

Article

Risk-Aware Assessment Framework for Industrial Renewable Energy Integration Using ISO 50001, a Digital-Twin-Ready Architecture, and Conditional Value-at-Risk

Łukasz Kański ¹, Jakub Pizoń ² , Arkadiusz Gola ^{3,*} , Jonas Matijošius ⁴  and Darius Vainorius ⁴

¹ Department of Information Systems and Logistics, Faculty of Economics, Maria Curie-Skłodowska University, Plac Marii Curie-Skłodowskiej 5, 20-031 Lublin, Poland; lukasz.kanski@umcs.pl

² Department of Enterprise Organisation, Faculty of Management, Lublin University of Technology, ul. Nadbystrzycka 38, 20-618 Lublin, Poland; j.pizon@pollub.pl

³ Department of Production Computerisation and Robotisation, Faculty of Mechanical Engineering, Lublin University of Technology, Nadbystrzycka 36, 20-618 Lublin, Poland

⁴ Mechanical Science Institute, Vilnius Gediminas Technical University—Vilnius Tech, Plytinės g. 25, LT-10105 Vilnius, Lithuania; jonas.matijosius@vilniustech.lt (J.M.); darius.vainorius@vilniustech.lt (D.V.)

* Correspondence: a.gola@pollub.pl

Abstract

Industrial energy transition has moved from pilot deployment to system integration, where renewable supply must be assessed together with process fit, organisational maturity, and uncertainty. This study proposes a risk-aware assessment framework integrating ISO 50001 energy-management maturity, ISO 31000 risk-management logic, a digital-twin-ready operational architecture, scenario simulation, Conditional Value-at-Risk (CVaR), and multi-criteria decision analysis. The study does not report a live plant-level digital twin or empirical survey validation. Instead, it specifies a five-layer implementation architecture, uses a synthetic survey-like dataset solely to demonstrate parameter recovery, and applies 350 Monte Carlo replications to an industrial energy hub comprising photovoltaic and wind generation, battery storage, and optional Power-to-H₂-to-Power storage. The quantitative workflow is reported with explicit equations, input assumptions, random seed, CVaR estimator, TOPSIS weights, and weight-sensitivity analysis. Under the adopted assumptions, the PV–wind–battery configuration achieved the lowest mean cost and CVaR, whereas hydrogen storage substantially reduced curtailment but increased mean cost and tail risk without materially reducing grid purchases. These results are conditional on the stated model assumptions and should not be generalised as empirical evidence. The framework supports structured investment and operational assessment by linking technical performance, organisational readiness, and cost–risk–decarbonisation trade-offs.

Keywords: energy transition; renewable energy supply; industrial integration; system performance assessment; energy management; ISO 50001; ISO 31000; digital twin; CVaR; Monte Carlo simulation



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1. Introduction

The complexity of the industrial energy transition today stems less from the lack of renewable energy technologies than from the need to integrate them durably with an organisation’s production, logistics, and managerial system [1]. At the global scale, record growth in renewable capacity and further reductions in the levelised cost of PV and wind reinforce the economic rationale for low-carbon supply [2–4]. At the same time, in the

IPCC perspective, electrification and the use of renewable energy, including hydrogen from electrolysis, constitute key pathways for emissions reduction in industry, provided they are accompanied by infrastructure development and active management of flexibility [5,6]. In Europe, this transition acquires an additional competitiveness dimension; in particular, the European Commission emphasises the need to reduce energy costs and accelerate industrial decarbonisation as levers of growth and economic resilience [7,8].

Three relevant bodies of research remain only partially connected. First, engineering studies optimise renewable generation and storage configurations and increasingly incorporate formal uncertainty measures such as CVaR [9,10]. Second, risk and energy-management research, including ISO 31000 risk-management guidance and ISO 50001 energy-management governance [11,12], shows that sustained energy-performance improvement depends on the integration of ESG/risk governance, EnPI measurement, production management, and continual-improvement routines rather than on technology acquisition alone [13–16]. Third, structured reporting and decision-analysis literature provides the review and MCDM basis used in this paper [17–19]. Fourth, sustainability-transition and digital-twin research emphasises institutional coordination, temporal dynamics, data integration, model calibration, and feedback between virtual and physical systems [20–24]. The unresolved issue is therefore not the availability of individual methods, but their integration into a transparent decision framework that connects organisational capability with technical cost, resilience, and decarbonisation outcomes.

The research problem addressed in this article is therefore formulated as follows: how can industrial renewable-energy integration be designed and assessed in a manner that is simultaneously performance-oriented, process-integrated, and risk-aware, while remaining compatible with quality-management and resilience principles? Three operational research questions follow: RQ1—how should EnMS maturity, digital readiness, process integration, perceived risk, and risk-aware tools be represented in one management model; RQ2—how do alternative renewable and storage architectures differ in expected cost, tail risk, renewable-energy share, curtailment, and grid dependence; and RQ3—how stable are multi-criteria rankings when decision-maker preferences change?

The aim of this paper is to develop and computationally illustrate this framework by combining the energy-management perspective (ISO 31000 [11], ISO 50001 [12]), BPMN-supported process integration, a digital-twin-ready architecture, scenario simulation, CVaR, and TOPSIS. The contribution is deliberately bounded: the literature component maps the conceptual gap, the synthetic component illustrates the statistical workflow, and the energy-hub simulation demonstrates technical decision logic. The study neither claims empirical confirmation of the hypotheses nor implementation of a live digital twin; both require subsequent validation with observed enterprise and plant data.

2. Literature Review and Gap Identification

The literature review followed PRISMA 2020 reporting logic [17] as a structured, PRISMA-informed mapping review. Its purpose was to identify how the literature connects three perspectives: (a) system performance, including cost, emissions, reliability, and continuity; (b) industrial integration, including process fit, governance, energy-management maturity, BPMN, and digital-twin logic; and (c) risk and uncertainty assessment, including VaR/CVaR and multi-criteria decision-making methods [18,19]. Because the objective was conceptual mapping rather than effect-size synthesis, the review combined openly accessible bibliographic resources, citation snowballing, and institutional reports.

