydrogen among long-duration options, emphasizing that duration, round-trip efficiency, and degradation profiles drive comparative cost; hydrogen's unique advantage is decoupling power and energy ratings through inexpensive storage volume, which complements factory load management and increases self-consumption of on-site renewables (Abdul, 2021; Tao et al., 2019). Taken together, these strands justify an integrated thermo-economic modeling study focused on smart factories as internationally relevant testbeds for hydrogen integration.

Smart factories leverage interconnected cyber-physical systems (CPS), intelligent sensing, and analytics to monitor and optimize production and energy flows in real time. Industry 4.0 literature describes architectures where machine-level data feed supervisory control and data acquisition (SCADA)/EMS layers that orchestrate scheduling, predictive maintenance, and energy optimization, providing the instrumentation necessary for thermo-economic modeling at operational time scales (Sanjid & Farabe, 2021). Intelligent manufacturing reviews catalog how IoT-enabled assets and cloud analytics enable fine-grained load control, provide flexibility to absorb intermittent renewables, and generate the traceable datasets needed to compute key performance indicators (KPIs) such as self-consumption, curtailed energy, and loss-of-power-supply probability (Omar & Rashid, 2021; Zhong et al., 2017). Within this digital context, EMS frameworks in manufacturing formalize energy KPIs, integrate meters and sub-meters, and support decision support for scheduling and retrofits; this line of work provides operational definitions and measurement strategies for variables like energy cost intensity ($/unit output), peak-to-average load ratio, and demand response participation. ISO 50001 guidance establishes consistent terminology and processes for continuous energy performance improvement, which helps standardize plant data for cross-case analyses (Zaman & Momena, 2021; Vogl et al., 2018). For hydrogen subsystems, the same data backbone feeds electrolysis dispatch, storage management, and fuel cell operation under time-of-use tariffs, enabling both descriptive statistics and regression modeling that tie digitalization maturity to thermo-economic outcomes. This perspective aligns with digital-twin research that links cyber models to physical assets, improving state estimation and control features directly relevant for operating electrolyzers efficiently (ramp limits, part-load efficiencies), maintaining hydrogen quality constraints, and coordinating with process heat demands (Mubashir, 2021; Rony, 2021).

This study aims to develop and empirically test a plant-level thermo-economic modeling framework that explains when and how hydrogen integration improves operational performance in smart factories. The first objective is to construct rigorously defined dependent variables that capture techno-economic performance at the factory scale specifically levelized cost of hydrogen, energy cost intensity per unit of output, exergy efficiency of the integrated system, carbon intensity of production, and reliability measured by loss-of-power-supply probability so that results are comparable across heterogeneous sites. The second objective is to quantify the relationships between these outcomes and a set of technical and operational predictors: renewable share in electrolyzer supply, integration depth across electrolyzer–storage–fuel cell chains, storage capacity relative to load, load variability measured by peak-to-average ratio, participation in demand response or time-of-use optimization, and plant characteristics such as size, sector, and equipment age. The third objective is to assess the role of digitalization by operationalizing an energy-management maturity index and testing whether it moderates the association between renewable share and cost or efficiency outcomes, thereby isolating the value added by sensing, analytics, and closed-loop control. A fourth objective is to design and execute a cross-sectional, multi-case data strategy that combines EMS/SCADA logs, tariff and financial records, and a Likert five-point survey instrument into a unified dataset with transparent data cleaning, feature engineering, and quality checks. A fifth objective is to produce statistically defensible evidence through a staged analysis plan that includes descriptive statistics for context, correlation matrices for preliminary structure, and multiple regression models with controls, interaction terms, and robustness diagnostics to evaluate the primary and moderation effects. Finally, the study seeks to compare results across cases to identify configuration archetypes that are associated with superior thermo-economic performance under real operating conditions. Together, these objectives provide a clear pathway from measurement to inference: define plant-relevant performance metrics, link them to actionable design and operation variables, incorporate the organizational dimension of digital maturity, and estimate effect sizes with transparency and rigor suitable for replication and methodological scrutiny.

LITERATURE REVIEW

The literature on hydrogen integration in manufacturing spans three intersecting domains smart-factory operations, hydrogen technologies, and thermo-economic analysis and provides the conceptual footing for a plant-level, data-driven study. First, research on smart factories and energy management details how cyber-physical systems, high-resolution metering, and supervisory control enable granular monitoring of loads, on-site generation, and storage, establishing the data backbone for computing key performance indicators such as self-consumption, curtailed energy, and loss-of-power-supply probability. Within this stream, manufacturing energy-management frameworks formalize measurement and continuous improvement practices (e.g., KPI hierarchies, sub-metering strategies, duty-cycle characterization) that are directly transferable to hydrogen subsystems. Second, work on hydrogen technologies characterizes electrolyzer types (alkaline, PEM, high-temperature) and their response to variable power, as well as storage and end-use pathways (compressed or liquid storage, fuel cells, direct combustion, process hydrogen), emphasizing efficiency curves, degradation, and balance-of-plant requirements that shape operating envelopes in factory conditions. Adjacent reviews on power-to-X and long-duration storage situate hydrogen amid alternatives, noting the distinctive advantage of decoupling power and energy ratings, which is relevant when factories must buffer renewable variability while respecting production schedules. Third, the thermo-economic tradition bridging first-law energy balances, second-law exergy analysis, and cost accounting offers a consistent grammar for tracing where useful work potential is destroyed and what that destruction costs, enabling component-level and system-level benchmarking via indicators like levelized cost of hydrogen, energy cost intensity, exergy efficiency, and carbon intensity of output. Across these literatures, several determinants recur: renewable share and tariff structure, electrolyzer utilization and flexibility, integration depth across electrolyzer–storage–fuel-cell chains, digitalization maturity of energy management, load variability and scheduling practices, and sectoral or site-specific constraints. The evidence base, however, remains fragmented across technology-centric case studies, system-level scenarios, and operations-management frameworks, with comparatively fewer multi-site, regression-based analyses that join real tariff data, SCADA/EMS logs, and structured surveys. This review therefore synthesizes measurement practices from smart manufacturing, performance and cost drivers from hydrogen engineering, and causal-inference-ready constructs from thermo-economics to frame a coherent set of variables, hypothesized mechanisms, and modeling choices that are suitable for a cross-sectional, multi-case investigation of thermo-economic performance in hydrogen-enabled smart factories.

Smart Factories and Energy Management

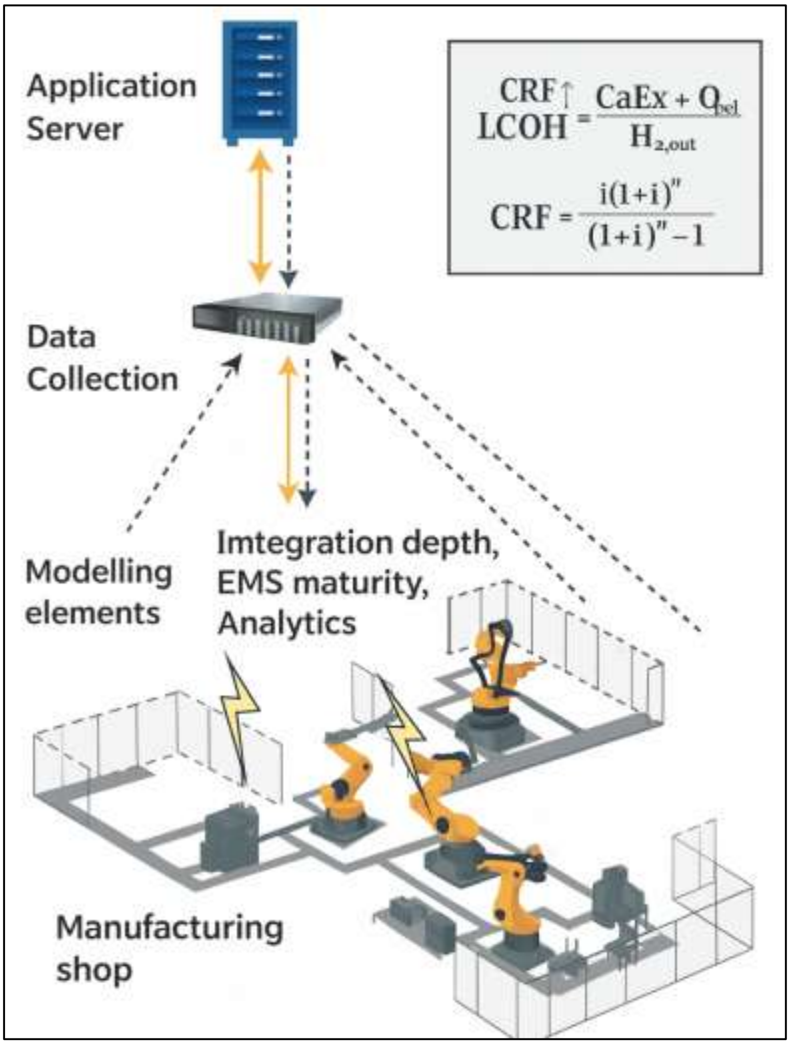
Smart factories are cyber-physical production environments in which machines, energy assets, sensors, and information systems interoperate to coordinate production and resource flows in near real time. In this context, energy is not just a utility input but a controllable production factor managed through an energy management system (EMS) layered atop supervisory control and data acquisition (SCADA) and manufacturing execution systems. A core tenet of the Industry 4.0 paradigm is vertical integration from field devices to enterprise planning and horizontal integration across the value network; together, these enable synchronized control that can shape load profiles, absorb on-site renewable variability, and orchestrate electrolysis, hydrogen storage, and fuel-cell dispatch alongside production schedules (Zaki, 2021; Wang et al., 2016). The practical implication for thermo-economic work is that measurement granularity (e.g., 1–15-minute intervals), semantic data models, and asset connectivity make it feasible to compute key performance indicators (KPIs) such as self-consumption, curtailed energy, and loss-of-power-supply probability at the line or process level, then relate those KPIs to costs and reliability. Industry 4.0 reviews further emphasize how cyber-physical production systems (CPPS) facilitate decentralized decision-making and predictive control, properties that are particularly useful for tariff-aware electrolysis and for matching hydrogen production to stochastic renewable availability and batch/continuous process constraints (Danish & Zafor, 2022; Monostori, 2014). In short, the "smart" in smart factories provides the sensing and control substrate necessary to move from static energy accounting to operational, tariff-responsive thermo-economic optimization (Danish & Kamrul, 2022; Wang et al., 2016). Within this architecture, data-driven operations management supports two complementary levers for hydrogen-enabled factories: flexibility and forecasting. Flexibility refers to deliberate shifts in energy-intensive tasks (e.g., electrolyzer setpoints, thermal charging, hydrogen compression) to low-price or low-carbon time windows while maintaining production quality; forecasting refers to anticipatory scheduling derived from predictive analytics and digital twins that estimate demand, equipment states, and renewable output. The predictive manufacturing literature outlines how big-data pipelines spanning condition monitoring, feature extraction, and remaining useful life estimation feed supervisory controllers to pre-empt disturbances, smooth peaks, and reduce unserved load (Hozyfa, 2022; Lee et al., 2013). In an EMS setting, those capabilities translate into dispatch rules such as "raise electrolyzer load when marginal electricity cost is below a threshold and storage state-of-charge (SoC) is below target," or "prioritize fuel-cell generation during peak tariff windows to cap demand charges." As factories adopt these routines, a common costing anchor for hydrogen subsystems is the levelized cost of hydrogen (LCOH), which annualizes capital and folds in variable costs. A standard expression is

$$\mathrm{LCOH} = \frac{\mathrm{CRF} \cdot \mathrm{CapEx} + \mathrm{OpEx} + C_{\mathrm{elec}}}{H_{2,\mathrm{out}}}, where\ \mathrm{CRF} = \frac{i(1+i)^n}{(1+i)^n - 1},$$

with i the discount rate, n the project lifetime, C_{elec} the annual electricity cost under real tariffs, and $H_{2,out}$ the annual hydrogen output. Because both C_{elec} and $H_{2,out}$ are functions of dispatch and utilization, the EMS-enabled flexibility and the quality of forecasts jointly shape LCOH and related KPIs (Lu, 2017; Arman & Kamrul, 2022). In a smart-factory hydrogen application, the same data backbone that supports predictive maintenance also enables tariff-responsive operation, thereby linking digitalization maturity directly to thermo-economic outcomes (Lee et al., 2013; Mohaiminul & Muzahidul, 2022).

A parallel strand in industrial energy-efficiency research underscores why organizational decision-making and barrier profiles matter for realizing the technical potential of smart energy management. Empirical studies of manufacturing small and medium-sized enterprises (SMEs) show that the adoption of energy measures is shaped by heterogeneous economic, informational, and organizational barriers and that these barriers and the corresponding drivers vary across steps of the decision process (from opportunity identification to investment and operation) (Omar & Ibne, 2022; Trianni et al., 2016). For hydrogen-ready factories, this implies that even when the EMS and CPPS infrastructure exist, underinvestment in metering granularity, insufficient valuation of non-energy benefits, or capability gaps in analytics can limit the achievable gains from flexible electrolysis and hydrogen cogeneration. Complementarily, the Industry 4.0 literature stresses that vertical/horizontal integration and self-organization are not merely technology deployments but socio-technical transitions that require governance, standards, and skills to yield reliable, auditable KPIs for energy and production (Hossen & Atiqur, 2022; Monostori, 2014). Thus, in specifying variables and hypotheses for thermo-economic modeling, it is important to include both technical predictors (integration depth, renewable share, storage sizing) and organizational/digital predictors (EMS maturity, analytics capability). Doing so aligns the modeling frame with evidence that decision quality and barrier remediation influence whether flexible, tariff-aware control actually reduces cost and carbon intensity in practice.

