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A framework for decision making under deep uncertainty in hard-to-abate industries: An application case for investment in a German steel plant

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ABSTRACT

Decarbonising hard-to-abate industries is necessary for climate goals, yet investment choices are hindered by deep uncertainty. This study develops an ambiguity-aware investment evaluation framework that accounts for parameter uncertainty, probability ambiguity, and downside risk. Scenario-level net present values are computed under alternative electricity and hydrogen system narratives and evaluated using a loss law–invariant model-set approach. Probability ambiguity is represented by an ambiguity set of admissible scenario-probability vectors defined through per-scenario bounds implied by multiple probability views, and performance is assessed using worst-case mean and worst-case expected shortfall over this set. The framework is applied to a primary steel investment in Germany, comparing Natural Gas–DRI–EAF, imported-hydrogen DRI–EAF, and on-site electrolysis based DRI–EAF configurations. Electricity procurement prices come from an agent based market simulation for 2035, while fuel and policy inputs vary across 18 discrete scenarios. Natural Gas–DRI–EAF is most robust with a worst-case mean NPV of €10.83 bn and a 4.7% reduction from the Base expected value. Electrolyser–DRI–EAF with lower CAPEX and tariff relief approaches this benchmark with a worst-case mean NPV of €10.53 bn, and tariff relief increases worst-case mean performance by about €4.9 bn relative to no discounts. Imported-hydrogen DRI–EAF is ambiguity-fragile, with Base expected NPV of €7.82 bn falling to €4.57 bn under worst-case mean. For industrial decision makers, the framework indicates whether a pathway remains acceptable under pessimistic probability weightings and tail protection, and it identifies which parameters drive downside exposure. For policy and regulatory analysts, the remaining robustness gap even under tariff relief indicates where additional risk-sharing or cost-relief instruments are needed to improve performance in the adverse states that determine worst-case and tail outcomes. A sensitivity analysis with non-stationary second-decade price regimes confirms that the main conclusions do not rely on stationary annual cash flows.

1. Introduction

Investment decision making in hard-to-abate industries such as steel, cement, and basic chemicals is increasingly shaped by deep uncertainty. These sectors are characterised by high capital intensity, long asset lifetimes, and a narrow set of technologically feasible decarbonisation options. Decisions taken today lock in production pathways for several decades, while future operating conditions remain highly uncertain. Firms therefore face uncertainty about energy prices, climate policy, infrastructure availability, and technology costs [1,2], which complicates risk-neutral capital budgeting based on a single "best-estimate" outlook.

Future electricity, hydrogen, and natural gas prices depend on uncertain developments in fuel markets, renewable deployment, grid expansion, and cross-sectoral electrification. Policy conditions including climate targets, carbon price trajectories, subsidy schemes, network tariffs, and regulatory exemptions evolve through political processes that are difficult to anticipate over long horizons [3,4]. Technological uncertainty adds further ambiguity, as emerging options such as hydrogen-based steelmaking or large-scale electrolysis involve uncertain cost trajectories, performance characteristics, and infrastructure needs [1,2].

These uncertainties are not only relevant at the level of individual firms. Industrial consumers account for a substantial share of electricity and fuel demand, and their technology choices influence load profiles, flexibility provision, infrastructure needs, and system costs. Because industrial investments are capital-intensive and downside sensitive,

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uncertainty affects both the timing of investment and the technologies adopted [5]. Understanding how uncertainty and risk shape industrial investment decisions is therefore essential for interpreting future energy system trajectories and for designing effective decarbonisation policies.

The framework developed in this paper is aimed at two groups. The first are industrial decision makers and analysts who assess decarbonisation investment options, including corporate strategists, finance functions, and risk managers. The second are policy and regulatory analysts who assess whether policy instruments reduce investment risk and improve the credibility of deployment pathways. For industrial users, the framework supports technology ranking when scenario probabilities are uncertain and differ across stakeholders, and it quantifies robustness in monetary terms. For policy analysts, it quantifies how policy levers (e.g., tariff relief) shift technologies on robustness metrics by improving performance in adverse futures. In both settings, a central challenge is that uncertainty concerns not only scenario outcomes but also the probabilities attached to them. Different stakeholders may hold different, internally consistent views on the likelihood of key drivers such as hydrogen prices, electricity prices, and policy support, and there is often insufficient empirical basis to identify one probability distribution as objectively correct. Relying on a single probability model can therefore be misleading, and expected-value comparisons can mask the downside and tail outcomes that often determine investment viability under adverse conditions. To address this, this paper develops a framework for investment evaluation under deep uncertainty that is tailored to hard to abate industries that combines scenario-based outcomes with probability bounds derived from multiple plausible stakeholder views and downside metrics that are well-defined under scenario loss law–invariance. In these sectors, decarbonisation options are limited and assets are long-term, so outcomes depend strongly on long horizon energy and carbon prices, infrastructure availability, and policy choices. The literature and official scenario sets offer multiple, different narratives for these drivers rather than one agreed trajectory. This implies that more than one probability assignment over scenarios can be plausible, which motivates treating probabilities as a set rather than a single vector. Investment performance is then assessed using two robustness metrics: the worst-case mean across all probability distributions within the bounds, and the worst-case expected shortfall, which captures tail-loss exposure under the same set. Together, these metrics distinguish options that perform well only under optimistic probability views from those that remain attractive even when greater weight is placed on adverse futures.