The review questions were: Q1—which metrics and objective functions dominate industrial renewable-integration studies; Q2—how is process-organisational integration operationalised; and Q3—which risk and uncertainty measures are combined with multi-criteria

assessment. The search returned 173 records; after removal of 41 duplicates, 132 records were screened, 35 full texts were assessed, and 28 studies were included, as shown in Figure 1. The protocol is reported in Table 1. Open resources were selected to make the search path directly accessible and reproducible; however, the absence of subscription databases limits coverage. Accordingly, the review is presented as transparent structured mapping, not as an exhaustive systematic synthesis of all indexed evidence.

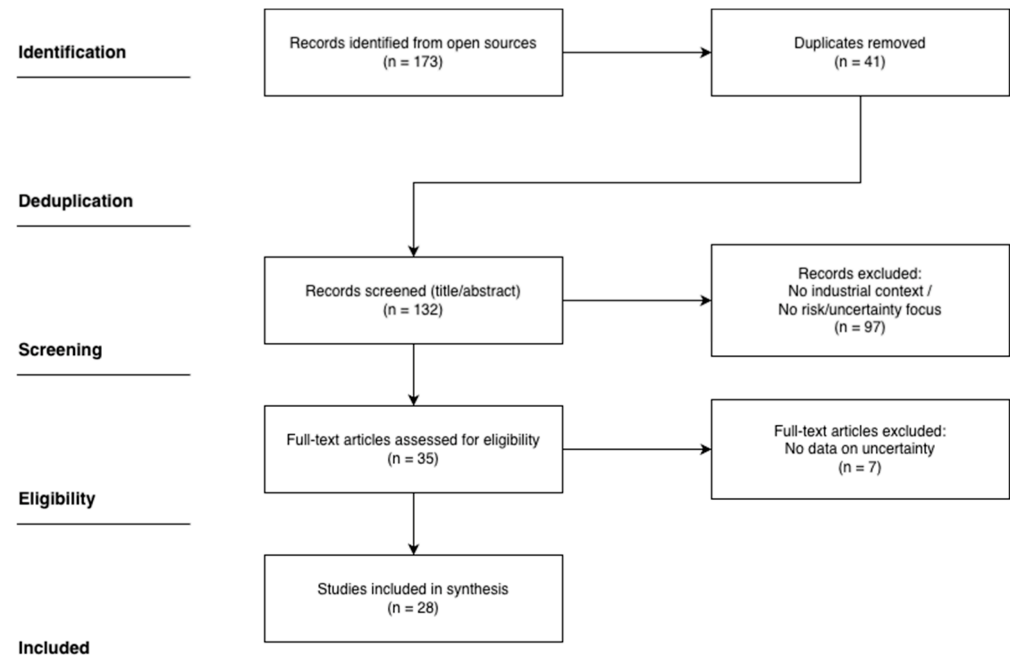


Figure 1. PRISMA 2020 flow diagram for source identification and selection. Source: own elaboration based on Page et al. [17].

Table 1. Literature review protocol (PRISMA 2020).

Item	Description
Review objective	Map research connecting industrial renewable-energy integration, system performance, organisational/process integration, and risk-aware assessment.
Search date	Search completed on 1 April 2026.
Sources	Open bibliographic resources (including Google Scholar and DOAJ), open repositories, citation snowballing, and institutional reports (IEA, European Commission, IPCC, NREL).
Example queries	“industrial” AND “renewable” AND (risk OR uncertainty OR CVaR); “energy investment” AND “industry” AND “multi-criteria”; “ISO 50001” AND “energy management” AND “sustainability”.
Inclusion criteria	Industrial or industrial-energy context; system-performance or techno-economic metrics; explicit risk/uncertainty or MCDM component; 2015–2026; full text accessible.
Exclusion criteria	No industrial context; no system-level assessment; no risk/uncertainty component; duplicates; non-verifiable or low-credibility sources.
Screening procedure	Title/abstract screening against pre-specified criteria, followed by full-text eligibility assessment; uncertain records were retained for full-text review.
Interpretive scope	PRISMA-informed structured mapping. The protocol supports transparency but does not claim exhaustive database coverage or meta-analytic synthesis.

Source: own elaboration.

The research gap lies in the lack of coherent, management-oriented, and externally validated frameworks for assessing renewables integration in industrial enterprises that simultaneously cover system performance, process-organisational integration, and risk-aware decision assessment; consequently, the literature still insufficiently develops [20–22]:

- Linkages between system performance metrics (cost, emissions, and reliability) and EnMS/quality maturity measures (EnPI/KPI and PDCA) [14,15];
- The operationalisation of industrial integration as process capability (BPMN), competence, and governance, rather than merely as a technological configuration [23,24];
- The embedding of formal risk measures (e.g., CVaR) and scenario analyses into portfolio-based assessments of RES and energy storage investments [25];
- Replicable validation of such frameworks on organisational and operational data across industrial sectors [8].

The thematic synthesis of the included studies indicates four recurring gaps: (L1) the separation of risk measures (VaR/CVaR) from organisational maturity and managerial standards; (L2) the predominance of techno-economic assessments over assessments of integration with processes, capabilities, and governance; (L3) limited operationalisation of system performance in industrial conditions, where not only costs and emissions matter but also impacts on production continuity; and (L4) insufficient linking of digital approaches (digital twins) with risk-aware decisions in energy investment portfolios.

For example, optimisation studies of micro- and multi-energy systems directly use CVaR as a measure of risk aversion [9,10], yet rarely connect it to the implementation of organisational energy management systems. Conversely, research from the perspective of risk management and sustainability points to the need to integrate ESG and organisational risks into decision procedures [13,26] but does not always reach the level of modelling industrial energy systems. Finally, the decision-analysis literature offers a rich MCDM toolkit for assessing renewable investments against multiple criteria and risks [27,28], yet it lacks links to process and quality maturity metrics.