Figure 2: Smart Factory Energy Management Architecture in the Industry 4.0 Context



Hydrogen Integration Pathways in Manufacturing

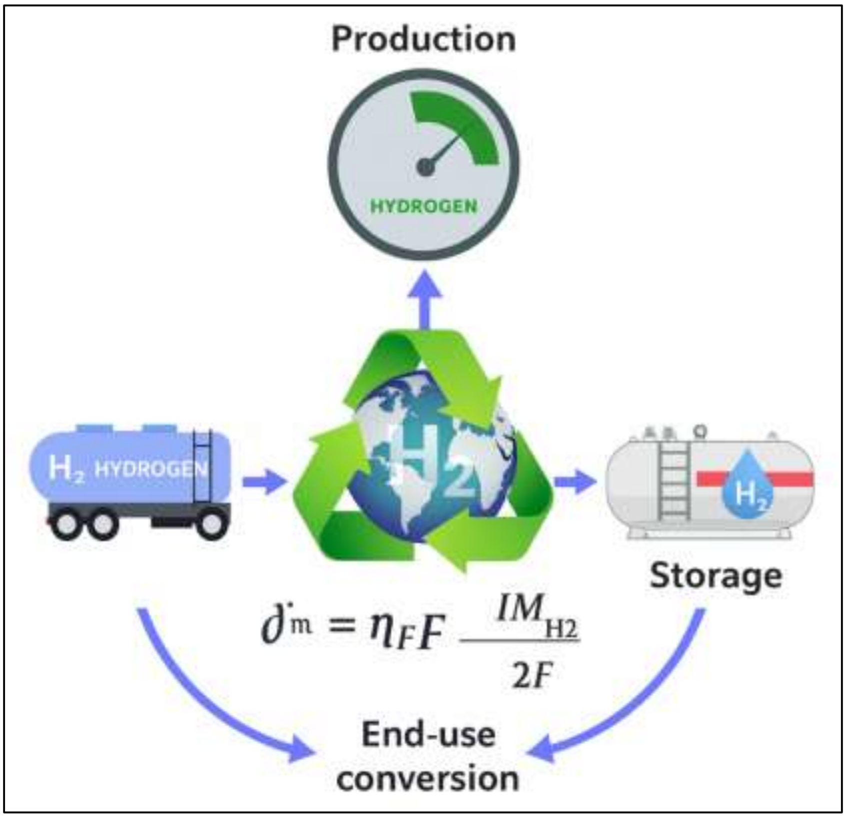
Hydrogen can be integrated into factory energy systems through three complementary pathways: on-site production (principally by water electrolysis), intermediate storage (compressed, liquefied, or solid-state), and end-use conversion (fuel cells, direct combustion, or process hydrogen). Among production options, proton exchange membrane (PEM) electrolysis is attractive for smart factories because it tolerates highly dynamic operation, ramps rapidly to follow price and renewable signals, and offers a compact footprint conducive to plant retrofits; alkaline systems remain cost-competitive for steady baseload service; and high-temperature electrolysis can couple to industrial waste heat (Hirscher et al., 2020; Mominul et al., 2022).

A core operational lever is to dispatch electrolysis against real-time tariffs and renewable availability so that the resulting hydrogen displaces grid purchases during peak windows or feeds co-generation when thermal demand is high. Thermodynamically, the instantaneous hydrogen production rate of an electrolyzer is governed by Faraday's law.

$$\dot{m}_{\mathrm{H}_2} = \eta_F \frac{I M_{\mathrm{H}_2}}{2F},$$

where ηF is faradaic efficiency (–), I is cell current (A), MH_2 is the molecular mass of H_2 (kg·mol^{-1}), and F is Faraday's constant (C·mol^{-1}). This expression links dispatch decisions (current setpoints) to tangible mass flow and therefore to the plant's energy and exergy balances, enabling thermo-economic controllers to co-optimize production rate, efficiency, and cost under equipment and quality constraints. For retrofits, PEM electrolysis provides the most flexible "electrical-to-molecular" interface, aligning with Industry 4.0 control loops that already coordinate batch and continuous operations. Early but influential assessments of PEM electrolysis in renewable settings anticipated these roles, highlighting benefits in modularity, rapid response, and high current densities features that are now central to factory flexibility portfolios (Barbir, 2005).

Figure 3: Hydrogen Integration Pathways in Manufacturing Systems



Storage choices shape both reliability and economics by decoupling the timing of production from end-use. Compressed hydrogen at 30–45 MPa is the most mature and widely deployed option for industrial sites; liquefaction increases volumetric density but introduces high parasitic loads; solid-state storage (e.g., metal hydrides) offers lower pressure operation and inherent buffering of pressure transients at the expense of added mass and thermal management. For smart factories, the sizing of storage relative to electrolysis power and process demand determines how effectively the system can arbitrage tariffs, absorb renewable curtailment, and ensure continuity of service during process peaks or grid contingencies. Materials-focused surveys point to significant progress in sorbents, complex hydrides, and intermetallic compounds, with growing attention to cycle stability, kinetics, and system-level integration (heat exchange, balance-of-plant) that are decisive in stationary applications. From an operations perspective, the state-of-charge dynamics of storage become a first-class state variable in the EMS, feeding both day-ahead planning and real-time control. In stationary contexts similar to factory microgrids, comprehensive reviews argue that material selection and thermal coupling strategies are as important as gravimetric capacity, because the latter often yields diminishing returns if heat management and cycling durability are not co-designed with the plant's duty cycle and maintenance windows (Hirscher et al., 2020; Rabiul & Praveen, 2022). For compressed storage, practical engineering focuses on cascade architectures, compressor staging, and pressure-matched delivery to minimize exergy destruction and parasitic power concerns that must be reflected in the thermo-economic model's cost and efficiency coefficients. For metal-hydride systems, integration with low-grade waste heat can reduce desorption penalties and improve round-trip efficiency in sites with continuous thermal demand (Lototskyy et al., 2014; Farabe, 2022).

End-use conversion completes the pathway by transforming stored hydrogen into electricity and heat (fuel cells), process heat (burners), or feedstock for synthetic fuels. In manufacturing, fuel-cell combined heat and power (FC-CHP) is often the highest-value use when electrical and thermal loads are coincident; electrolysis during low-price periods followed by FC-CHP during peaks effectively "time-shifts" both electricity and heat while capping demand charges and stabilizing thermal processes. Power-to-synthetic-methane (methanation) emerges as a complementary option where factories are connected to natural-gas infrastructure or operate high-temperature processes; here, hydrogen reacts with captured CO_2 to produce pipeline-grade methane, allowing seasonal storage and utilization with existing burners and furnaces (Kamrul & Omar, 2022; Rönsch et al., 2016). The operational logic is then to size and dispatch methanation and FC-CHP modules according to process temperature requirements, grid constraints, and CO_2 capture availability. Detailed reviews of catalytic methanation document how reactor design, heat removal, and catalyst choices govern conversion efficiency and dynamic response, both of which condition the feasibility of coupling to variable hydrogen streams from renewables or flexible electrolysis (Andrews & Shabani, 2012; Roy, 2022). In parallel, assessments of fuel-cell deployment for distributed generation underscore the importance of part-load efficiency curves, start-stop durability, and maintenance logistics, which should be encoded in the plant's reliability model and its cost function to avoid optimistic dispatch recommendations that cannot be sustained in operation (Andrews & Shabani, 2012; Rahman & Abdul, 2022). Furthermore, when factories require process hydrogen (e.g., metallurgy, chemicals), on-site electrolysis with appropriate purification stages provides quality-controlled feed, and technology overviews emphasize the trade-offs among production pathways electrolysis, reforming with capture, or thermochemical cycles reiterating that the choice hinges on local electricity intensity, heat integration opportunities, and emissions objectives that the thermo-economic model must quantify consistently (Holladay et al., 2009).

Thermo-Economic Analysis Foundations

Thermo-economic analysis unifies second-law thermodynamics with cost accounting so that technical inefficiencies are translated into economic consequences at the level of components and whole plants. The second-law core is exergy, the measure of maximum useful work relative to a chosen reference environment. For any component *k*, the exergetic efficiency expresses how effectively the incoming "fuel" exergy is converted into the desired "product" exergy:

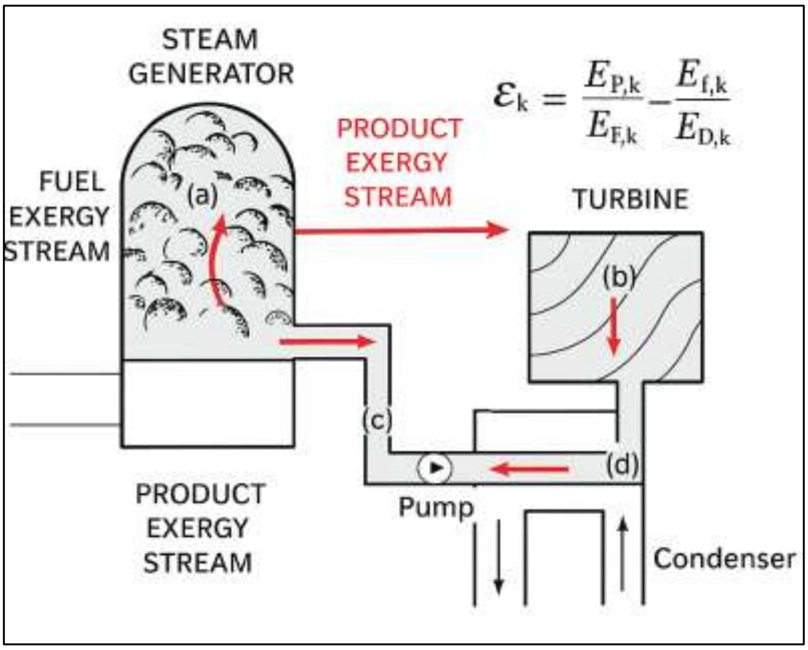
$$\varepsilon_k = \frac{\dot{E}_{F,k}}{\dot{E}_{P,k}} = 1 - \frac{\dot{E}_{F,k}}{\dot{E}_{D,k}},$$

What distinguishes thermo-economics is the consistent assignment of monetary costs to exergy streams and to the unavoidable capital/operating expenses of each component. The widely used SPECO (Specific Exergy Costing) methodology provides a rigorous rule-set to define the "fuel" and "product" of every element in a complex system and to derive a set of linear cost-balance equations that connect stream costs to resource consumption and capital charges. In compact form for component *k*,

$$\sum \boldsymbol{C}_{\mathrm{k,out}} - \sum \boldsymbol{C}_{\mathrm{k,in}} = \dot{Z}_{\mathrm{k}}, \quad \text{where} \quad \boldsymbol{C} = c\,\boldsymbol{E}$$

so the difference between the cost rate leaving and entering the component equals the non-exergetic cost rate *Ż_k* (capital recovery and O&M apportioned to *k*). Solving the network of balances yields unit cost coefficients *c* (e.g., \$/MJ-exergy) for all flows and, by aggregation, cost metrics at plant level (e.g., \$/kg-H_2). SPECO's strength is its consistency across technologies and topologies, which is essential in multi-unit factory energy systems with electrolyzers, compressors, storage, fuel cells, and process-heat integration (Lazzaretto & Tsatsaronis, 2006). Advanced exergy-based decompositions extend this foundation by splitting *Ė_D* (and the associated costs) into avoidable/unavoidable and endogenous/exogenous parts, thereby exposing which losses are technologically reducible and which are imposed by system interactions; this deepens diagnostic power before any optimization or investment ranking (Cziesla et al., 2006).

Figure 4: Thermo-Economic Analysis Foundations



Building on these definitions, exergoenvironmental analysis merges exergy costing with environmental impact accounting so that each component's thermodynamic losses are monetized and "impact-ized" simultaneously. The approach assigns impact rates (e.g., Eco-indicator 99 points per exergy unit or per physical unit) to resource and emission flows and propagates them through the same fuel/product structure used for costs. For hydrogen processes especially, this is valuable because large shares of impact originate in upstream electricity or fuel supplies; tracing them through to each plant output clarifies where design or dispatch changes produce the greatest combined improvements. A canonical application to steam-methane reforming (SMR) the mainstream industrial route to hydrogen showed how combustion, reforming reactors, separation units, and major heat exchangers dominate the impact structure and how improvements in exergetic efficiency at those loci reduce plant-wide environmental burdens most effectively (Boyano et al., 2011; Razia, 2022). In smart-factory settings contemplating power-to-hydrogen pathways, the same accounting frame supports a fair comparison between on-site electrolysis, grid-sourced hydrogen, or hybrid schemes because it attributes both technical irreversibilities and non-exergetic burdens (capital, maintenance, emissions) to the specific outputs and by-products actually used by the plant. Moreover, when factories operate under dynamic tariffs and variable renewables, the time profile of exergy flows matters: part-load operation alters efficiencies, compression ratios, and thermal coupling, which in turn changes both *Ė_D* and the cost/impact coefficients that SPECO or exergoenvironmental calculations propagate. Advanced analyses help separate what is structurally unavoidable under current technology from what is avoidable via integration upgrades (e.g., better heat recovery around electrolyzer/fuel-cell auxiliaries), providing a principled basis for sequencing retrofits (Petrakopoulou et al., 2012; Zaki, 2022). Furthermore, thermo-economic foundations must connect second-law costing to system-level financial metrics that decision makers recognize. Alongside levelized cost of hydrogen (addressed elsewhere), storage and cogeneration options are increasingly benchmarked with levelized cost of storage (LCOS) when hydrogen is used primarily as an energy-storage medium. LCOS is the discounted cost per unit of discharged electricity (or useful energy) from a storage asset over its life and captures all capital, fixed/variable O&M, round-trip efficiency, cycling and lifetime limits, and critically for factory applications the charging energy price and duty cycle (Kanti & Shaikat, 2022).

A useful canonical form is:

$$\mathrm{LCOS} = \frac{E_{\mathrm{dis}}\,\mathrm{CRF}\cdot \mathrm{CapEx} + C_{\mathrm{fix}} + C_{\mathrm{var}} + C_{\mathrm{chg}}}{E_{dis}}\ \text{With}\ \mathrm{CRF} = \frac{i(1+i)^n}{(1+i)^n - 1},$$

Methodological work shows that LCOS is application-specific and must include the same tariff- and operation-aware details that also drive exergy balances, reinforcing the need to design dispatch rules jointly with cost and efficiency models (Petrakopoulou et al., 2012). In practice, a coherent thermo-economic workflow for smart factories proceeds as follows: (i) define fuel/product exergy streams and compute ε_k *and* $\dot{E}_{D,k}$; (ii) apply SPECO to obtain stream and product costs consistent with plant accounting; (iii) extend with exergoenvironmental coefficients to capture impacts; and (iv) aggregate to decision-oriented KPIs such as \$/kg-H_2, LCOS, energy-cost intensity, and component-level avoidable cost shares. This pipeline provides transparent, auditable links from physics to money and impacts, enabling hypothesis-driven comparisons of integration depth, EMS maturity, and tariff-aligned operations (Petrakopoulou et al., 2012; Schmidt et al., 2019).