The framework is illustrated with a primary steel investment in Germany. Steel is chosen because the set of feasible decarbonisation pathways is limited, the economics depend strongly on electricity and hydrogen markets, and outcomes are sensitive to policy and tariff design [1,6]. The application compares natural gas based direct reduction, hydrogen based direct reduction with imported hydrogen, and direct reduction supplied by on site electrolysis. Scenarios reflect different assumptions about future energy system developments and policy environments. The aim is to show how ambiguity-aware evaluation can change conclusions relative to conventional expected value comparisons. The objective is methodological to provide decision support through robustness diagnostics and policy-relevant comparisons, rather than plant-specific investment advice.

The remainder of the paper is organised as follows. Section 2 reviews the literature on frameworks under deep uncertainty and highlights gaps related to probability ambiguity and monetary downside-risk evaluation in hard-to-abate investment decision. Section 3 presents the ambiguity-aware, loss law–invariant evaluation framework. Section 4 describes the use case, data, and scenario construction. Section 5 reports scenario-wise, belief-conditioned, and ambiguity-aware robustness results. Section 6 discusses implications, limitations, and conclusions.

2. Literature review

This review covers two distinct but closely related strands of work. First, it synthesises investment decision studies in hard-to-abate industries, focusing on how uncertainty is represented and how risk enters financial evaluation. Second, it reviews decision making frameworks developed for deep uncertainty. The aim is not to provide an exhaustive catalogue. Instead, the review highlights gaps that are especially consequential for capital-intensive decarbonisation projects. Existing studies often treat probability ambiguity and belief heterogeneity only partially. Downside and tail risk are quantified less frequently. These elements are also not consistently translated into investor-relevant monetary metrics. These gaps motivate the framework developed in this paper.

2.1. Investment under deep uncertainty in hard-to-abate industries

Investment decision making in hard-to-abate industries such as steel, cement, and basic chemicals is widely recognised as challenging because choices are capital intensive, with long operating lifetimes, and difficult to reverse. Once an investment decision is taken, production routes and energy carriers are effectively locked in for several decades. This exposes firms to substantial losses if market or policy conditions evolve unfavourably. In the steel sector, the lock in effect is particularly pronounced because the transition away from blast furnace production requires large irreversible capital commitments under uncertain future operating conditions [1,6].

The uncertainty surrounding such investments extends beyond short term price fluctuations. Future electricity, hydrogen, and natural gas prices depend on uncertain developments in fuel markets, renewable deployment, grid expansion, and cross sectoral electrification. Policy conditions include climate targets, carbon pricing trajectories, subsidy schemes, and network tariff structures that evolve through political processes which are difficult to anticipate over long horizons [4]. These uncertainties interact and accumulate over time, making it difficult to justify a single probabilistic representation of future states. Haas et al. frame this environment as one of deep uncertainty, in which neither the correct model nor the associated probability distribution can be identified with confidence [1,2].