The identified gap provides the direct basis for constructing the proposed theoretical model and the research hypotheses developed in Section 3.1. Specifically, we assume that energy management maturity, digitalisation, process integration, and risk-aware tools jointly determine transition performance, while perceived risk acts as a constraining factor.

3. Materials and Methods

A framework-development and computational-demonstration design was adopted: (i) PRISMA-informed structured mapping; (ii) conceptualisation of the management model and parameter-recovery demonstration on synthetic survey-like data; (iii) hourly simulation of an industrial energy hub with Monte Carlo uncertainty and CVaR; and (iv) TOPSIS ranking with explicit weight-sensitivity analysis. The components serve different purposes and are not treated as mutually validating datasets. The synthetic component tests whether the specified statistical workflow recovers imposed relationships, whereas the energy-hub component evaluates conditional cost–risk trade-offs under stated technical assumptions. The computational workflow was implemented in Python 3.11 using NumPy 1.26, pandas 2.2, SciPy 1.12, statsmodels 0.14, and Matplotlib 3.8; no chemicals, reagents, commercial cell lines, physical samples, or laboratory devices were used.

3.1. Hypothesis Model and Construct Operationalisation

Based on the literature synthesis, the framework integrates EnMS maturity (ISO 50001 [12]), digital readiness, process integration, perceived transition risk, and risk-aware tools. Figure 2a presents the six hypothesised relationships H1–H6. Figure 2b specifies the digital-twin-ready operational architecture through which organisational constructs can be connected to plant data and decision processes.

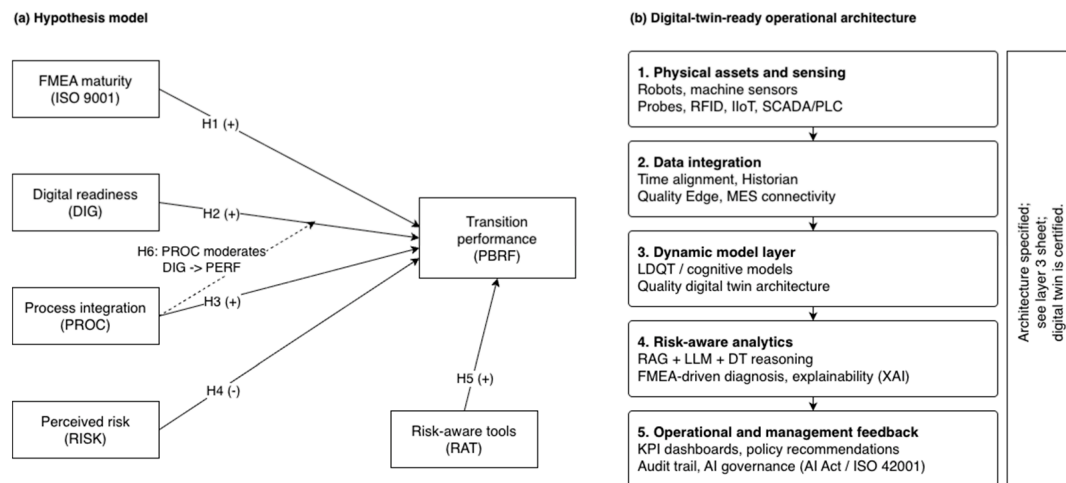


Figure 2. Proposed framework: (a) hypothesis model; (b) digital-twin-ready operational architecture linking plant sensing, data integration, dynamic modelling, risk-aware analytics, and ISO 50001 [12]/BPMN feedback. Source: own elaboration.

H1. *EnMS maturity (ISO 50001) positively affects the enterprise's energy transition performance (PERF).*

H2. *Digital readiness (DIG) positively affects PERF.*

H3. *Process integration (PROC) positively affects PERF.*

H4. *Perceived transition risk (RISK) negatively affects PERF.*

H5. *The use of risk-aware tools (RAT) positively affects PERF.*

H6. *Process integration (PROC) positively moderates the DIG → PERF relationship, strengthening the impact of digitalisation on outcomes.*

Scope and Operationalisation of the Digital-Twin and BPMN Components

The digital-twin component is specified as an implementation architecture rather than reported as a deployed live twin. In an industrial setting, operationalisation would require: (1) a physical layer of smart meters, weather sensors, PV/wind inverters, BESS/H₂ states, and SCADA/MES signals; (2) a time-synchronised historian with quality flags and cybersecurity controls; (3) calibrated load, generation, and storage models updated on a rolling window and monitored using forecast-error measures; (4) Monte Carlo, CVaR, and TOPSIS decision services; and (5) feedback through dispatch recommendations, EnPI/KPI review, and corrective action under ISO 50001.

BPMN complements this architecture by defining data hand-offs, decision gates, process ownership, exception handling, and escalation. It does not replace the physical energy model. A real implementation would be considered a digital twin only after bidirectional data exchange, recurrent model calibration, and an operational feedback mechanism had been established; these elements are proposed here but not empirically demonstrated.

The operationalisation of the key constructs (ENMS, DIG, PROC, RISK, RAT, and PERF), together with example questionnaire items, is summarised in Table 2.

Table 2. Construct operationalisation (abridged).

Construct	Items	Content Description (Likert 1–7)
ENMS	ENMS1–ENMS4	ISO 50001 practices: energy objectives, management reviews, EnPI indicators, audits.
DIG	DIG1–DIG4	Availability and time alignment of IoT/SCADA data, analytics, model calibration, forecasting, and IT/OT integration.
PROC	PROC1–PROC4	BPMN process mapping, standardisation, process ownership, cross-functional coordination, change control, and exception handling.
RISK	RISK1–RISK4	Regulatory/market/technical/cyber risk; uncertainty of prices and renewable resources.
RAT	RAT1–RAT4	Use of scenario analyses, stress tests, VaR/CVaR, MCDM.
PERF	PERF1–PERF4	Transition outcomes: cost and emissions reduction, resilience, supply stability, stakeholder acceptance.

Source: own elaboration (measurement instrument developed based on the literature review).