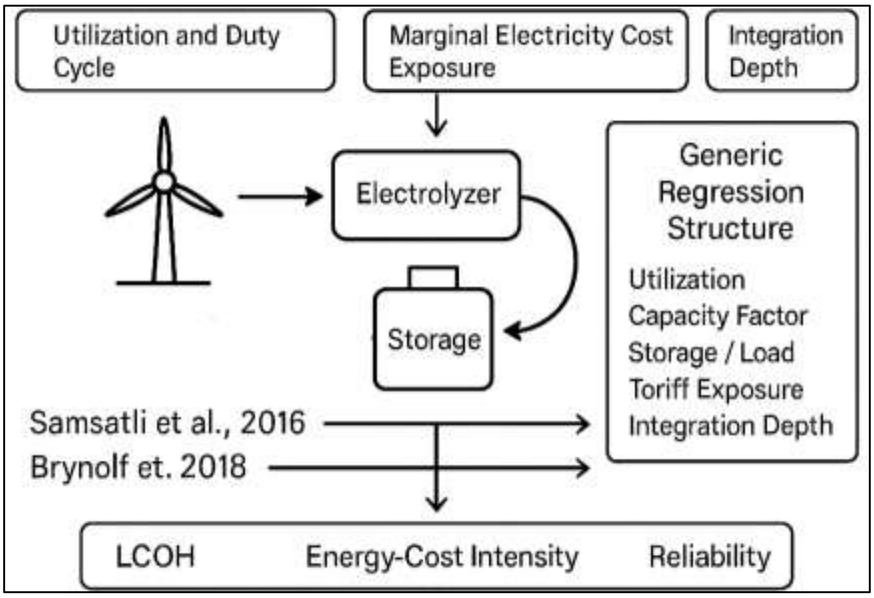
Determinants of Thermo-Economic Performance

A growing empirical and modeling literature identifies the variables that most strongly govern the thermo-economic performance of hydrogen integration when real operating constraints, tariffs, and multi-energy interactions are considered. Early cross-tool reviews of energy-system models emphasized how representation of temporal resolution, storage, and sector coupling choices can change cost and reliability outcomes by orders of magnitude a caution that is directly relevant to plant-level hydrogen studies because electrolyzer utilization, storage sizing, and end-use coupling are all time-sensitive (Connolly et al., 2010). In this perspective, determinants cluster around (i) utilization and duty cycle (capacity factor, start-stop frequency), (ii) marginal electricity cost exposure (tariff structure, demand charges), (iii) integration depth (electrolyzer-only vs. electrolyzer+storage vs. electrolyzer+storage+fuel cell or methanation), and (iv) modeling granularity (sub-hourly dispatch, part-load efficiency curves). A recurring insight is that systems evaluated with inadequate temporal fidelity overestimate average efficiency and underestimate both electricity cost and wear-related OpEx, thereby biasing levelized cost of hydrogen (LCOH) downward; conversely, high-resolution dispatch reveals value in flexible operation, storage arbitrage, and co-generation that coarse models miss (Budischak et al., 2013). To translate these drivers into an empirical frame suitable for factory studies, a generic regression structure that links plant outcomes to measurable predictors is useful:

$$\begin{aligned}\mathrm{KPI}_i = \beta_0 + \beta_1 \mathrm{Utilization}_i + \beta_2 \mathrm{CF}_i + \beta_3 \frac{\mathrm{Storage}}{\mathrm{Load}}_i + \beta_4 \mathrm{Tariff\ Exposure}_i + \beta_5 \mathrm{IntegrationDepth}_i \\ + \gamma' \mathrm{Controls}_i + \varepsilon_i,\end{aligned}$$

where KPI_i = LCOH can be LCOH, energy-cost intensity, exergy efficiency, or CO_2 intensity; CF denotes renewable/electrolyzer capacity factors; and Storage/Load captures duration-scalable storage relative to peak or average demand. This structure mirrors system-level findings while enabling case-study estimation at the plant scale (Samsatli et al., 2016).

Figure 5: Empirical Evidence and Determinants of Thermo-Economic Performance



Evidence from optimization studies coupling variable renewables to hydrogen infrastructure shows that co-optimized design and dispatch are essential to realize both cost and reliability benefits. In a milestone MILP study, Samsatli (2016) simultaneously optimized locations, sizes, and hourly operation of wind, electrolysis, compression, storage, transmission (electric and hydrogen), and fuelling assets; the work demonstrates that (a) spatial diversity of renewables and network constraints shape feasible operating envelopes, (b) storage duration and siting co-determine electrolyzer utilization, and (c) the marginal value of additional integration (e.g., hydrogen pipelines versus electricity lines) depends on congestion and temporal mismatch between supply and demand. These results generalize to factory campuses: when on-site generation, tariffs, and process loads are jointly modeled, optimal electrolysis setpoints and storage state-of-charge trajectories align with low-price/low-carbon hours while fuel cells or hydrogen-to-heat are prioritized in peak tariff windows improving both reliability and effective LCOH without oversizing equipment. Complementary system-wide studies reinforce the sensitivity of economics to assumed technology learning and utilization: reviews of electrofuel cost assessments find that electricity price, electrolyzer lifetime, and capacity factor are the dominant cost drivers, and that cross-study differences often trace back to inconsistent assumptions about these variables and about balance-of-plant (Brynolf et al., 2018). For factory practitioners, the implication is to parameterize models with site-specific tariff structures, measured load distributions, and realistic part-load curves rather than static averages; doing so aligns with the determinants identified by co-optimization studies and yields robust effect-size estimates for integration depth and flexibility.

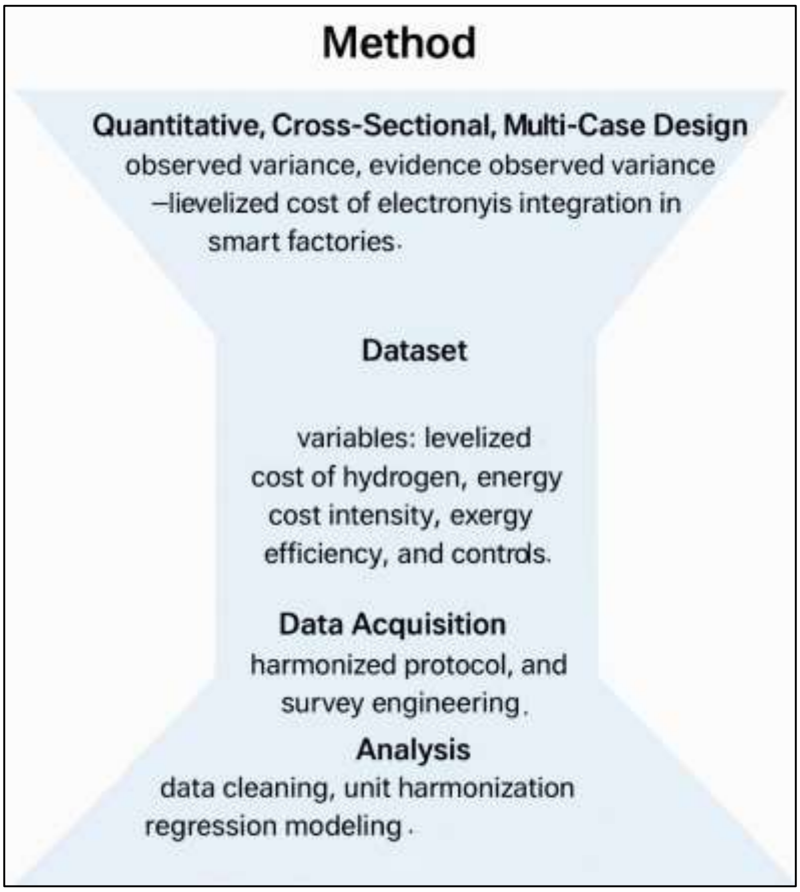
A second empirical thread comes from cost-minimization under high renewable penetrations, which repeatedly highlights how cheap energy capacity (kWh) and more expensive power capacity (kW) combine to determine total system cost. In a large-scale modeling of a real grid region, Budischak et al. (2013) show that portfolios of wind/solar with storage (including fuel cells/hydrogen) can meet load >99% of hours at least cost when designed with the right mix of generation diversity and storage durations; crucially, the study quantifies how duration-scalable storage (a hallmark of hydrogen) helps span multi-day lulls that are uneconomic for batteries sized for power-dense, short-duration needs. At the technology-comparison level, a life-cycle-cost meta-analysis across storage options found that application and duty cycle (bulk shifting vs. peak shaving vs. regulation) dominate relative economics, with hydrogen storage becoming comparatively attractive at long durations, provided utilization and charging costs are favorable (Zakeri & Syri, 2015). Extending that logic to power-to-X, techno-economic assessments of power-to-liquids identify electricity price, full-load hours, and plant scale as first-order cost determinants, mirroring the sensitivity seen in hydrogen-only pathways and underscoring that operational context often matters more than nominal efficiency differences (Fasihi, Bogdanov, &

Breyer, 2018). Together, these strands supply empirically grounded priors for factory-level modeling: prioritize accurate representation of utilization and tariffs; evaluate integration depth in terms of both kW and kWh capacity needs; and treat storage duration and duty cycle as central levers when estimating LCOH, energy-cost intensity, and reliability outcomes (Fasihi et al., 2018).

METHOD

This study has adopted a quantitative, cross-sectional, multi–case design to evaluate thermo-economic performance of hydrogen integration in smart factories. We have combined operational telemetry, financial/tariff records, and a structured Likert five-point survey to construct a plant-level dataset suitable for descriptive statistics, correlation analysis, and regression modeling. Cases have been purposively selected to span sectors, integration depths (electrolyzer only; electrolyzer + storage; electrolyzer + storage + fuel cell), and levels of digital maturity, so that observed variance has supported identification of technical, operational, and organizational determinants. We have defined four primary dependent variables levelized cost of hydrogen, energy cost intensity, exergy efficiency, and CO_2 intensity and we have specified predictors that include renewable share to electrolysis, integration depth, storage capacity relative to load, demand-response participation, load variability, and an energy-management maturity index, alongside controls for plant size, sector, climate, equipment age, and tariff class. Data acquisition has followed a harmonized protocol. EMS/SCADA logs have been extracted at 15-minute to hourly resolution for electricity demand, on-site generation, electrolyzer operation, hydrogen storage state-of-charge, and fuel-cell output. Financial data have included capital expenditures, operating expenses, maintenance logs, and applicable tariff schedules, which we have aligned to metered intervals to compute price-exposed costs.

Figure 6: Methodological Framework for Thermo-Economic Analysis



The survey instrument has captured digitalization practices, operational policies, and perceived reliability; it has undergone expert review and pilot testing before deployment. We have implemented data cleaning, unit harmonization, and feature engineering (e.g., renewable fraction during electrolyzer uptime, peak-to-average ratio, and EMS maturity scores), and we have documented missing-data handling and outlier screening. Analytically, we have reported sample characteristics and descriptive statistics, computed Pearson/Spearman correlations, and estimated multiple linear regressions with robust standard errors, including an interaction term between renewable share and EMS maturity to test moderation. Model diagnostics have addressed multicollinearity, heteroskedasticity, residual normality, and influence. Robustness checks have included alternative KPI definitions, sector fixed effects, and sensitivity to price and efficiency assumptions. All procedures have adhered to informed consent, confidentiality, and anonymization requirements. Computation has been implemented in R and Python for reproducibility, and a preregistered analysis plan has guided all decisions to limit researcher degrees of freedom.

Design

This research has adopted a quantitative, cross-sectional, multi–case design to examine how hydrogen integration has related to thermo-economic performance under real industrial operating conditions. We have purposively selected multiple factories that have differed in sector, scale, climate exposure, tariff class, and hydrogen configuration (electrolyzer only; electrolyzer + storage; electrolyzer + storage + fuel cell), so the design has captured meaningful variance rather than a single-site snapshot. The unit of analysis has been the plant, with standardized case protocols that have ensured commensurable measurement across sites. To reduce confounding, we have specified ex-ante inclusion criteria (operational EMS/SCADA metering, accessible tariff/financial data, and documented hydrogen operating histories) and exclusion criteria (pilot rigs, incomplete metering, or atypical commissioning periods). The design has combined three evidence streams high-resolution telemetry, audited financial/tariff records, and a Likert five-point survey on energy-management maturity and operational practices so triangulation has been feasible. Temporal scope has been fixed to the most recent continuous 12-month window available per case, which has allowed capacity-factor and tariff effects to be represented without seasonal bias while maintaining the cross-sectional character of the study. We have predefined dependent variables (levelized cost of hydrogen, energy cost intensity, exergy efficiency, and CO_2 intensity) and predictors (renewable share to electrolysis, integration depth, storage-to-load ratio, demand-response participation, load variability, and EMS maturity), with plant size, sector, equipment age, and climate zone as controls. To preserve internal validity, we have preregistered the analysis plan, locked model specifications before inspecting outcome patterns, and implemented uniform data-cleaning and feature-engineering rules across cases. External validity has been enhanced by selecting cases that have spanned discrete process types (continuous and batch) and distinct tariff regimes. The cross-sectional, multi-case structure has therefore provided the statistical leverage to estimate associations and test moderation while remaining grounded in operationally realistic, factory-level data.

Cases

The study has assembled a purposive sample of operating factories that have represented diverse sectors, scales, and tariff environments so that variation in hydrogen integration has been observable and analytically useful. Candidate sites have been screened through a standardized intake, and inclusion has required: (i) an operational energy management or SCADA system that has logged electricity, on-site generation, electrolyzer power, hydrogen storage state-of-charge, and fuel-cell output at 15- to 60-minute granularity; (ii) at least one continuous 12-month interval of telemetry aligned with auditable tariff and billing records; and (iii) a commissioned hydrogen subsystem electrolyzer only, electrolyzer plus storage, or electrolyzer plus storage and fuel cell that has operated under routine production schedules. Exclusion criteria have eliminated pilot rigs and demonstration skids that have not supported regular production, sites with substantial data gaps or sensor failure exceeding 5% of the observation window, facilities undergoing major outages or capital retooling that have confounded baseline demand, and cases without verifiable cost ledgers for capital and O&M. Within these bounds, sampling has followed a maximum-variation logic: we have recruited cases from discrete industries (e.g., food and beverages, fabricated metals, electronics assembly) across different climate zones and grid contexts, and we have ensured spread over tariff classes with and without demand charges. To mitigate selection bias, invitations have been issued to an over-complete pool, and final enrollment has been governed by data readiness rather than performance expectations. Each enrolled plant has designated a technical focal point and a finance contact, and site access protocols have been formalized to standardize extracts and metadata (instrument lists, calibration dates, and maintenance logs). The measurement setting has included both continuous and batch operations, thereby capturing distinct load shapes and flexibility constraints. Across sites, the sampling frame has delivered heterogeneity in integration depth, renewable share, and digital maturity while holding constant the minimum metering and documentation standards necessary for cross-case comparability, which has positioned the dataset for credible descriptive, correlational, and regression analyses.