Applied studies in Germany and Europe identify these uncertainties as a major source of firm level investment risk. Country specific work shows that the technoeconomic outcomes of steel decarbonisation depend strongly on scenario assumptions and policy design. For Poland, Hetmanski et al. [7] evaluates hydrogen-based DRI, CCS, and conventional routes under alternative electricity and CO_2 price trajectories and shows that cost competitiveness hinges on a narrow set of favourable assumptions, with substantial downside risk under adverse price combinations. Similarly, Harpprecht et al. [8] analyse German steel decarbonisation pathways under electrification, hydrogen, and CCS scenarios and show that, despite deep emission reductions, cumulative carbon budgets are exceeded unless investments are accelerated early, highlighting the risk of lock-in under delayed action. The FlexIPro project [9] analyses electrified industrial processes and shows that decarbonisation investments become economically attractive only if additional capital costs for capacity, infrastructure, and storage can be compensated by electricity-cost savings or flexibility revenues. Importantly, the study cautions that electricity price assumptions derived from system-optimised models may understate real-market features such as scarcity pricing and strategic bidding, which can affect profitability assessments. Similarly, the SynErgie study on industrial flexibility highlights that regulatory design and tariff structures can weaken investment incentives when effective industrial electricity prices do not reflect wholesale signals, thereby increasing downside risk for capital-intensive investments [10]. The SynErgie study on electricity-market flexibilisation further emphasises that firms face uncertain developments in both wholesale and flexibility-market prices, complicating long-term investment evaluation [11]. While this work introduces probabilistic approaches for short-term market participation, it notes that robust quantification of investment benefits is constrained by limited empirical data and the demonstrator status of many technologies. Across these studies, uncertainty is acknowledged as a central barrier to investment, yet it is typically addressed through deterministic scenario comparisons or qualitative assessments rather than through explicit treatment of probability ambiguity.

A common feature of the existing literature is its focus on average outcomes or best-case performance metrics, such as expected net present value. For capital-intensive investments with large irreversible costs, however, downside outcomes and tail risks are often decisive for investment viability. Several studies qualitatively note that adverse combinations of high energy prices and unfavourable policy conditions can deter investment, but systematic quantification of such risks remains rare. In particular, few contributions assess how investment performance deteriorates under the most adverse but still plausible futures, or how sensitive alternative technology pathways are to these outcomes.

These limitations matter beyond individual firms. Industrial investment decisions shape future demand levels, load profiles, flexibility provision, and infrastructure requirements. Because industrial actors are highly sensitive to downside risk, uncertainty influences not only whether investments occur but also which technologies are adopted and when. Understanding how deep uncertainty affects industrial investment decisions is therefore essential for interpreting future energy-system trajectories and for designing effective decarbonisation policies [5]. Taken together, the literature agrees that uncertainty represents a major barrier to decarbonisation investment in hard to abate industries. However, most existing studies rely on deterministic scenario comparisons or qualitative discussions of risk. They rarely translate probability ambiguity or exposure to extreme outcomes into monetary risk measures that are directly relevant for investment decisions. As a result, current approaches provide limited support for robust, risk aware investment choices under conditions of deep uncertainty.

2.2. Decision-making frameworks under deep uncertainty

A broad methodological literature has emerged to support long-term investment decisions when futures cannot be credibly captured by a single forecast or probability distribution. In energy and industrial applications, the motivation is that capital-intensive assets with long operating lifetimes face uncertainty that is fundamental and subject to disagreement. Decision support must therefore go beyond best estimate scenarios and expected values. Recent syntheses show that advanced frameworks tend to outperform expected-value appraisal when uncertainty is deep, because they test strategies across a wider range of futures, reduce exposure to misspecified assumptions, and incorporate risk and robustness more explicitly [12,13]. At the same time, the literature points to recurring gaps that are especially relevant for hard-to-abate investments. Probability ambiguity and belief heterogeneity are often treated weakly. Tail-focused risk metrics are used less systematically. Many approaches also face a persistent tension between modelling realism and computational tractability [14,15].

One major stream is robust decision making (RDM) and related scenario based robustness approaches. RDM evaluates candidate strategies across large ensembles of scenarios and typically selects options that meet performance thresholds or minimise regret across futures [16]. This is attractive when probabilities are disputed, since it does not require commitment to a single distribution. However, the same feature can limit interpretability for investors. Outputs are often framed in satisficing or regret terms rather than monetary risk measures, and tail exposure is not always quantified in a form that maps cleanly to investment appraisal [16]. Closely related adaptive approaches, including dynamic adaptive policy pathways and dynamic programming variants, extend this logic by emphasising staged decisions and learning over time. They support flexibility and adaptation, but they often rely on known transition probabilities or fixed scenario structures. This can reintroduce strong probability assumptions once the analysis moves beyond static robustness screening [17].

A second stream uses stochastic optimisation and multistage programming. These methods represent uncertainty through scenario trees with assigned probabilities and then optimise expected objective values, sometimes with additional dispersion penalties [18–20]. Their strength is internal consistency and the ability to model sequential decisions, but they require a fully specified probability model. This is problematic under deep uncertainty because probability estimates are subjective, contested across stakeholders, and unstable under structural change. Reviews repeatedly note that this expected-value orientation can understate downside exposure, particularly when extreme outcomes drive viability [21,22]. Risk-averse extensions exist, for example through variance penalties or Value-at-Risk constraints. Expected Shortfall and related coherent tail risk measures remain uncommon in many investment studies despite their relevance for capital-intensive decisions [23].