3.2. Synthetic-Data Demonstration and Statistical Procedure

3.2.1. Rationale, Data Generation, and Synthetic Sample Structure

A synthetic survey-like dataset ($N = 348$) was chosen because no observed multi-firm dataset jointly covering ISO 50001 maturity, digital readiness, process integration, risk perceptions, risk-aware tools, and transition outcomes was available, while enterprise energy and control data are commercially sensitive. The dataset is used only to demonstrate construct operationalisation and parameter recovery, so no managers or enterprises were surveyed, and no claim of population representativeness or empirical hypothesis confirmation is made. Planned validation comprises cognitive pretesting with energy managers, a pilot survey, a multi-sector sample of at least 300 firms, confirmatory SEM, and triangulation with 12 months of EnPI and SCADA/EMS records in selected case plants.

For reproducibility, the generation procedure used a random seed of 20260401. Five independent standardised latent predictors (ENMS, DIG, PROC, RISK, and RAT) were generated from $N(0,1)$. PERF was generated from the pre-specified structural equation $PERF = 0.15 \cdot ENMS + 0.35 \cdot DIG + 0.16 \cdot PROC - 0.23 \cdot RISK + 0.16 \cdot RAT + 0.10 \cdot (DIG \times PROC) + \epsilon$, with normally distributed residual variance selected to produce a latent R^2 of 0.45, and was then standardised. The coefficients are target parameters, so subsequent regression and bootstrap calculations constitute a recovery check rather than empirical hypothesis tests.

Each construct was represented by four reflective indicators generated as $x_j = \text{roundclip}[4 + 1.10(\lambda_j\eta + \epsilon_j)]$, with $\lambda = (0.72, 0.76, 0.80, 0.84)$, $\epsilon_j \sim N(0, 1 - \lambda_j^2)$, and values clipped to the 1–7 range. Industry, firm size, and ISO 50001 labels were allocated independently to reproduce the marginal shares in Table 3. This procedure fully determines the synthetic dataset while separating the numerical illustration from any claim about an observed industrial population.

Table 3. Synthetic sample characteristics used in the demonstration ($N = 348$).

Category	Level	N	Share (%)
Industry	Chemical and petrochemical	62	17.8
Industry	Metallurgy and materials	58	16.7
Industry	Automotive and machinery	76	21.8
Industry	Food industry	55	15.8
Industry	Pulp, paper and wood	37	10.6
Industry	Other manufacturing	60	17.2
Firm size	50–249 employees	112	32.2
Firm size	250–999 employees	146	42.0
Firm size	≥ 1000 employees	90	25.9
ISO 50001	Implemented/certified	168	48.3
ISO 50001	In implementation	94	27.0
ISO 50001	Not implemented	86	24.7

Source: own elaboration.

As shown in Table 3, the synthetic structure is dominated by medium and large enterprises and relatively energy-intensive industries. This mirrors the type of decision context for which the proposed framework is intended but does not establish representativeness of any real population of firms.

3.2.2. Parameter-Recovery Estimation and Measurement Checks

Construct scores were calculated as item means and standardised. Internal consistency was described using Cronbach's α , composite reliability (CR), and average variance extracted (AVE). The structural equation was re-estimated by ordinary least squares with PERF as the dependent variable and ENMS, DIG, PROC, RISK, RAT, and the standardised DIG $\times$ PROC interaction as predictors. Percentile 95% confidence intervals were calculated from 2000 bootstrap resamples using the same random seed. Tables 4 and 5 report descriptive and measurement-quality checks; these statistics describe the internal behaviour of the synthetic instrument and do not establish external validity.

Table 4. Descriptive statistics of constructs (N = 348).

Construct	Mean	SD	Min	Max
ENMS	3.990	0.980	1.25	7.00
DIG	4.047	0.996	1.50	6.75
PROC	3.991	0.858	1.75	6.75
RISK	3.927	0.895	1.50	6.50
RAT	4.013	0.883	2.00	6.75
PERF	4.019	0.927	1.50	6.50

Source: own elaboration.

Table 5. Internal consistency and convergent validity indicators for the synthetic measurement model.

Construct	Cronbach's α	CR	AVE
ENMS	0.862	0.907	0.708
DIG	0.859	0.904	0.703
PROC	0.814	0.878	0.642
RISK	0.839	0.893	0.675
RAT	0.827	0.886	0.659
PERF	0.836	0.891	0.671

Source: own elaboration.

The values presented in Table 4 indicate the central tendency generated by the synthetic data process, with a moderate level of perceived risk. Table 5 confirms that common reliability and convergent validity thresholds are met (e.g., α and CR > 0.70; AVE > 0.50). These statistics assess internal consistency of the synthetic instrument and are not evidence of external validity.

3.3. Simulation Study: Industrial Energy Hub and CVaR Assessment

The engineering component uses an hourly energy-hub balance for one synthetic industrial plant. For every hour t , grid import, PV, wind, battery discharge, and fuel-cell output equal industrial demand, battery charging, electrolyser demand, and curtailed energy: $G_t + PV_t + W_t + B_{dis,t} + FC_t = L_t + B_{ch,t} + EL_t + Curt_t$. Electricity export and involuntary load shedding are not allowed. Annual system cost equals purchased electricity plus annualised capital expenditure and fixed/variable O&M. Capital expenditure is annualised using $CRF = r(1 + r)^n / [(1 + r)^n - 1]$, with the discount rate and asset lives reported in Table 6.

Table 6. Technical, financial, uncertainty, and dispatch assumptions for the energy-hub demonstration.