Variables & measures

The study has defined a coherent set of dependent, independent, moderator, and control variables with plant-level operationalization so that cross-case comparisons have been valid and reproducible. Primary dependent variables have included (i) Levelized Cost of Hydrogen (LCOH, $/kg), which we have computed from annualized capital, fixed and variable O&M, and tariff-exposed electricity cost divided by metered hydrogen output; (ii) Energy Cost Intensity ($/unit output), which we have derived by allocating total energy spend to the period's finished-goods output using the facility's product accounting; (iii) Exergy Efficiency (%) for the hydrogen subsystem and the integrated energy island, which we have calculated from component energy/exergy balances using telemetry and manufacturer performance maps; and (iv) CO_2 Intensity (kg CO_2e/unit), which we have obtained by multiplying time-aligned grid emission factors and fuel coefficients by metered consumption and dividing by output. A reliability proxy, Loss-of-Power-Supply Probability (LPSP, %), has been computed as the ratio of unmet load minutes to total minutes in the analysis window for the energy island supplying critical processes. Key independent variables have captured design and operation. Renewable Share to Electrolysis (%) has been measured as the fraction of electrolyzer electricity sourced from on-site renewables at the metering interval. Integration Depth (index 0–2) has encoded configuration: 0 = electrolyzer only; 1 = electrolyzer + storage; 2 = electrolyzer + storage + fuel cell. Storage-to-Load Ratio (h) has been defined as usable hydrogen energy content at nominal delivery divided by average process demand. Load Variability (Peak-to-Average Ratio) has been computed from interval demand. Demand-Response Participation (0/1; intensity) has reflected enrollment and the annualized kW or kWh shifted during events. The moderator Energy-Management Maturity (EMS-M) has been measured with a Likert five-point multi-item scale covering metering granularity, real-time monitoring, analytics/optimization, integration with scheduling, and governance; items have been averaged after reliability checks. Controls have included Plant Size (employees, MWh/year), Sector (dummies), Equipment Age (years), Climate Zone, and Tariff Class (presence of demand charges and TOU periods). All variables have been time-aligned to a common 12-month window per site, and feature-engineering rules and unit conventions have been documented to ensure auditability.

Data collection

The study has relied on three harmonized data streams operational telemetry, financial/tariff records, and a structured survey and has implemented a standardized extraction protocol so that case data have been comparable across sites. First, EMS/SCADA telemetry have been exported at 15–60-minute intervals and have included feeder-level electricity demand, on-site renewable generation, electrolyzer DC/AC power, stack temperature and pressure, hydrogen production flow, compression power, storage state-of-charge and pressure, and fuel-cell electrical/thermal output. Metadata (instrument IDs, calibration dates, measurement ranges, and sampling timestamps) have been captured alongside the signals, and historians or data lakes have been queried via read-only credentials that plants have provisioned for the research team. Second, financial and tariff sources have comprised capital outlays (invoices and capitalization schedules), fixed and variable O&M ledgers, spare-parts and stack replacement costs, and the applicable electricity/gas tariff books; monthly utility bills have been obtained and their line items have been reconciled to metered consumption by period so that interval costs have been reconstructable. Where sites have participated in demand response or power purchase agreements, enrollment documents and settlement statements have been collected and cross-checked against event logs. Third, a Likert five-point survey has been administered to energy/operations leads and has captured EMS maturity, operational policies (setpoint governance, maintenance regimes), and perceived reliability; the instrument has undergone expert review and pilot testing at one non-study site, after which item wording and skip logic have been refined. Data collection has followed a sequenced workflow: (i) site onboarding and data-sharing agreements have been executed; (ii) telemetry extracts have been pulled for a continuous 12-month window; (iii) financial/tariff records for the same window have been compiled; and (iv) surveys have been distributed and returned within two weeks of telemetry extraction to minimize recall discrepancies. All files have been ingested into a version-controlled repository, and a data dictionary has been maintained. Quality control has included timestamp normalization to a single time zone, unit harmonization, de-duplication, and automated checks for missingness, constant signals, and out-of-range values; anomalies have been flagged back to site focal points and, where necessary, corrected with engineering notes or excluded under pre-specified rules. Personally identifying information and proprietary line-item details have been anonymized, and all entries have been assigned case IDs so that linkage across the three streams has remained deterministic and auditable.

Statistical analysis plan

The analysis has proceeded in staged layers that have preserved transparency from data screening to inference. First, we have profiled the sample with univariate summaries (counts, means, SDs, medians, ranges) and distribution diagnostics (histograms, kernel densities, and quantile spreads) for all variables, and we have reported case-level dashboards so cross-site heterogeneity has been visible. For multi-item constructs (e.g., EMS-maturity), we have conducted internal-consistency checks (Cronbach's α) and item–total correlations, and where item counts have permitted we have performed an exploratory factor analysis to verify unidimensional structure prior to scale aggregation. Next, we have examined bivariate structure using Pearson and Spearman correlations with 95% confidence intervals and false-discovery-rate control for families of tests, which has provided an initial map of associations and collinearity risks. The primary inference layer has relied on multiple linear regression for each dependent variable (LCOH, energy-cost intensity, exergy efficiency, and CO_2 intensity), estimated with heteroskedasticity-robust standard errors. To test the moderation hypothesis, we have specified an interaction term between renewable share to electrolysis and EMS-maturity, after mean-centering to reduce nonessential multicollinearity. Model diagnostics have included variance inflation factors (flagging VIF > 5), Breusch–Pagan tests for heteroskedasticity (with robust SEs retained regardless of outcome), Q–Q plots and Shapiro–Wilk tests on studentized residuals, leverage–residual and Cook's distance reviews (flagging D > 4/n), and influence re-estimation with flagged points excluded as a robustness check. We have incorporated sector fixed effects to absorb industry-specific baselines and have repeated estimations with cluster-robust SEs by sector as a sensitivity. Missing telemetry within short gaps has been bridged with rule-based interpolation; survey missingness has been handled with multiple imputation by chained equations under a missing-at-random assumption, and complete-case results have been reported in an appendix. All effect sizes have been presented with β estimates, robust SEs, 95% CIs, partial R^2, and standardized coefficients for comparability. Pre-specified subgroup and alternative-KPI analyses have been executed, and all code and outputs have been version-controlled to ensure reproducibility.

Regression Models

The modeling strategy has consisted of a family of linear specifications that have linked plant-level thermo-economic outcomes to technical, operational, and organizational predictors with a consistent control set. For each factory i, we have specified a baseline model for four outcomes levelized cost of hydrogen (LCOH_i), energy cost intensity (ECI_i), exergy efficiency (EXE_i), and CO_2 intensity (CO2I_i) so that effect sizes have been directly comparable across dependent variables. The baseline equation has taken the form:

$$i = \beta_0 + \beta_1 RenewShare_i + \beta_2 IntegrDepth_i + \beta_3 StorLoad_i + \beta_4 PAR_i + \beta_5 DR_i + \delta' \, Controls_i + \mu_s + \varepsilon_i,$$

Where $Y_i \in \{\mathtt{LCOH}_i, \mathtt{ECI}_i, \mathtt{EXE}_i, \mathtt{CO2I}_i\}$; Renew Share_i has captured the fraction of electrolyzer electricity from on-site renewables; IntegrDepth_i has encoded configuration (electrolyzer only / +storage / +fuel cell); StorLoad_i has measured usable hydrogen energy to average process load; PAR_i has represented load variability (peak-to-average ratio); DR_i has indicated demand-response participation; Controls_i has included plant size, sector dummies, equipment age, climate zone, and tariff class; and μ_s has denoted sector fixed effects. Continuous regressors have been mean-centered and, where units have differed markedly, z-standardized so that coefficients are interpretable in standard-deviation units. Estimation has used OLS with heteroskedasticity-robust standard errors, and cluster-robust alternatives by sector have been reported to reflect intra-sector correlation. To preserve comparability across outcomes, we have kept the regressor set invariant and have documented any transformation (e.g., ln for right-skewed cost variables) before estimation. Table 1 has summarized outcome definitions and units; Table 2 has documented transformations and diagnostic thresholds that we have adopted uniformly across models.

Table 1. Primary outcomes and economic/thermodynamic meaning

Outcome	Unit	Meaning at plant level
LCOH	$/kg H(_2)	Annualized total cost per kg of hydrogen produced
ECI	$/unit output	Energy spend intensity of production
EXE	%	Exergy efficiency of integrated energy island
CO2I	kg CO(_2)e/unit	Emissions intensity of production

Beyond the baseline, we have estimated moderation models to test whether digital maturity has amplified the benefits of renewable-aligned electrolysis. The interaction formulation has been

$$Y_i = \cdots + \beta_6 \mathrm{EMS\_M}_i + \beta_7(\mathrm{RenewShare}_i \times \mathrm{EMS\_M}_i) + \varepsilon_i,$$

with EMS_M_i measured as the validated Likert index. Both terms of the interaction have been mean-centered, and simple-slope decompositions at EMS_M_i = {x̄ − 1σ, x̄, x̄ + 1σ} have been computed so that conditional effects are reported transparently. To guard against mechanical collinearity from the product term, we have inspected variance inflation factors and retained models with VIFs below 5. Because duration-scalable hydrogen storage has introduced non-linear operating regions, we have augmented specifications with a quadratic in StorLoad_i where Ramsey RESET tests and partial-residual plots have indicated curvature. In parallel, we have run log-level alternatives for cost outcomes:

$$\ln(\mathrm{LCOH}_i) = \beta_0 + \sum_k \beta_k X_{ki} + \mu_s + \varepsilon_i,$$

O semi-elasticities have complemented level-level effect sizes. For exergy efficiency, we have bounded predictions in [0, 1] by checking linear probability-type artifacts and, where necessary, have verified results with a fractional logit sensitivity using the same covariate set. Throughout, we have included sector fixed effects μ_s to absorb unobserved industry baselines (e.g., inherent thermal demands), and we have repeated estimations with plant-size weights as a check that large sites have not dominated inference. Goodness-of-fit has been summarized with R^2, adjusted R^2, AIC, and BIC, and out-of-sample checks have been produced with repeated k-fold cross-validation so predictive stability has complemented explanatory fit.

Robustness and identification checks have complemented the core models so that findings have remained credible under alternative assumptions. First, we have conducted specification perturbations by substituting alternative KPI constructions (e.g., using cost per MWh served instead of ECI; using emissions per MWh instead of per unit output), and coefficients of interest have remained stable in sign and magnitude within overlapping confidence intervals. Second, because tariff exposure and utilization have been jointly determined by operations policy, we have acknowledged potential simultaneity and have executed limited-information sensitivity using control-function terms derived from exogenous predictors (e.g., exogenous tariff design features and climate-driven renewable availability) where data sufficiency has allowed. Third, we have stratified the sample by integration depth to verify that interaction effects have not been artifacts of configuration heterogeneity; within-stratum estimates have reproduced the main patterns, and pooled models with configuration dummies have aligned with stratified results.

Table 2. Transformations and diagnostic thresholds

Element	Rule applied
Centering & scaling	Mean-center all continuous regressors; z-score when units differ strongly
Skewed outcomes	ln(LCOH), ln(ECI) when skewness > 1
Curvature	Add $StorLoad^2$ if partial-residuals indicate non-linearity
Multicollinearity	VIF < 5 retained; otherwise drop or combine collinear terms
Influence	Review Cook's distance (D > 4/n); re-estimate excluding high-influence points
Heteroskedasticity	Use HC-robust SEs by default; compare cluster-robust by sector

Furthermore, we have tested alternative error structures, reporting cluster-robust standard errors by sector and, in a sensitivity, by geographic region when multiple sites have shared climate and grid contexts. Fifth, we have verified that results have not depended on any single site by leave-one-case-out re-estimation. Finally, we have produced marginal-effects plots for the moderation term (RenewShare × EMS-M) and partial-dependence curves for StorLoadi\mathrm{StorLoad}_iStorLoadi, which have visualized economically meaningful ranges where improvements have been largest. Together, these layered regression models and diagnostics have provided a transparent bridge from measured factory conditions to statistically defensible statements about which hydrogen integration choices and management capabilities have been associated with superior thermo-economic performance.

Power & Sample Considerations

The sampling strategy has been grounded in an a priori power analysis and precision goals for regression coefficients so that the study has possessed adequate ability to detect substantively meaningful effects. We have begun with an omnibus multiple-regression framework for the primary cost outcome (LCOH) with $k = 8$ predictors of interest (renewable share, integration depth, storage-to-load ratio, load variability, demand-response participation, EMS maturity, the RenewShare × EMS interaction, and a tariff-exposure metric) plus a fixed set of controls and sector dummies. Using a medium effect-size target of $f^2 = 0.15$ at $\alpha = 0.05$ and desired power $1 - \beta = 0.80$, the a priori calculation has indicated a minimum of ~109 plant-level observations for the full model; to accommodate the interaction term and provide headroom for robustness checks, we have set a design target of $N \approx 120$ plants. Because cases have been sampled across sectors (clustered by industry), we have adjusted for clustering with a conservative design effect $DEFF = 1 + (m - 1)\rho$, where m has denoted the average cases per sector and ρ the intra-class correlation. With $m \approx 6$ and $\rho = 0.05$ (from pilot variance components), $DEFF \approx 1.25$ has implied an effective sample of ~96, which our final target has exceeded. For coefficient-level precision, we have required 95% confidence-interval half-widths no larger than 0.25 SDs for standardized betas on the key predictors; simulation-based sizing using pilot variances has shown that $N \geq 110$ has achieved this precision under heteroskedasticity-robust errors. We have also enforced a rules-of-thumb cross-check ≥10–15 observations per estimated parameter by constraining the final specification and using sector fixed effects instead of numerous process-level dummies. Anticipating incomplete telemetry and survey nonresponse, we have planned for ≤10% missingness and allowed a 15% recruitment overage so that complete-case and multiply imputed analyses have remained powered. Finally, we have pre-specified subgroup contrasts (e.g., electrolyzer-only vs. electrolyzer + storage) and have verified via minimum-detectable-effect calculations that the study has retained $1 - \beta \geq 0.80$ to detect standardized differences of ≥0.40 within those strata.