Item	Description
System scale	Annual demand 393,952 MWh; peak demand 62 MW; one-hour time step; no export and no involuntary load shedding.
Scenarios and capacities	S0: grid only; S1: PV 120 MW _p + BESS; S2: PV 120 MW _p + wind 65 MW + BESS; S3: S2 + Power-to-H ₂ -to-Power.
BESS parameters	30 MW/120 MWh; round-trip efficiency 90%; state-of-charge range 10–90%.
Hydrogen parameters	Electrolyser 25 MW, efficiency 70%; H ₂ storage 1200 MWhH ₂ ; fuel cell 12 MW, efficiency 50%; chain round-trip efficiency 35%.
CAPEX baseline	PV: 900; wind: 1500; BESS: 350/kWh + 150/kW; electrolyser: 700/kW; fuel cell: 900/kW; H ₂ storage: 5/kWhH ₂ (model monetary units).
Finance	WACC 8%; asset lives: PV/wind 25 years, BESS 15 years, electrolyser/fuel cell 20 years, H ₂ storage 25 years; O&M included in annual cost.
Uncertainty	Demand Ntr(1, 0.05 ²); PV Ntr(1, 0.10 ²); wind Ntr(1, 0.12 ²); price lognormal, mean 1, CV 0.20; 350 annual replications; seed 20260401.
Baseline dispatch	Renewables → load; surplus → BESS → H ₂ → curtailment; deficit → BESS → H ₂ → grid.
Risk-aware dispatch	Grid charging below the 25th price percentile and 20% BESS reserve for forecast top-decile price hours.
Risk metric	Empirical CVaR0.95: mean of the 18 highest annual-cost observations.

Source: own elaboration.

The computational demonstration used 350 annual Monte Carlo replications and a random seed of 20260401. Scenario-level demand, PV yield, and wind yield multipliers followed truncated normal distributions $N(1, 0.05^2)$ on $[0.85, 1.15]$, $N(1, 0.10^2)$ on $[0.70, 1.30]$, and $N(1, 0.12^2)$ on $[0.65, 1.35]$, respectively. The electricity-price multiplier was lognormal with a mean of 1 and a coefficient of variation of 0.20. Baseline dispatch serves demand from renewables first, charges BESS before H₂, curtails residual surplus, and covers deficits from BESS, then H₂, then the grid.

For annual cost C , $\text{VaR}_{0.95}$ is the empirical 95th percentile, and $\text{CvaR}_{0.95}$ is the mean of observations at or above that percentile. With $N = 350$, the sample estimator averages the 18 highest annual-cost outcomes. The risk-aware BESS variant permits grid charging below the 25th price percentile and preserves a 20% state-of-charge reserve for forecast top-decile price hours. These rules are deliberately transparent heuristics rather than an optimal control claim.

3.4. TOPSIS Procedure and Weight-Sensitivity Analysis

TOPSIS used five criteria: mean annual cost, $\text{CVaR}_{0.95}$, renewable-energy share, curtailment, and grid purchase. Mean cost, CVaR , curtailment, and grid purchase were treated as cost criteria; renewable share was treated as a benefit criterion. The decision matrix was vector-normalised, multiplied by criterion weights, and compared with positive and negative ideal solutions. The closeness coefficient was $\text{CC}_i = \text{Di}^- / (\text{Di}^+ + \text{Di}^-)$, where larger values indicate greater proximity to the positive ideal.

Two transparent profiles were applied: P1 financial risk, with weights (0.40, 0.40, 0.10, 0.05, 0.05), and P2 decarbonisation, with weights (0.15, 0.15, 0.35, 0.175, 0.175), in the criterion order above. Sensitivity was examined by varying the joint weight of mean cost and CVaR from 0.10 to 0.90 in 0.005 increments, splitting that weight equally between the two criteria and allocating the remainder as 50% renewable share, 25% curtailment, and 25% grid purchase.

4. Results

4.1. Parameter-Recovery Demonstration Using Synthetic Data

The estimation recovers the signs and approximate magnitudes imposed by the synthetic data-generating equation. This is an internal consistency check, not statistical evidence about industrial enterprises. The largest recovered coefficient is $\text{DIG} \rightarrow \text{PERF}$ ($\beta = 0.395$), followed by $\text{ENMS} \rightarrow \text{PERF}$ ($\beta = 0.253$) and the negative $\text{RISK} \rightarrow \text{PERF}$ coefficient ($\beta = -0.161$). The $\text{DIG} \times \text{PROC}$ interaction is positive ($\beta = 0.121$), reproducing

the intended proposition that process integration strengthens the contribution of digital readiness. Table 7 provides the recovered estimates and percentile bootstrap intervals; Figure 3 visualises them and Figure 4 displays the implied simple slopes. The intervals quantify resampling variation within the synthetic dataset only.

Table 7. Recovered structural coefficients and bootstrap intervals in the synthetic demonstration.

Hypothesis	Relationship	β (Std.)	95% CI
H1	ENMS $\rightarrow$ PERF	0.253	[0.157; 0.349]
H2	DIG $\rightarrow$ PERF	0.395	[0.311; 0.490]
H3	PROC $\rightarrow$ PERF	0.102	[0.013; 0.190]
H4	RISK $\rightarrow$ PERF	−0.161	[−0.248; −0.072]
H5	RAT $\rightarrow$ PERF	0.156	[0.076; 0.238]
H6	DIG $\times$ PROC $\rightarrow$ PERF	0.121	[0.020; 0.215]

Source: own elaboration.

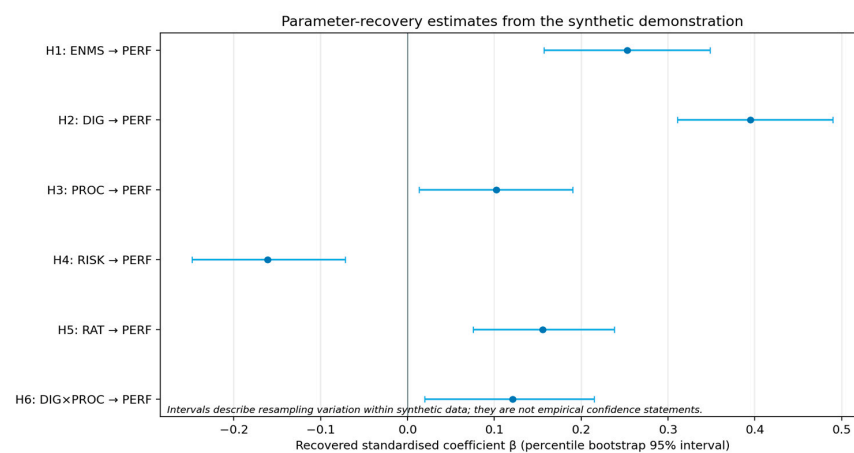


Figure 3. Parameter-recovery estimates for H1–H6 (standardised β ; percentile bootstrap 95% intervals; synthetic dataset, $N = 348$). Source: own elaboration based on Table 7. Dots denote recovered standardised coefficients, horizontal lines denote percentile bootstrap 95% intervals.

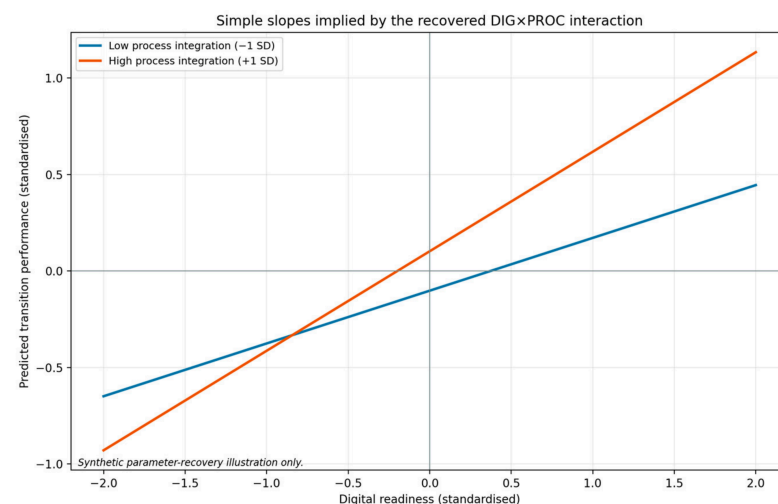


Figure 4. Simple-slope illustration of the imposed DIG $\times$ PROC interaction in the synthetic parameter-recovery model. Source: own elaboration based on Table 7.

4.2. Scenario Simulation Results and Cost–Risk Analysis

Table 8 reports the scenario outcomes. Relative to grid-only S0, S2 lowers mean annual cost by 4.4%, CVaR0.95 by 22.6%, cost dispersion by 70.9%, and grid purchases by

86.2%, while supplying 86.2% of demand from renewables. S1 reduces tail risk and grid dependence but increases mean cost by 3.3%. Adding H₂ in S3, relative to S2, reduces curtailment by 61.7% but increases mean cost by 16.8%, CVaR by 13.8%, and grid purchases by 1.4%, with virtually unchanged renewable share. Under the adopted sizing and dispatch assumptions, the additional annualised hydrogen-chain cost and 35% round-trip efficiency are not offset by sufficient utilisation. Figure 5 shows the cost–risk position, Figure 6 the annual-cost distributions, and Figure 7 the incremental S3-versus-S2 effects.

Table 8. Monte Carlo outcomes for the four industrial energy-supply scenarios (350 annual replications).

Scenario	Mean Annual Cost (Model Units/Year)	Cost SD (Model Units/Year)	CVaR0.95 (Model Units/Year)	RES Share	Curtailment (MWh)	Grid Purchase (MWh)
S0_Grid	35,454,207.0	6,195,190.0	49,932,777.0	0.000	0.0	393,952.0
S1_PV + BESS	36,607,840.0	3,689,891.0	45,814,769.0	0.406	0.0	234,170.0
S2_PV + Wind + BESS	33,905,278.0	1,803,304.0	38,655,457.0	0.862	4704.0	54,172.0
S3_PV + Wind + BESS + H ₂	39,612,465.0	1,879,206.0	43,976,151.0	0.861	1802.0	54,905.0

Source: own elaboration (Monte Carlo simulation).

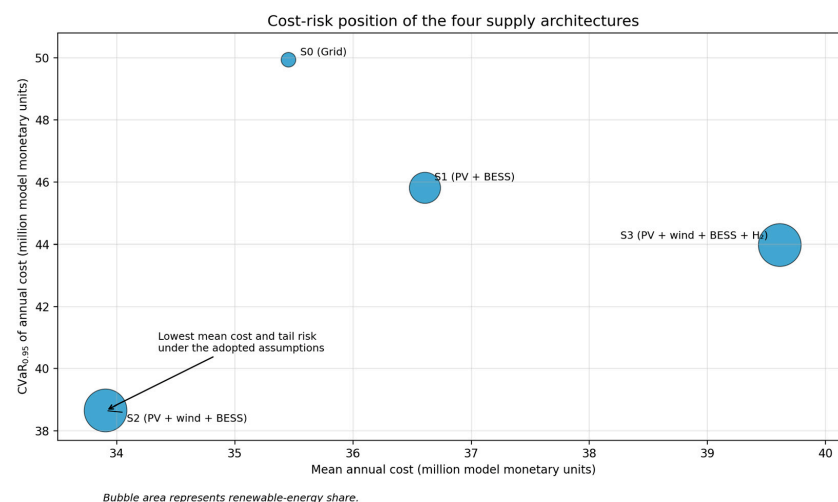


Figure 5. Mean annual cost and CVaR0.95 by scenario; bubble area represents renewable-energy share. Source: own elaboration based on Table 8.

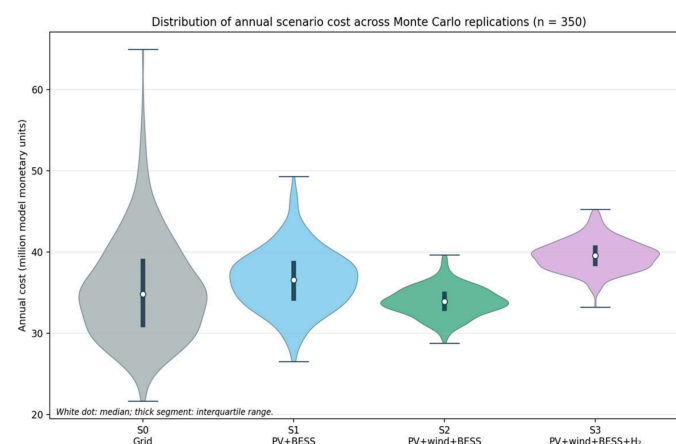


Figure 6. Distribution of annual scenario cost across 350 Monte Carlo replications; white dots denote medians and thick segments interquartile ranges. Source: own elaboration based on the simulation assumptions in Table 6.