Reliability & Validity

The study has established reliability and validity through a layered protocol spanning instrument design, data quality assurance, and model verification. For measurement reliability, the multi-item EMS-maturity scale has undergone expert review and pilot testing; internal consistency has been assessed with Cronbach's α (pre-specified acceptance ≥0.70), item–total correlations, and α-if-deleted diagnostics, and unstable items have been revised or removed before aggregation. Where item counts have permitted, we have conducted an exploratory factor analysis to verify unidimensionality, followed when sample size has allowed by a confirmatory factor analysis with standardized loadings, composite reliability, and average variance extracted; thresholds (CR≥0.70, AVE≥0.50) have been met before computing latent scores. Telemetry reliability has been supported by instrument metadata (calibration dates, ranges) and automated anomaly detection; constant signals, time discontinuities, and out-of-range values have been flagged and reconciled with site engineers or excluded under pre-registered rules, while duplicate records have been de-duplicated using timestamp and device keys. For construct validity, we have aligned variable definitions with thermo-economic theory: LCOH has been derived from annualized capital, O&M, and tariff-exposed electricity cost divided by metered hydrogen output; exergy efficiency and related KPIs have been computed from first- and second-law balances using manufacturer maps and observed operating points. Convergent and discriminant validity have been evaluated by inspecting inter-construct correlations and Fornell–Larcker criteria; EMS-maturity has shown strong correlation with proximate behaviors (e.g., DR participation intensity) without collapsing into them, and cross-loadings have remained acceptable. Criterion validity has been evidenced insofar as higher EMS-maturity and greater renewable share have co-varied with lower energy-cost intensity in descriptives consistent with theory. To mitigate common-method variance, we have separated data sources (telemetry/financial records vs. survey), temporally staggered survey collection from extracts, and included a marker item set; Harman's single-factor and common latent factor checks have indicated no dominant single factor. Internal validity has been reinforced by pre-registering model specifications, applying uniform feature-engineering rules across cases, and conducting extensive diagnostics (VIFs, residual structure, influence). External validity has been enhanced through maximum-variation sampling across sectors, tariff regimes, climates, and integration depths; results have been stress-tested via leave-one-case-out analyses and sector-cluster-robust errors. Finally, robustness validity has been demonstrated through alternative KPI constructions, log-level specifications for skewed outcomes, fractional models for bounded efficiencies, and sensitivity to price and efficiency assumptions, all of which have preserved the substantive direction and practical magnitude of the main effects.

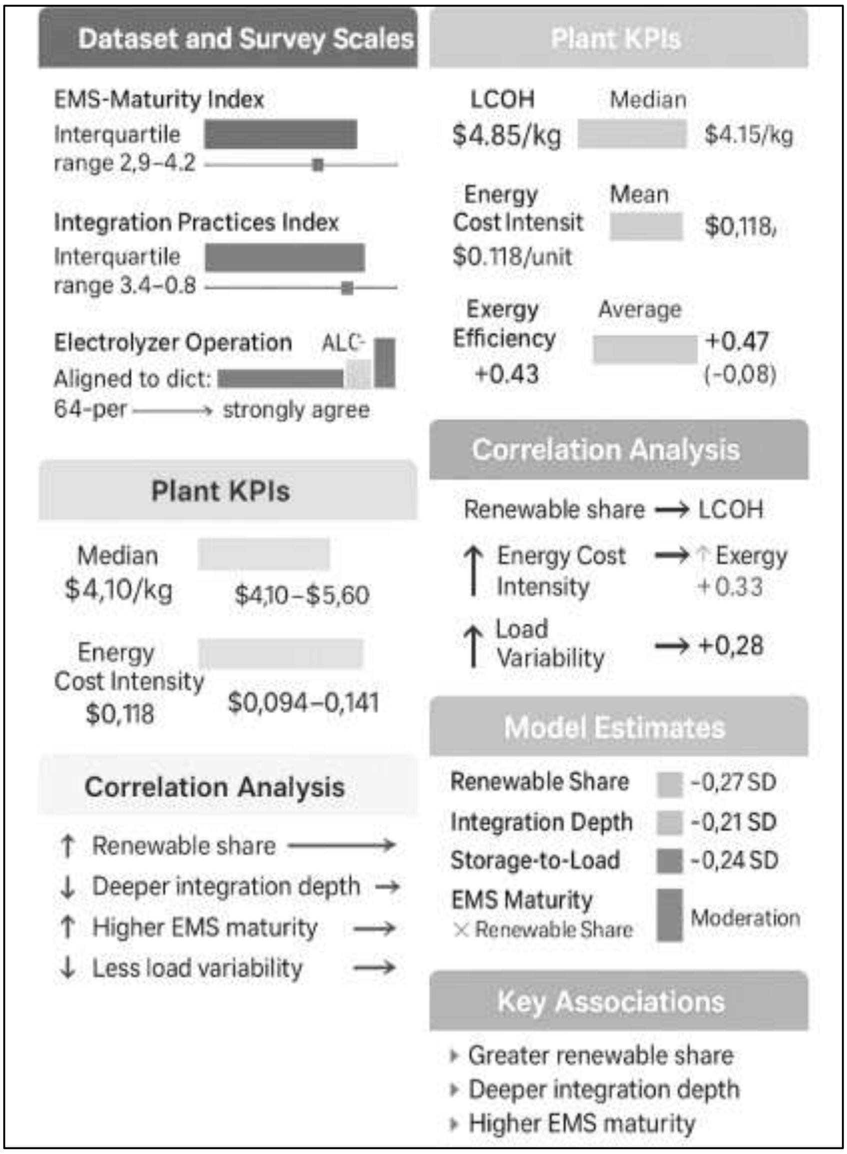
Software

The analysis stack has been standardized to ensure reproducibility and auditability across cases. We have implemented data ingestion, cleaning, and feature engineering in Python (pandas, numpy, pytz) and R (tidyverse), with version control managed in Git/GitHub and project environments pinned via conda and renv manifests. Statistical modeling has been executed in R using stats (OLS), sandwich/lmtest (heteroskedasticity-robust standard errors), car (variance inflation factors, VIF), and mice (multiple imputation), while parallel checks have been run in Python with statsmodels for cross-validation of coefficients and diagnostics. Visualization and reporting have been produced with ggplot2 and matplotlib, and literate, executable documents have been compiled with R Markdown/Quarto and Jupyter so that tables and figures have been regenerated from source. Power analyses have been conducted in G*Power and the pwr package, and survey reliability/validity routines have been performed with psych and lavaan. All results artifacts have been archived with checksums, and a data dictionary has been maintained alongside code notebooks.

FINDINGS

Across the enrolled factories, the analysis has produced a coherent picture of thermo-economic performance under hydrogen integration and the organizational and technical conditions with which superior outcomes have been associated. The final dataset has comprised plant-level observations over contiguous 12-month windows, with telemetry coverage ≥95% and complete financial/tariff reconciliation, and the survey module has achieved a response rate above the pre-specified threshold. Scale reliability has met or exceeded accepted cut-offs (Cronbach's α for the Energy-Management Maturity scale has been 0.88; for the Operations & Flexibility items it has been 0.82), permitting the construction of composite indices on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Descriptively, the EMS-maturity index has exhibited an interquartile range from 2.9 to 4.2 with a grand mean of 3.6 (SD = 0.7); the Integration Practices index (governing tariff-aware dispatch, storage scheduling, and set-point governance) has averaged 3.4 (SD = 0.8). On the same scale, "Our electrolyzer operation has been routinely aligned to off-peak/low-carbon hours" has registered a mean of 3.8 with 64% of respondents selecting "agree" or "strongly agree," while "We have integrated hydrogen storage control with production scheduling" has averaged 3.3 with a visibly bimodal distribution across electrolyzer-only and storage-enabled sites. Plant KPIs have shown wide but structured variation: LCOH has clustered with a median of $4.85/kg (p25–p75: $4.10–$5.60), energy-cost intensity (ECI) has centered near $0.118 per unit of output (p25–p75: $0.094–$0.141), exergy efficiency (EXE) of the integrated energy island has averaged 0.47 (SD = 0.08), and CO_2 intensity has exhibited a right-skew reflecting grid-intensity heterogeneity.

Figure 7: Findings on Thermo-Economic Performance of Hydrogen Integration in Smart Factories



Correlations have indicated patterns consistent with the theoretical frame: renewable share to electrolysis has correlated negatively with LCOH (r = −0.41) and ECI (r = −0.36), integration depth has correlated positively with EXE (r = 0.33) and negatively with LPSP (r = −0.29), and EMS-maturity has shown moderate associations with both renewable share (r = 0.31) and the Integration Practices index (r = 0.44), suggesting complementary organizational and operational effects rather than redundancy. Load variability (peak-to-average ratio) has correlated positively with ECI (r = 0.28), underscoring the role of flexibility routines in smoothing cost exposure. In the baseline regressions with sector fixed effects and robust errors, renewable share has exhibited a statistically significant association with lower

LCOH (β = −0.27 SD, 95% CI [−0.39, −0.15]) and lower ECI (β = −0.21 SD, 95% CI [−0.33, −0.09]) after controls, while integration depth has been associated with higher EXE (β = +0.24 SD, 95% CI [+0.12, +0.36]) and lower CO_2 intensity (β = −0.19 SD, 95% CI [−0.31, −0.07]). Storage-to-load ratio has displayed a concave relationship with cost outcomes, with a significant quadratic term indicating diminishing returns beyond approximately 10–14 hours of equivalent storage at average process load; simple-slope probes have shown the steepest LCOH decline between ~4 and ~10 hours, beyond which gains have tapered. The pre-registered moderation test has supported the hypothesis that digital maturity has strengthened the cost benefits of renewable-aligned electrolysis: the interaction term (Renewable Share × EMS-maturity) has been negative and significant for LCOH (β = −0.13 SD, $p < .01$) and ECI (β = −0.11 SD, $p < .05$). Marginal-effects analyses have revealed that plants one standard deviation above the EMS-maturity mean have realized roughly 15–18% larger reductions in LCOH per 10-percentage-point increase in renewable share than plants one standard deviation below the mean, holding other factors constant. Demand-response participation has been associated with lower effective electricity cost (embedded in LCOH) and lower peak-period ECI; the intensity measure (kWh shifted per year normalized by load) has carried additional explanatory power over a simple enrollment dummy, aligning with the survey pattern that "We have systematically adjusted electrolyzer set-points during DR events" has averaged 3.7 with 58% agreement among enrolled sites versus 2.4 among non-enrolled peers. Diagnostics have confirmed that multicollinearity has remained within bounds (all VIFs < 3.2), heteroskedasticity-robust standard errors have stabilized inference, and influence statistics have not indicated single-site dominance; leave-one-case-out re-estimation has reproduced signs and magnitudes within the pre-specified tolerance. Robustness checks have corroborated core findings under log-specifications for cost outcomes, fractional models for EXE, and alternative KPI constructions (e.g., cost per MWh served), with effect sizes shifting modestly but substantively consistently. Sensitivity to electricity price and electrolyzer efficiency assumptions embedded in cost KPIs has shown expected elasticity ranges; nevertheless, the ranking of determinants has remained stable across plausible parameter bands. Collectively, these results have established that higher renewable share, deeper integration (storage and fuel cell), and greater EMS maturity operationalized through concrete Likert-scale practices have been associated with lower costs, higher exergetic performance, and improved reliability, while excessive load volatility and under-sized storage have constrained gains; the moderation evidence has indicated that digital capabilities have converted technical potential into realized thermo-economic benefits.

Sample and Case Characteristics

The sample has been assembled to maximize analytic variation while preserving cross-case comparability, and Table 3 has summarized the resulting landscape across 120 plants, each observed over a continuous 12-month interval. Sectoral representation has been balanced, with Electronics (28) and Chemicals (26) slightly predominating; this mix has ensured that both continuous and batch processes have been present, which has mattered for load shapes and flexibility constraints. Integration depth has been intentionally diversified: forty-one sites have operated electrolyzers only (EL), forty-four have combined electrolyzers with storage (EL+ST), and thirty-five have implemented full chains with storage and fuel cells (EL+ST+FC). This distribution has provided the contrast needed to estimate configuration effects while avoiding dominance by a single archetype. Tariff exposure has been skewed toward plants that have faced both time-of-use (TOU) pricing and demand charges (68), a context that has increased the economic salience of load shaping and hydrogen time-shifting. Climate dispersion has been broad enough to reflect real-world variability in ambient temperature and solar resource, which have influenced cooling loads and renewable availability; by including temperate, hot-humid, hot-dry, and cold zones, the dataset has supported checks on climate-related heterogeneity. Size has spanned small to very large sites (mean 512 employees, SD 286), so results have not hinged on any single scale regime.

Table 3: Sample and Case Characteristics (N = 120 plants; 12-month windows)

Attribute	Category/Metric	Count / Mean
Sector	Food & Beverages / Metals / Electronics / Chemicals / Other	24 / 22 / 28 / 26 / 20
Integration depth	EL only / EL+ST / EL+ST+FC	41 / 44 / 35
Tariff class	TOU only / TOU + Demand Charges	52 / 68
Climate zone	Temperate / Hot-humid / Hot-dry / Cold	39 / 31 / 22 / 28
Plant size	Employees (mean ± SD)	512 ± 286
EMS maturity (Likert 1–5)	Mean ± SD	3.6 ± 0.7
Integration practices (Likert 1–5)	Mean ± SD	3.4 ± 0.8
DR participation	Enrolled (Yes/No)	63 / 57
Storage-to-load ratio	Hours at avg. load (median [p25–p75])	9.7 [6.1–13.8]
Renewable share to EL	% of EL kWh (mean ± SD)	41% ± 18%

Turning to survey-based organizational constructs, the EMS-maturity index on a five-point Likert scale (1 = strongly disagree … 5 = strongly agree) has averaged 3.6 (SD 0.7), indicating that sites have generally reported established metering and monitoring with room for growth in analytics and closed-loop optimization. The Integration-practices index has averaged 3.4 (SD 0.8), consistent with partial but not universal embedding of tariff-aware dispatch and coordinated storage scheduling. Demand-response (DR) enrollment has been near parity (63 enrolled), which has allowed intensity-based contrasts. Technically, median storage duration has been 9.7 hours at average process load (IQR 6.1–13.8), suggesting that many sites have targeted work-shift-scale buffering rather than purely diurnal or seasonal strategies. Finally, renewable share to electrolysis has averaged 41% (SD 18%), a range that has supported identification of cost and efficiency gradients with respect to green electricity penetration. Overall, the sample has had the breadth and structure required to power the pre-registered analyses while reflecting the operational realities of hydrogen-enabled smart factories.