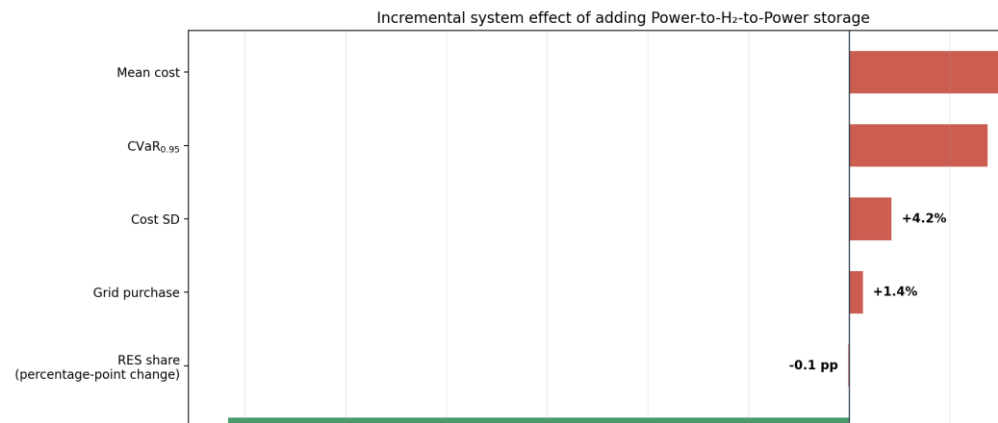


Figure 7. Incremental effect of adding Power-to-H₂-to-Power storage (S3 relative to S2). Negative curtailment denotes an improvement, whereas increases in cost, CVaR, dispersion, or grid purchase denote deterioration. Source: own elaboration based on Table 8. Green bars indicate improvement under the relevant criterion; red bars indicate deterioration.

4.3. Multi-Criteria Ranking of Alternatives (TOPSIS)

Table 9 reports the TOPSIS results using the weights specified in Section 3.4. Under P1, S2 ranks first (CC = 0.674), narrowly ahead of S3 (CC = 0.665); under P2, S3 ranks first (CC = 0.816) because the lower curtailment receives greater relative importance. Figure 8 shows that this conclusion is not weight-invariant; S3 remains preferred until the joint weight of mean cost and CVaR reaches approximately 0.794, after which S2 becomes preferred. S0 does not rank first over the examined range. Thus, the ranking is stable within each stated preference regime but changes at a clearly identified financial-risk threshold.

Table 9. TOPSIS closeness coefficients and ranks under the financial-risk (P1) and decarbonisation (P2) weight profiles.

Scenario	CC_P1	Rank_P1	CC_P2	Rank_P2
S0_Grid	0.361	4	0.379	4
S1_PV + BESS	0.544	3	0.592	3
S2_PV + Wind + BESS	0.674	1	0.622	2
S3_PV + Wind + BESS + H2	0.665	2	0.816	1

Source: own elaboration (TOPSIS ranking).

Table 10 compares baseline and risk-aware dispatch for S2. The heuristic reduces CVaR_{0.95} by 2.4% and mean cost by 0.1%, but renewable share falls by 4.4 percentage points because low-price grid charging displaces part of direct renewable utilisation. The result illustrates a specific operational trade-off rather than proving the universal superiority of the heuristic.

Table 10. Effect of the risk-aware BESS dispatch heuristic in scenario S2.

Operating Policy	Mean Annual Cost (Model Units/Year)	CVaR _{0.95} (Model Units/Year)	RES Share
S2 baseline	33,905,278	38,655,457	0.862
S2 risk-aware	33,871,711	37,738,375	0.818

Source: own elaboration (paired policy demonstration using the assumptions in Table 6).

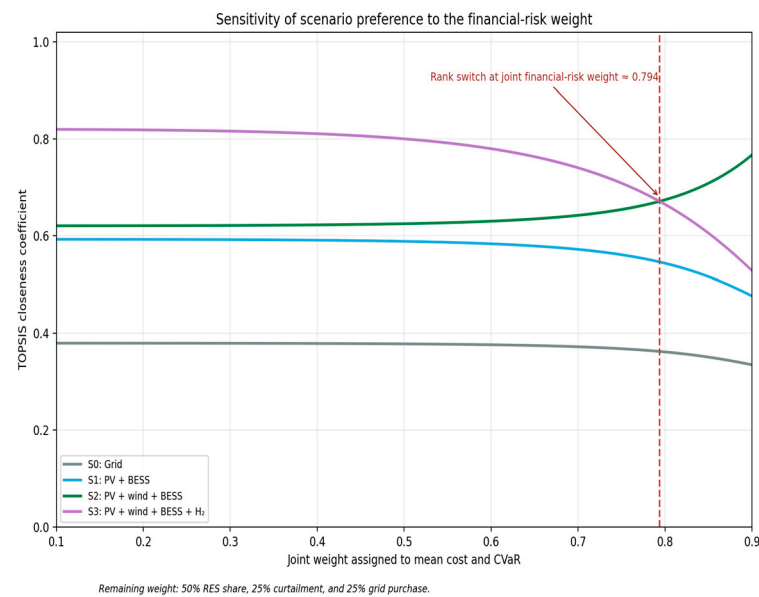


Figure 8. Sensitivity of TOPSIS closeness coefficients to the joint weight assigned to mean cost and CVaR. The rank switch between S3 and S2 occurs at approximately 0.794. Source: own elaboration based on Table 8 and the procedure in Section 3.4.