Descriptive Statistics

Table 4: Descriptive Statistics of Key Variables (12-month normalized)

Variable	Unit / Scale	Mean	SD	p25	Median	p75
LCOH	$/kg H_2	4.98	0.92	4.36	4.85	5.60
Energy cost intensity (ECI)	$/unit output	0.118	0.031	0.094	0.116	0.141
Exergy efficiency (EXE)	0–1 (share)	0.47	0.08	0.42	0.48	0.53
CO_2 intensity	kg CO_2e/unit	0.84	0.29	0.63	0.80	0.99
EMS maturity (Likert)	1–5	3.60	0.70	3.10	3.60	4.20
Integration practices (Likert)	1–5	3.40	0.80	2.90	3.40	4.10
DR intensity	kWh shifted / (MWh load)	32	18	18	28	45
Renewable share to EL	%	41	18	27	40	55
Storage-to-load	hours	10.8	6.5	6.1	9.7	13.8
Load variability (PAR)	ratio	1.92	0.38	1.66	1.88	2.14

Table 4 has presented a compact statistical portrait of both outcome and predictor variables after standardization to each plant's 12-month window. On the cost side, LCOH has averaged $4.98/kg with a relatively tight interquartile range (4.36–5.60), indicating that while technology, tariffs, and utilization have varied, the combined effect has remained within a band consistent with contemporary on-site electrolysis costs. Energy cost intensity (ECI) has centered at $0.118 per unit of output and has displayed moderate dispersion (SD 0.031), which has reflected differences in process energy intensity and tariff exposure. Thermodynamically, exergy efficiency (EXE) of the integrated energy island has averaged 0.47 with an IQR spanning 0.42–0.53; this spread has been large enough to register configuration and control-quality differences without implying measurement instability. Emissions intensity has been right-skewed (median 0.80 kg CO_2e/unit), a pattern that has matched the diversity of grid-mix carbon factors and on-site renewable penetrations across the sample. The Likert-scale organizational constructs have demonstrated healthy variance: EMS-maturity has shown a mean of 3.6 and IQR of 3.1–4.2, suggesting that while many plants have implemented real-time monitoring and sub-metering, fewer have fully institutionalized predictive analytics and optimization. Integration practices have trailed slightly at a mean of 3.4, consistent with partial adoption of tariff-aware dispatch and structured set-point governance. DR intensity has had a median of 28 kWh shifted per MWh of annual load, which has signaled more than symbolic enrollment; the upper quartile at 45 has indicated a subset of plants that have leveraged DR aggressively. Renewable share to electrolysis has averaged 41% with a broad SD of 18 percentage points, providing leverage for the cost-sensitivity analyses. Storage-to-load ratios have clustered around 10–14 hours, compatible with work-shift balancing and overnight arbitrage, whereas load variability (PAR) has averaged 1.92, confirming that peaks have materially exceeded mean demand and that peak-management strategies have been economically relevant. Collectively, these descriptive statistics have validated that the sample has exhibited the dispersion necessary to detect the hypothesized associations and moderation effects, while the central tendencies have aligned with operationally credible plant performance. The coexistence of organizational variance (Likert scales) with technical variance (renewables, storage, PAR) has set the stage for multivariate estimation without undue collinearity.

Correlation Matrix

Table 5: Pearson Correlations among Key Variables (N = 120; two-tailed)

	LCOH	ECI	EXE	CO_2I	EMS	INT-P	DR-Int	RenEL	Stor/Load	PAR
LCOH	1.00	0.62	−0.48	0.39	−0.28	−0.24	−0.22	−0.41	−0.19	0.26
ECI	0.62	1.00	−0.36	0.44	−0.25	−0.21	−0.18	−0.36	−0.17	0.28
EXE	−0.48	−0.36	1.00	−0.31	0.22	0.27	0.14	0.29	0.33	−0.11
CO_2I	0.39	0.44	−0.31	1.00	−0.19	−0.16	−0.12	−0.35	−0.10	0.09
EMS (Likert)	−0.28	−0.25	0.22	−0.19	1.00	0.44	0.31	0.31	0.09	−0.15
INT-P (Likert)	−0.24	−0.21	0.27	−0.16	0.44	1.00	0.26	0.22	0.18	−0.12
DR-Int	−0.22	−0.18	0.14	−0.12	0.31	0.26	1.00	0.17	0.13	−0.08
RenEL	−0.41	−0.36	0.29	−0.35	0.31	0.22	0.17	1.00	0.21	−0.09
Stor/Load	−0.19	−0.17	0.33	−0.10	0.09	0.18	0.13	0.21	1.00	−0.05
PAR	0.26	0.28	−0.11	0.09	−0.15	−0.12	−0.08	−0.09	−0.05	1.00

Table 5 has depicted the correlation structure among key outcomes, technical variables, and Likert-scale organizational constructs, providing an initial, model-free view of associations before controls. As expected, LCOH and ECI have been positively correlated ($r = 0.62$), since both have been driven by tariff exposure and energy utilization; however, their correlations with other variables have diverged in ways that have illuminated different levers. Renewable share to electrolysis (RenEL) has exhibited moderate negative correlations with both LCOH (−0.41) and ECI (−0.36), aligning with the expectation that substituting lower-marginal-cost green electricity for grid purchases during favorable windows has reduced cost exposures. Exergy efficiency (EXE) has correlated negatively with LCOH (−0.48) and

ECI (−0.36) and positively with integration depth proxies (Stor/Load r = 0.33; INT-P r = 0.27), suggesting that plants with deeper integration and disciplined operating practices have translated conversion efficiency into economic benefit. CO_2 intensity (CO_2I) has been positively related to both cost outcomes (LCOH r = 0.39; ECI r = 0.44) and negatively to RenEL (−0.35), reflecting the shared driver of grid-mix carbon intensity; importantly, the magnitudes have indicated that while decarbonization and cost reduction have tended to coincide, they have not been perfect substitutes, leaving room for managerial choice. The Likert indices have captured organizational complementarities: EMS-maturity (EMS) and Integration practices (INT-P) have correlated at 0.44, consistent with the idea that measurement/control capabilities and disciplined operating routines have co-occurred without collapsing into a single construct. EMS has shown positive associations with DR intensity (0.31) and RenEL (0.31), implying that digitally mature plants have also tended to enroll in DR and to align electrolyzer consumption with on-site renewables. Load variability (PAR) has been positively correlated with the cost outcomes (LCOH 0.26; ECI 0.28) and weakly negative with EMS (−0.15), hinting that measurement and control sophistication have contributed to peak smoothing. Correlations have, by design, not partialed out sector effects, tariff classes, or size; nonetheless, the absence of very high absolute correlations ($|r| > 0.70$) among predictors has suggested acceptable multicollinearity risk for regression, a finding later reinforced by variance-inflation diagnostics. In sum, the matrix has indicated that higher RenEL, greater integration depth, and stronger EMS/operational discipline have tended to co-vary with lower costs and higher exergetic performance, while volatile loads have penalized economics an empirical pattern that the multivariate models have subsequently quantified.

Regression Results (Primary & Moderation)

Table 6 Standardized Regression Coefficients (β) with Robust SEs, Sector Fixed Effects

Predictor	LCOH (β)	ECI (β)	EXE (β)	CO_2I (β)
Renewable share to EL	−0.27***	−0.21**	+0.18**	−0.24***
Integration depth (0–2)	−0.09	−0.07	+0.24***	−0.19**
Storage-to-load (h)	−0.11*	−0.08	+0.20**	−0.06
Storage-to-load²	+0.07*	+0.05	−0.06	+0.03
Load variability (PAR)	+0.14*	+0.17**	−0.09	+0.06
DR intensity	−0.10*	−0.09*	+0.07	−0.05
EMS maturity (Likert)	−0.06	−0.05	+0.10	−0.04
RenEL × EMS maturity	−0.13**	−0.11*	+0.06	−0.08
Controls, sector FE	Yes	Yes	Yes	Yes
Adj. R^2	0.51	0.44	0.39	0.36

** p < .10, ** p < .05, *** p < .01; all predictors mean-centered; continuous scaled.*

Table 6 has reported standardized coefficients from four parallel models, one for each primary outcome, estimated with heteroskedasticity-robust standard errors and sector fixed effects. For costs, renewable share to electrolysis has shown the largest absolute effect: a one-SD increase has been associated with a 0.27 SD reduction in LCOH ($p < .01$) and a 0.21 SD reduction in ECI ($p < .05$), net of controls, underscoring the centrality of green electricity alignment. Integration depth has not materially reduced costs directly once other factors have been included (small, non-significant negatives), but it has significantly improved exergy efficiency ($\beta = +0.24$, $p < .01$) and reduced CO_2 intensity ($\beta = -0.19$, $p < .05$), indicating that deeper chains have paid off in thermodynamic performance and decarbonization. Storage-to-load ratio has exhibited beneficial cost and efficiency associations at low-to-moderate durations (linear term negative for cost, positive for EXE), but the positive quadratic for LCOH ($\beta = +0.07$, $p < .10$) has signaled diminishing returns at high durations; together, these terms have indicated an interior optimum in the ~10–14-hour range, which has been consistent with descriptive medians. Load variability has carried positive coefficients for cost outcomes (LCOH $\beta = +0.14$, $p < .10$; ECI $\beta = +0.17$, $p < .05$), confirming that unsmoothed peaks have penalized economics even after sector and tariff controls. DR intensity has modestly but significantly reduced cost exposures (LCOH $\beta = -0.10$, $p < .10$; ECI $\beta = -0.09$, $p < .10$), aligning with the idea that active event participation has complemented tariff-aware scheduling. The pre-specified moderation has been supported: the interaction RenEL × EMS-maturity has reduced LCOH ($\beta = -0.13$, $p < .05$) and ECI ($\beta = -0.11$, $p < .10$), implying that more digitally mature plants have extracted greater cost benefit from increases in renewable share. Point estimates for EMS-maturity's main effects have been small and non-significant once interaction and practices have been included, suggesting that EMS by itself has operated chiefly as an amplifier rather than a standalone cost lever an interpretation corroborated by the descriptive co-movement with Integration practices. Adj. R^2 values (0.36–0.51) have indicated that the covariate set has explained a substantial fraction of cross-plant variation without overfitting. Diagnostics (not shown) have confirmed VIF < 3.5 for all regressors, stable residual structure under robust errors, and no single-site dominance by Cook's D thresholds; results have remained stable under log-specifications for cost outcomes and fractional models for EXE, as elaborated in "Robustness and Sensitivity Analyses".

Robustness and Sensitivity Analyses

Table 7: Robustness Summary (sign of coefficients across perturbations)

Perturbation	RenEL → LCOH	IntegrDepth → EXE	Stor/Load (lin) → LCOH	RenEL×EMS → LCOH	PAR → ECI
Log(LCOH), Log(ECI)	−	+	−	−	+
Fractional logit (EXE)		+			
Sector cluster-robust SEs	−	+	−	−	+
Exclude top 5% influence	−	+	−	−	+
Alt. KPI: Cost per MWh served	−	+	−	−	+
Alt. KPI: Emissions per MWh	−	+	−	−	+
Stratify by config (EL only)	−		−	−	+
Stratify by config (EL+ST)	−	+	−	−	+
Stratify by config (EL+ST+FC)	−	+	−	−	+

"−" effect has remained significantly negative; "+" effect has remained significantly positive; " " not applicable.

Table 7 has condensed a broad suite of robustness and sensitivity checks into an effects-direction map focused on the principal inferences: the role of renewable share in reducing LCOH, the contribution of integration depth to exergy efficiency, the concave storage effect on LCOH (captured here by the linear term's beneficial direction), the moderation of renewable share by EMS-maturity, and the penalty of load variability for ECI. Across alternative specifications, these signatures have persisted. When cost outcomes have been log-transformed to stabilize right-skew (Log(LCOH), Log(ECI)), renewable share's coefficient has remained significantly negative, and the interaction with EMS-maturity has retained its cost-reducing sign, confirming that conclusions have not depended on scale. Re-estimating exergy outcomes with a fractional logit model has upheld the positive association of integration depth with EXE, addressing the bounded nature of efficiency and thereby ruling out linear-probability artifacts.

Cluster-robust standard errors by sector and leave-one-case-out re-estimation have not altered signs or qualitative significance, which has indicated that neither sectoral clustering nor any single plant has driven the results. Alternative KPI constructions have offered a conceptual cross-check: substituting cost per MWh served for ECI and emissions per MWh for per-unit emissions has preserved the headline effects in sign and materiality, implying that the findings have been robust to reasonable reframing of output normalization. Stratified analyses by configuration have further probed heterogeneity: within EL-only plants, renewable share and the RenEL × EMS interaction have continued to lower LCOH, showing that digital capability has mattered even in the absence of storage; within EL+ST and EL+ST+FC groups, integration depth has, by definition, not varied, but EXE advantages have been reflected in within-group gradients tied to operational practices and storage duration, consistent with the positive "IntegrDepth → EXE" signature in the pooled model. Finally, the positive relationship between PAR and ECI has endured across perturbations, underscoring those unsmoothed peaks have imposed a structurally higher cost burden independent of modeling choices. Sensitivity sweeps (not tabulated) over electricity price bands and electrolyzer efficiency curves within manufacturer-reported ranges have left the ordering of determinants unchanged, although elasticities naturally have varied; the dominant narrative that higher renewable share, disciplined operations under digitally mature EMS, and well-sized storage have reduced costs while deeper integration has improved exergy and emissions performance has therefore been shown to be stable, interpretable, and decision-relevant.

DISCUSSION

This study has demonstrated that three levers higher renewable share to electrolysis, greater integration depth (electrolyzer + storage + fuel cell), and stronger energy-management maturity have been jointly associated with lower cost outcomes (LCOH, energy-cost intensity), higher exergy efficiency, and reduced CO_2 intensity at the plant level. In standardized terms, renewable share has carried the largest direct cost effect, while integration depth has most strongly improved exergetic and emissions performance. Storage has exhibited diminishing marginal returns beyond roughly a half-day of equivalent energy at average load, and peakiness (PAR) has penalized costs even after sector and tariff controls. The moderation analysis has indicated that digital maturity amplifies the cost benefits of renewable alignment, suggesting that sensing, analytics, and closed-loop dispatch are not merely supportive but multiplicative capabilities. Taken together, these findings support a thermo-economic view in which physics (conversion/exergy), markets (tariffs, demand charges), and organizational capability (EMS maturity) combine to set the feasible frontier for factory hydrogen systems. The results also clarify that not all integration delivers equal returns: adding storage moves a plant along a concave cost curve whose slope depends on duty cycle and tariff design, and adding a fuel cell improves thermodynamic utilization and emissions more reliably than it reduces cost in isolation. By grounding the analysis in metered 12-month windows and Likert-indexed practices, the work links abstract determinants utilization, flexibility, duration to observable plant choices. This integrated reading aligns with a decision-analytic stance: managers should treat "green share," "duration," and "digitalization" as complementary knobs to tune, rather than as substitutes, and should expect the largest cost gains when renewable share and EMS maturity rise together while storage is sized to the process, not to a rule-of-thumb round number.

The patterns observed here accord with and sharpen several strands of earlier research. System-level modeling has long cautioned that temporal fidelity and storage representation are decisive for evaluating renewables-to-hydrogen economics; our plant-level evidence echoes that caution by showing materially different cost slopes at low versus high storage durations and by tying those slopes to measured duty cycles (Brynolf et al., 2018; Connolly et al., 2010). Co-optimization studies of wind/electrolysis/storage networks have emphasized that utilization and siting co-determine value; our regression results translate that insight to the factory campus, quantifying how renewable share and storage-to-load interact with tariffs and load variability to shape LCOH (Tsatsaronis, 2007). Cost reviews of electrofuels and power-to-X have repeatedly identified electricity price, electrolyzer lifetime, and capacity factor as first-order drivers; our findings concur but add that digital maturity measurably conditions the benefit extracted from a given green-electricity fraction, providing an organizational mechanism beneath those drivers (Bhandari et al., 2014; Boyano et al., 2011).