5. Discussion

The principal contribution is a decision architecture rather than an empirically validated causal model. The synthetic parameter-recovery exercise shows that the proposed constructs and estimation workflow are internally coherent, but managerial implications must be read as testable propositions. In practice, firms should not infer effect sizes from Table 7; they should use the model to structure data collection, assign process ownership, and define validation criteria before investment decisions.

The energy-hub results indicate when battery storage may be sufficient. Under the adopted assumptions—substantial daily renewable complementarity, accessible grid backup, moderate curtailment, and a four-hour BESS—S2 provides the lowest mean cost and tail risk. This is consistent with flexibility research showing that short-duration storage is effective when imbalance is predominantly intra-day [6]. The result is conditional on the assumed load profile, capacities, prices, and absence of network constraints.

The hydrogen result is more informative when interpreted operationally. S3 reduces curtailment but does not reduce grid dependence because the hydrogen chain is used too infrequently to recover its additional annualised cost and because its 35% round-trip efficiency is substantially below that of BESS. Hydrogen would become more attractive under persistent multi-day or seasonal surplus, severe grid-capacity constraints, high penalties for curtailment or prolonged peak-price exposure, higher full-load hours, lower electrolyser/fuel-cell costs, or when hydrogen has an additional process-use value. Figure 7, therefore, identifies a boundary condition rather than a general rejection of hydrogen storage.

The digital-twin-ready architecture clarifies how ISO 50001 maturity and digitalisation can change actual investment decisions. A reliable baseline, governed EnPI definitions, time-aligned SCADA/EMS data, recurrent model calibration, and explicit approval gates allow the enterprise to compare forecast and realised performance, update CVaR estimates, and revise dispatch or capacity decisions. Without these process controls, digitalisation may increase data volume without improving decision quality [12,14,15,24]. BPMN is consequently used to govern the decision cycle, not as a substitute for physical modelling.

The TOPSIS sensitivity analysis also limits overinterpretation. S2 and S3 exchange first place when the joint financial-risk weight crosses approximately 0.794. This means that a ranking reported without weights and stability analysis is not decision-transparent. A practical governance implication is that criterion definitions and weights should be approved before alternatives are scored, and the rank-switch threshold should be disclosed to investment committees and operational stakeholders [18,19,27,28].

CVaR adds information that means cost alone cannot provide because it isolates the expected cost within the worst 5% of annual outcomes [9,10,29,30]. Table 10 further shows that operational risk can be reduced without changing installed capacity, although the reduction may conflict with renewable-utilisation objectives. ISO 50001 review cycles can make this trade-off explicit by reporting expected cost, CVaR, renewable share, curtailment, and grid dependence as a joint performance dashboard rather than as separate technical indicators.

Overall, the framework connects engineering and management layers that are usually assessed separately. Its immediate use is diagnostic: to identify missing data, unclear process ownership, unreported risk preferences, and technology choices that are sensitive to modelling assumptions. External validity requires observed multi-firm and plant-level evidence; until such validation is completed, the framework should support structured deliberation and pilot design rather than serve as a universal investment rule. Related process-modelling, Industry 4.0, assistive manufacturing-technology, and regional renewable-potential studies further support the need for context-specific implementation assessment [31–34].

6. Conclusions

This study proposes a risk-aware assessment framework for industrial renewable-energy integration that combines ISO 50001-based energy management, BPMN-supported process governance, a digital-twin-ready architecture, Monte Carlo simulation, CVaR, and TOPSIS. Its contribution is a structured decision-support approach, not an empirical confirmation of firm-level causal relationships.

Three conclusions follow from the analyses. First, the synthetic parameter-recovery exercise confirms only the internal coherence of the proposed measurement and estimation logic and should be treated as preparation for empirical testing. Second, under the adopted energy-hub assumptions, the PV-wind-BESS scenario (S2) provided the best cost-risk balance, whereas the hydrogen scenario (S3) mainly reduced curtailment but did not improve cost or grid-dependence performance. Third, the TOPSIS results show that the preferred scenario is weight-dependent, so stakeholder priorities and sensitivity thresholds should be reported together with mean cost, CVaR, renewable share, curtailment, and grid purchases.

For industrial practice, the framework supports a disciplined ISO 50001-compatible decision process: define energy-performance indicators, map responsibilities and approval gates, calibrate plant-level models, simulate uncertainty, calculate tail-risk indicators, and document multi-criteria trade-offs before investment approval. In this role, the framework is diagnostic and decision-supportive rather than prescriptive.

Future work should validate the survey model on observed industrial data and implement the digital-twin layer in a real plant with live metering, recurrent calibration, and feedback to dispatch decisions. Such validation is necessary before the framework can be used as evidence of generalisable managerial or engineering effects.

7. Limitations and Future Research

Four limitations define the interpretation of the study. First, the survey-like dataset is synthetic and supports parameter recovery only. Second, the digital-twin component is an implementation architecture without live data exchange, calibration, or plant feedback. Third, the energy-hub model uses stylised demand, price, and renewable distributions and omits network constraints, export, degradation, demand response, and alternative hydrogen uses. Fourth, the open-corpus literature mapping is transparent but not exhaustive.

- Empirical validation should proceed through cognitive pretesting and a pilot survey, followed by a multi-sector sample of at least 300 industrial firms and confirmatory SEM. Organisational responses should then be linked to observed EnPI, meter, SCADA/EMS, price, and production data in longitudinal case studies.
- Plant-level research should implement the five-layer architecture in Figure 2b, calibrate models on rolling windows, compare forecast and realised errors out of sample, and evaluate whether CVaR-informed dispatch improves cost resilience without unacceptable losses in renewable utilisation.
- Further simulation should test alternative BESS and H₂ sizes, degradation, grid-capacity limits, process heat and direct hydrogen demand, export options, correlated price–weather extremes, and alternative risk measures. These extensions would establish the operating conditions under which the scenario rankings remain stable.

A database-complete review using Scopus and Web of Science should also be conducted when access permits, enabling bibliometric analysis and a more exhaustive assessment of the framework’s conceptual boundaries.

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