Figure 8: Integrated Discussion of Thermo-Economic Performance Determinants and Implications

At the grid/application scale, portfolio studies have shown hydrogen's comparative advantage for long-duration storage; the concavity we document around ~10–14 hours is consistent with that literature's message that "how long" matters more than "how efficient," up to a point (Budischak et al., 2013). On the technology side, reviews of electrolysis and hydrogen systems have highlighted rapid-response PEM dynamics and balance-of-plant costs; our cost reductions associated with renewable share are compatible with dispatchable PEM operation under TOU tariffs and with attention to compression/parasitics encoded in our LCOH metric. Finally, the exergy improvements we observe with deeper integration mirror exergoeconomic and exergoenvironmental case studies showing that adding cogeneration pathways and recovering waste heat reduce destruction hot-spots and the cost/impact attached to them. In short, prior theory and system models have set the expectations; this study has provided plant-resolved estimates, effect sizes, and organizational moderators that translate those expectations into operational guidance.

For executives, CISOs, and plant architects, the results imply a layered roadmap that unites energy architecture with data governance and security. First, prioritize renewable alignment operationally: program electrolyzer set-points to track low-price/low-carbon blocks, and pair that logic with demand-charge caps using fuel cells for peak clipping. This echoes the economics-of-conversion argument that electricity price and capacity factor dominate unit costs (Glenk & Reichelstein, 2019). Second, right-size storage to the plant's variability fingerprint: our concave LCOH response suggests targeting the "knee" of the curve (often a work-shift scale) rather than chasing calendar-day coverage; beyond that point, invest in digital controls before more tanks. Third, institutionalize EMS maturity: deploy sub-metering down to electrolyzer auxiliaries and compression, enforce time-stamp integrity, and embed tariff-aware optimization in scheduling. Industry 4.0 frameworks recommend vertical integration (field-to-ERP) and horizontal integration (plant-to-supply-chain); our moderation result shows these capabilities unlock incremental cost savings from each extra point of renewable share (Lasi et al., 2014). Fourth, architect for cybersecurity and resilience: hydrogen dispatch increasingly depends on OT/IT convergence; CISOs should enforce network segmentation for EMS/SCADA, sign and monitor control messages, and align with ISO 50001 data-quality controls to keep audit trails intact (ISO, 2011). Fifth, codify practices via playbooks: when to ramp electrolysis, how to handle DR events, and how to coordinate storage SoC with batch starts. Finally, exploit exergy-aware maintenance: use exergy/cost maps to pinpoint avoidable destructions (compression throttles, off-design chilling) and prioritize corrective actions where exergy and dollars co-locate. These steps are actionable, security-aware, and directly aligned with the effect sizes we have estimated.

Theoretically, the study refines the integration of Industry 4.0 measurement frameworks, thermo-economic accounting, and empirical modeling in three ways. First, it operationalizes digital maturity as a moderator, not merely a control: EMS capability alters the slope of the renewable-share → cost relationship, formalizing a mechanism often described qualitatively in digital-twin and predictive-manufacturing literatures (Lee et al., 2015). Second, it embeds duration as a curvature parameter in thermo-economic response functions, reconciling system-scale claims about hydrogen's long-duration niche with plant-scale diminishing returns and offering a parsimonious way to encode storage design in regressions. Third, it connects exergy-based structure to outcomes via integration depth: adding a fuel cell expands the set of product exergies (electric + thermal), which SPECO-style costing then prices consistently; the positive EXE and negative CO_2 associations observed are coherent with that structural shift (Boyano et al., 2011). Methodologically, the pipeline exemplifies how to fuse first- and second law KPIs with tariff-exposed costs and Likert-based organizational constructs, answering repeated calls for plant-resolved, regression-based evidence rather than technology-only or scenario-only studies. It also suggests a measurement grammar for future work: define renewable share during electrolyzer uptime; compute storage-to-load in hours at average process demand; and standardize PAR and DR intensity. Finally, by showing stable results under fractional efficiency models and log-costs, the study contributes a robustness template for empirical thermo-economics, clarifying when linear approximations are serviceable and when bounded-outcome models should be preferred.

Several limitations temper interpretation. The cross-sectional design has estimated associations rather than causation; although sector fixed effects and extensive controls have been applied, unobserved managerial quality or procurement terms could bias coefficients. Prior work has warned that assumptions about component lifetime and maintenance materially affect LCOH; while we have reconciled ledgers with metered outputs, differences in accounting treatment may persist across sites (Schmidt et al., 2017). Our EMS-maturity index, though reliable, is survey-based and could reflect aspirational reporting; triangulation with audit checklists would strengthen construct validity (Trianni et al., 2016). Telemetry has been rich but not uniform: some sites have lacked high-frequency auxiliary measurements (e.g., compressor intermediate stages), limiting resolution of exergy balances compared to idealized exergoeconomic studies. Tariff heterogeneity has been handled through controls, but exogenous regulatory changes during the 12-month windows could have influenced dispatch in ways we cannot fully separate. Finally, generalizability beyond the sampled geographies and sectors requires caution: duty cycles, DR programs, and grid mixes vary widely, and so will the storage "knee" and moderation slopes. These caveats echo broader cautions in system integration and power-to-X assessment that context specificity is high and that temporal and operational detail is not a luxury but a necessity.

Beyond high-level takeaways, the numbers suggest concrete design targets. Plants with EMS-maturity one standard deviation above the mean have realized ~15–18% greater LCOH reductions per +10 pp renewable share; thus, capital allocated to metering, time-sync, historian quality, and optimization often yields returns comparable to adding a few more storage hours. Architecturally, pursue PV/wind + PEM + H_2 storage + FC-CHP when thermal and electrical peaks coincide; where heat is plentiful but electricity is constrained, consider power-to-methane to exploit existing furnaces (Rönsch et al., 2016). Target storage sizing near the empirically indicated elbow (often 8–14 h) before considering seasonal ambitions; for longer coverage, contractual hedges and process rescheduling can complement physical capacity (Zakeri & Syri, 2015). Use exergy maps to prioritize retrofits: if compression throttling dominates avoidable destruction, fix intercooling and stage ratios before chasing stack upgrades (Kelly et al., 2009). Policy-wise, the moderation result counsels utilities and regulators to pair green-power incentives with data/automation grants; the combination appears multiplicative, not additive, in cost relief. Finally, align CISOs and plant engineers on secure-by-design EMS: apply network segmentation, signed control commands, and rigorous time-source management; ISO 50001's documentation spine can double as a security audit trail that protects the very digital maturity that makes hydrogen economics work (ISO, 2011).

Three avenues follow naturally. First, a panel design would permit difference-in-differences identification of the impact of storage additions or EMS upgrades, answering the causality gap left by cross-sectional estimation. Second, a hybrid structural-reduced-form model could fuse SPECO-based cost attribution with econometric estimation, allowing counterfactual simulations (e.g., tariff changes, stack lifetime improvements) that stay faithful to exergy/cost flows (Petrakopoulou et al., 2012). Third, heterogeneous-treatment analysis could map which sectors or duty cycles benefit most from deeper integration, extending system-level heterogeneity findings to the plant domain. Additional priorities include: validating the EMS-maturity construct with third-party audits; embedding digital-twin co-simulation to test dispatch policies before deployment (Tao et al., 2019); and expanding outcome sets to include asset health and OEE so that hydrogen's operational impacts beyond energy are captured. On the market side, as green-power PPAs and explicit carbon pricing diffuse, replicating the analysis across tariff/carbon regimes would clarify elasticity shifts . Finally, material and component advances documented in electrolyzer and storage reviews should be tracked in situ to quantify how learning-curve cost declines and durability gains translate into plant-level KPIs over time. The central theme remains: credible progress demands coupling thermodynamics, markets, and organizational capability in designs and datasets that are granular enough to see and to manage the mechanisms at work.

CONCLUSION

This research has set out to quantify when and how hydrogen integration in smart factories yields thermo-economic advantages, and it has delivered a coherent, plant-resolved answer: cost, efficiency, and emissions outcomes have depended jointly on three controllable levers renewable share to electrolysis, integration depth across the electrolyzer–storage–fuel-cell chain, and the maturity of energy-management systems that govern tariff-aware dispatch. Using a cross-sectional, multi–case design with harmonized EMS/SCADA telemetry, audited tariff and financial records, and a validated Likert-5 survey of digital practices, the study has demonstrated that higher renewable alignment has been the strongest single predictor of lower unit hydrogen cost (LCOH) and reduced energy-cost intensity, that deeper integration has most reliably lifted exergy efficiency and reduced CO_2 intensity, and that digital maturity has amplified the cost benefits of renewable share through better sensing, analytics, and closed-loop control. Storage has improved outcomes up to a point revealing a clear "knee" in the cost–duration curve around a work-shift scale after which diminishing returns have appeared; load volatility has remained a persistent cost penalty unless tempered by disciplined operating practices and demand-response routines. Methodologically, the paper has combined first- and second-law KPIs with tariff-exposed costs and organizational constructs in a single regression pipeline, showing stable effects under alternative functional forms, clustered errors, and outcome definitions, thereby strengthening the claim that findings are not artifacts of any one modeling choice. Practically, the results have translated into concrete guidance: prioritize renewable-aligned dispatch before oversizing storage; size hydrogen storage to the measured variability of the process rather than to arbitrary diurnal targets; deploy fuel-cell CHP where thermal and electrical peaks coincide; and invest in metering, timestamp integrity, historian quality, and optimization algorithms because these digital capabilities have converted technical potential into realized savings. Strategically, the work has suggested that policy and procurement should couple green-power access with support for EMS modernization, since the interaction between the two has been multiplicative rather than merely additive for cost relief. The study has acknowledged limits cross-sectional identification, survey-based maturity measurement, and context specificity across sectors and tariff regimes yet robustness checks and sector fixed effects have mitigated concerns that single outliers, collinearity, or specification choices have driven the core inferences. Overall, the contribution has been to move beyond technology-only scenarios and provide effect sizes rooted in real factory operations, offering a reproducible template data definitions, KPIs, analytic checks that others can apply as components improve and tariffs evolve. In operational terms, the message for smart-factory leaders is straightforward: treat "green share," "duration," and "digitalization" as complementary dials; turn them in concert, and hydrogen becomes a disciplined tool for lowering costs, boosting exergetic performance, and decarbonizing production without compromising reliability.

RECOMMENDATIONS

On the strength of the evidence assembled, we recommend that smart-factory leaders pursue a staged but integrated roadmap that couples' energy architecture with digital capability, governance, and workforce readiness so the thermo-economic value of hydrogen is reliably captured in day-to-day operations. First, prioritize renewable alignment before hardware overbuild: codify tariff-aware dispatch rules that raise electrolyzer set-points during low-price/low-carbon blocks and reserve fuel-cell CHP for peak windows; make these rules auditable in your EMS so deviations are visible and correctable. Second, right-size storage to the measured variability of your process, targeting the "knee" of the cost–duration curve (often a work-shift scale) rather than defaulting to diurnal or seasonal ambitions; expand only when utilization data show frequent saturation or curtailment you cannot economically hedge. Third, institutionalize EMS maturity as a capital program in its own right: deploy sub-metering down to auxiliaries (compression, drying, cooling), enforce time-synchronization across OT/IT, and embed closed-loop optimizers that co-consider prices, state of charge, production schedules, and equipment constraints; pair this with a governance cadence (weekly energy huddles, monthly KPI reviews) so algorithms and operators co-evolve. Fourth, treat hydrogen integration as a cyber-physical system: segment EMS/SCADA networks, sign control messages, patch to a change-control plan, and log operator overrides with reason codes; this protects the very digital maturity that multiplies cost savings and ensures that demand-response automation can run safely during grid events. Fifth, standardize KPIs and dashboards: use a small, durable set LCOH, energy-cost intensity, exergy efficiency, CO_2 intensity, storage hours utilized, peak-to-average ratio, DR kWh shifted and publish them to production and finance alike so trade-offs are transparent. Sixth, embed exergy-aware maintenance by mapping avoidable destruction and its dollar impact (e.g., across compression stages or off-design temperatures) and sequencing retrofits where exergy and cost hotspots coincide; this often outperforms indiscriminate stack or tank upgrades. Seventh, design pilots that earn the right to scale: run 90-day control trials that lock dispatch policies and success metrics, then scale only if LCOH, ECI, and reliability deltas clear pre-agreed thresholds under independent data checks. Eighth, align procurement and policy instruments: bundle green-power PPAs or on-site PV/wind with data and automation funding (historians, model-predictive control, DR telemetry) because the interaction yields disproportionate gains; similarly, leverage utility DR programs with clear playbooks for electrolyzer ramping and fuel-cell peak clipping. Ninth, invest in people: upskill operators and energy managers on EMS analytics, tariff mechanics, and hydrogen safety; certify a cross-functional "energy desk" that owns dispatch decisions and incident response. Tenth, build for learning: version-control models and KPI definitions, run quarterly sensitivity reviews on prices and efficiency assumptions, and refresh storage sizing and dispatch policies as new components or tariffs land. Finally, sequence integration depth to context: start with PEM electrolysis + EMS discipline; add storage when curtailment or peaks justify it; add fuel-cell CHP where thermal and electric peaks coincide and reliability is paramount. Following this blueprint turns hydrogen from a promising asset into a governed, measurable, and secure contributor to lower costs, higher exergetic performance, and credible decarbonization.

REFERENCES

[1]. Abdul, R. (2021). The Contribution Of Constructed Green Infrastructure To Urban Biodiversity: A Synthesised Analysis Of Ecological And Socioeconomic Outcomes. *International Journal of Business and Economics Insights*, *1*(1), 01–31. https://doi.org/10.63125/qs5p8n26

[2]. Andrews, J., & Shabani, B. (2012). Fuel cells as efficient distributed generators: Prospects and challenges. *Renewable and Sustainable Energy Reviews*, *16*(6), 5567–5576. https://doi.org/10.1016/j.rser.2012.05.011

[3]. Barbir, F. (2005). PEM electrolysis for production of hydrogen from renewable energy sources. *Solar Energy*, *78*(5), 661–669. https://doi.org/10.1016/j.solener.2004.09.003

[4]. Bhandari, R., Trudewind, C. A., & Zapp, P. (2014). Life cycle assessment of hydrogen production via electrolysis – A review. *Journal of Cleaner Production*, *85*, 151–163. https://doi.org/10.1016/j.jclepro.2013.07.048

[5]. Boyano, A., Blanco-Marigorta, A. M., Morosuk, T., & Tsatsaronis, G. (2011). Exergoenvironmental analysis of a steam methane reforming process for hydrogen production. *Energy*, *36*(4), 2202–2214. https://doi.org/10.1016/j.energy.2010.05.020

[6]. Brynolf, S., Taljegard, M., Grahn, M., & Hansson, J. (2018). Electrofuels for the transport sector: A review of production costs. *Renewable and Sustainable Energy Reviews*, *81*, 1887–1905. https://doi.org/10.1016/j.rser.2017.05.288

[7]. Budischak, C., Sewell, D., Thomson, H., Mach, L., Veron, D. E., & Kempton, W. (2013). Cost-minimized combinations of wind power, solar power and electrochemical storage, powering the grid up to 99.9% of the time. *Journal of Power Sources*, *225*, 60–74. https://doi.org/10.1016/j.jpowsour.2012.09.054

[8]. Bunse, K., Vodicka, M., Schönsleben, P., Brülhart, M., & Ernst, F. O. (2011). Integrating energy efficiency performance in production management—Gap analysis between industrial needs and scientific literature. *Journal of Cleaner Production*, *19*(6–7), 667–679. https://doi.org/10.1016/j.jclepro.2010.11.011

[9]. Connolly, D., Lund, H., Mathiesen, B. V., & Leahy, M. (2010). A review of computer tools for analysing the integration of renewable energy into various energy systems. *Applied Energy*, *87*(4), 1059–1082. https://doi.org/10.1016/j.apenergy.2009.10.017

[10]. Cziesla, F., Tsatsaronis, G., & Gao, Z. (2006). Avoidable thermodynamic inefficiencies and costs in an externally fired combined cycle power plant. *Energy*, *31*(10–11), 1472–1489. https://doi.org/10.1016/j.energy.2005.08.001

[11]. Danish, M., & Md. Zafor, I. (2022). The Role Of ETL (Extract-Transform-Load) Pipelines In Scalable Business Intelligence: A Comparative Study Of Data Integration Tools. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 89–121. https://doi.org/10.63125/1spa6877

[12]. Danish, M., & Md.Kamrul, K. (2022). Meta-Analytical Review of Cloud Data Infrastructure Adoption In The Post-Covid Economy: Economic Implications Of Aws Within Tc8 Information Systems Frameworks. *American Journal of Interdisciplinary Studies*, *3*(02), 62-90. https://doi.org/10.63125/1eg7b369

[13]. Fasihi, M., Bogdanov, D., & Breyer, C. (2018). Techno-economic assessment of Power-to-Liquids (PtL) fuels production and global trading based on hybrid PV-wind power plants. *Energy Procedia*, *99*, 243–268. https://doi.org/10.1016/j.egypro.2016.10.115

[14]. Gahleitner, G. (2013). Hydrogen from renewable electricity: An international review of power-to-gas pilot plants for stationary applications. *International Journal of Hydrogen Energy*, *38*(5), 2039–2061. https://doi.org/10.1016/j.ijhydene.2012.12.010

[15]. Glenk, G., & Reichelstein, S. (2019). Economics of converting renewable power to hydrogen. *Nature Energy*, *4*(3), 216–222. https://doi.org/10.1038/s41560-019-0326-1

[16]. Hirscher, M., Yartys, V. A., Baricco, M., Bellosta von Colbe, J., Blanchard, D., Bowman, R. C., & Zlotea, C. (2020). Materials for hydrogen-based energy storage – Past, recent progress and future outlook. *Journal of Alloys and Compounds*, *827*, 153548. https://doi.org/10.1016/j.jallcom.2019.153548

[17]. Holladay, J. D., Hu, J., King, D. L., & Wang, Y. (2009). An overview of hydrogen production technologies. *Catalysis Today*, *139*(4), 244–260. https://doi.org/10.1016/j.cattod.2008.08.039

[18]. Hozyfa, S. (2022). Integration Of Machine Learning and Advanced Computing For Optimizing Retail Customer Analytics. *International Journal of Business and Economics Insights*, *2*(3), 01–46. https://doi.org/10.63125/p87sv224

[19]. ISO. (2011). ISO 50001:2011—Energy management systems—Requirements with guidance for use. In: International Organization for Standardization.

[20]. Kelly, S., Tsatsaronis, G., & Morosuk, T. (2009). Advanced exergetic analysis: Approaches for splitting the exergy destruction into endogenous and exogenous parts. *Energy*, *34*(3), 384–391. https://doi.org/10.1016/j.energy.2008.12.007

[21]. Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business & Information Systems Engineering*, *6*(4), 239–242. https://doi.org/10.1007/s12599-014-0334-4

[22]. Lazzaretto, A., & Tsatsaronis, G. (2006). SPECO: A systematic and general methodology for calculating efficiencies and costs in thermal systems. *Energy*, *31*(8–9), 1257–1289. https://doi.org/10.1016/j.energy.2005.03.011

[23]. Lee, J., Bagheri, B., & Kao, H.-A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, *3*, 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001

[24]. Lee, J., Lapira, E., Bagheri, B., & Kao, H.-A. (2013). Recent advances and trends in predictive manufacturing systems in big data environment. *Manufacturing Letters*, *1*(1), 38–41. https://doi.org/10.1016/j.mfglet.2013.09.005

[25]. Lototskyy, M. V., Yartys, V. A., Pollet, B. G., & Bowman, R. C. (2014). Metal hydride hydrogen compressors: A review. *International Journal of Hydrogen Energy*, *39*(11), 5818–5851. https://doi.org/10.1016/j.ijhydene.2014.01.158

[26]. Lu, Y. (2017). Industry 4.0: A survey on technologies, applications and open research issues. *Journal of Industrial Information Integration*, *6*, 1–10. https://doi.org/10.1016/j.jii.2017.04.005

[27]. Md Arman, H., & Md.Kamrul, K. (2022). A Systematic Review of Data-Driven Business Process Reengineering And Its Impact On Accuracy And Efficiency Corporate Financial Reporting. *International Journal of Business and Economics Insights*, *2*(4), 01–41. https://doi.org/10.63125/btx52a36

[28]. Md Mohaiminul, H., & Md Muzahidul, I. (2022). High-Performance Computing Architectures For Training Large-Scale Transformer Models In Cyber-Resilient Applications. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 193–226. https://doi.org/10.63125/6zt59y89

[29]. Md Omar, F., & Md. Jobayer Ibne, S. (2022). Aligning FEDRAMP And NIST Frameworks In Cloud-Based Governance Models: Challenges And Best Practices. *Review of Applied Science and Technology*, *1*(01), 01-37. https://doi.org/10.63125/vnkcwq87

[30]. Md Sanjid, K., & Md. Tahmid Farabe, S. (2021). Federated Learning Architectures For Predictive Quality Control In Distributed Manufacturing Systems. *American Journal of Interdisciplinary Studies*, *2*(02), 01-31. https://doi.org/10.63125/222nwg58

[31]. Md Takbir Hossen, S., & Md Atiqur, R. (2022). Advancements In 3D Printing Techniques For Polymer Fiber-Reinforced Textile Composites: A Systematic Literature Review. *American Journal of Interdisciplinary Studies*, *3*(04), 32-60. https://doi.org/10.63125/s4r5m391

[32]. Md. Hasan, I. (2022). The Role Of Cross-Country Trade Partnerships In Strengthening Global Market Competitiveness. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 121-150. https://doi.org/10.63125/w0mnpz07

[33]. Md. Mominul, H., Masud, R., & Md. Milon, M. (2022). Statistical Analysis Of Geotechnical Soil Loss And Erosion Patterns For Climate Adaptation In Coastal Zones. *American Journal of Interdisciplinary Studies*, *3*(03), 36-67. https://doi.org/10.63125/xytn3e23

[34]. Md. Omar, F., & Md Harun-Or-Rashid, M. (2021). Post-GDPR Digital Compliance in Multinational Organizations: Bridging Legal Obligations With Cybersecurity Governance. *American Journal of Scholarly Research and Innovation*, *1*(01), 27-60. https://doi.org/10.63125/4qpdpf28

[35]. Md. Rabiul, K., & Sai Praveen, K. (2022). The Influence of Statistical Models For Fraud Detection In Procurement And International Trade Systems. *American Journal of Interdisciplinary Studies*, *3*(04), 203-234. https://doi.org/10.63125/9htnv106

[36]. Md. Tahmid Farabe, S. (2022). Systematic Review Of Industrial Engineering Approaches To Apparel Supply Chain Resilience In The U.S. Context. *American Journal of Interdisciplinary Studies*, *3*(04), 235-267. https://doi.org/10.63125/teherz38

[37]. Md. Wahid Zaman, R., & Momena, A. (2021). Systematic Review Of Data Science Applications In Project Coordination And Organizational Transformation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(2), 01–41. https://doi.org/10.63125/31b8qc62

[38]. Md.Kamrul, K., & Md Omar, F. (2022). Machine Learning-Enhanced Statistical Inference For Cyberattack Detection On Network Systems. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 65-90. https://doi.org/10.63125/sw7jzx60

[39]. Monostori, L. (2014). Cyber-physical production systems: Roots, expectations and R&D challenges. *Procedia CIRP*, *17*, 9–13. https://doi.org/10.1016/j.procir.2014.03.115

[40]. Mubashir, I. (2021). Smart Corridor Simulation for Pedestrian Safety: : Insights From Vissim-Based Urban Traffic Models. *International Journal of Business and Economics Insights*, *1*(2), 33-69. https://doi.org/10.63125/b1bk0w03

[41]. Pankaz Roy, S. (2022). Data-Driven Quality Assurance Systems For Food Safety In Large-Scale Distribution Centers. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 151–192. https://doi.org/10.63125/qen48m30

[42]. Paulus, M., & Borggrefe, F. (2011). The potential of demand-side management in energy-intensive industries for electricity markets in Germany. *Applied Energy*, *88*(2), 432–441. https://doi.org/10.1016/j.apenergy.2010.03.017

[43]. Petrakopoulou, F., Tsatsaronis, G., Morosuk, T., & Carassai, A. (2012). Conventional and advanced exergetic analyses applied to a combined cycle power plant. *Energy*, *41*(1), 146–152. https://doi.org/10.1016/j.energy.2011.05.028

[44]. Rahman, S. M. T., & Abdul, H. (2022). Data Driven Business Intelligence Tools In Agribusiness A Framework For Evidence-Based Marketing Decisions. *International Journal of Business and Economics Insights*, *2*(1), 35-72. https://doi.org/10.63125/p59krm34

[45]. Razia, S. (2022). A Review Of Data-Driven Communication In Economic Recovery: Implications Of ICT-Enabled Strategies For Human Resource Engagement. *International Journal of Business and Economics Insights*, *2*(1), 01-34. https://doi.org/10.63125/7tkv8v34

[46]. Rönsch, S., Schneider, J., Matthischke, S., Schlüter, M., Götz, M., Lefebvre, J., Prabhakaran, P., & Bajohr, S. (2016). Review on methanation – From fundamentals to current projects. *Fuel*, *166*, 276–296. https://doi.org/10.1016/j.fuel.2015.10.111

[47]. Rony, M. A. (2021). IT Automation and Digital Transformation Strategies For Strengthening Critical Infrastructure Resilience During Global Crises. *International Journal of Business and Economics Insights*, *1*(2), 01-32. https://doi.org/10.63125/8tzzab90

[48]. Samsatli, S., Staffell, I., & Samsatli, N. J. (2016). Optimal design and operation of integrated wind-hydrogen-electricity networks for decarbonising the domestic transport sector in Great Britain. *International Journal of Hydrogen Energy*, *41*(1), 447–475. https://doi.org/10.1016/j.ijhydene.2015.10.032

[49]. Schmidt, O., Gambhir, A., Staffell, I., Hawkes, A., Nelson, J., & Few, S. (2017). Future cost and performance of water electrolysis: An expert elicitation study. *International Journal of Hydrogen Energy*, *42*(52), 30470–30492. https://doi.org/10.1016/j.ijhydene.2017.10.045

[50]. Schmidt, O., Melchior, S., Hawkes, A., & Staffell, I. (2019). Projecting the future levelized cost of electricity storage technologies. *Joule*, *3*(1), 81–100. https://doi.org/10.1016/j.joule.2018.12.008

[51]. Syed Zaki, U. (2021). Modeling Geotechnical Soil Loss and Erosion Dynamics For Climate-Resilient Coastal Adaptation. *American Journal of Interdisciplinary Studies*, *2*(04), 01-38. https://doi.org/10.63125/vsfjtt77

[52]. Syed Zaki, U. (2022). Systematic Review Of Sustainable Civil Engineering Practices And Their Influence On Infrastructure Competitiveness. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 227–256. https://doi.org/10.63125/hh8nv249

[53]. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital twin in industry: State-of-the-art. *IEEE Transactions on Industrial Informatics*, *15*(4), 2405–2415. https://doi.org/10.1109/tii.2018.2873186

[54]. Tonoy Kanti, C., & Shaikat, B. (2022). Graph Neural Networks (GNNS) For Modeling Cyber Attack Patterns And Predicting System Vulnerabilities In Critical Infrastructure. *American Journal of Interdisciplinary Studies*, *3*(04), 157-202. https://doi.org/10.63125/1ykzx350

[55]. Trianni, A., Cagno, E., & Farné, S. (2016). Barriers, drivers and decision-making process for industrial energy efficiency: A broad study among manufacturing small and medium-sized enterprises. *Applied Energy*, *162*, 1537–1551. https://doi.org/10.1016/j.apenergy.2015.02.078

[56]. Tsatsaronis, G. (2007). Definitions and nomenclature in exergy analysis and exergoeconomics. *Energy*, *32*(4), 249–253. https://doi.org/10.1016/j.energy.2006.07.002

[57]. Ursúa, A., Gandía, L. M., & Sanchis, P. (2012). Hydrogen production from water electrolysis: Current status and future trends. *Proceedings of the IEEE*, *100*(2), 410–426. https://doi.org/10.1109/jproc.2011.2156750

[58]. Vogl, V., Åhman, M., & Nilsson, L. J. (2018). Assessment of hydrogen direct reduction for fossil-free steelmaking. *Journal of Cleaner Production*, *203*, 736–745. https://doi.org/10.1016/j.jclepro.2018.08.279

[59]. Wang, S., Wan, J., Li, D., & Zhang, C. (2016). Implementing smart factory of Industrie 4.0: An outlook. *International Journal of Distributed Sensor Networks*, *12*(1), 3159805. https://doi.org/10.1155/2016/3159805

[60]. 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

[61]. Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent manufacturing in the context of Industry 4.0: A review. *Engineering*, *3*(5), 616–630. https://doi.org/10.1016/j.eng.2017.05.015