Real options analysis forms a third stream, motivated by irreversibility and the value of waiting, staging, or abandoning investment. By modelling uncertainty as stochastic processes, real options captures managerial flexibility and timing, which is central when investments are large and sunk [24]. A key limitation highlighted in recent reviews is that real options typically assumes a specific stochastic process and often uses risk neutral valuation. This compresses tail risks and does not directly address probability ambiguity or divergent beliefs about long-run transitions [25].

Non-probabilistic robustness approaches such as Info-Gap Decision Theory (IGDT) provide an alternative when probabilities are viewed as unknowable. IGDT evaluates how much deviation from a nominal estimate can be tolerated before performance becomes unacceptable. It is transparent and conservative, which can be appealing when evidence is scarce, but it can also become overly pessimistic and is less directly aligned with the monetary performance metrics used in investment appraisal [26]. Multi-criteria decision analysis and fuzzy extensions add further tools for incorporating qualitative criteria and stakeholder preferences. They are useful for structuring trade-offs across economic, environmental, and technical objectives, but they often remain weak in probabilistic representation and rarely quantify tail exposure in ways that support downside-focused financial appraisal [27,28].

Previous work most directly aligned with probability ambiguity is distributionally robust optimisation (DRO) and robust risk evaluation. In investment contexts, ambiguity sets can be constructed not only from statistical confidences, but also from structured belief sets reflecting divergent stakeholder expectations about future market and policy developments. This interpretation is particularly relevant for long-term industrial investments, where disagreement about plausible futures is normative rather than statistical. DRO generalises stochastic optimisation by replacing a single probability distribution with an ambiguity set of distributions and then evaluating worst-case performance over that set. This allows probability ambiguity to be treated explicitly and makes it possible to represent belief heterogeneity through bounds or sets derived from multiple priors or stakeholder views [13,29]. DRO can be combined with coherent tail-risk measures such as Expected Shortfall, resulting in investor-relevant monetary risk metrics that focus on adverse outcomes rather than averages [23,30]. Practical adoption is often constrained by computational burden, particularly for multistage problems or large ambiguity sets, which is repeatedly identified as a barrier to real-world implementation [13,19,20].

Across the reviewed studies, three points stand out for decision support in hard-to-abate investments. First, the scale of uncertainty facing industrial investors remains large even in well developed scenario exercises. For France, I4CE (2023) estimates cumulative decarbonisation investment needs for heavy industry ranging from e 3 bn to e

Table 1
Treatment of uncertainty and risk in existing investment studies.

Dimension	Dominant practice in literature	Representative studies	Key limitation
Scenario construction	Discrete techno-economic scenarios	[32–36]	Scenario sets are limited and often treated deterministically
Probability assignment	Equal weighting or expert judgement	[37–39]	Probabilities are subjective and rarely scrutinised
Belief heterogeneity	Mostly ignored or implicit	[37,40]	Divergent stakeholder expectations are not represented
Risk metrics	Expected value, levelised cost, MAC	[32,34,36,41]	Downside and tail outcomes are not systematically assessed
Advanced risk measures	Rare use of regret or CVaR	[38,42]	Probability ambiguity remains unaddressed
Policy uncertainty	Scenario comparison	[43,44]	Structural policy risk not integrated into decision metrics

14 bn by 2050, depending on technology choice and energy-system assumptions [31]. While such scenario ranges are informative, they do not indicate how investors should evaluate exposure to adverse outcomes within these ranges, nor how probability disagreement across stakeholders affects investment robustness. Second, parameter uncertainty in key drivers such as energy prices and future energy-system conditions should be represented explicitly and carried through the analysis, rather than fixed at single best guess values or treated only through a small set of deterministic sensitivity cases. Third, probability ambiguity should be made transparent rather than hidden behind a single set of scenario weights, since long-term futures are contested and belief heterogeneity is unavoidable [1,13]. Finally, risk evaluation should quantify downside and tail exposure using monetary metrics aligned with investor decision making, rather than relying solely on expected values or qualitative robustness narratives [23].

Taken together, these requirements motivate an ambiguity-aware, loss law-invariant framework that makes belief heterogeneity an explicit modelling input through belief-based bounds and evaluates outcomes using worst-case mean and worst-case Expected Shortfall. This ensures that conclusions depend on the implied loss distribution rather than scenario labels. Under box-type ambiguity sets, these risk functionals can be computed via linear programmes, enabling a single, internally consistent assessment of parameter uncertainty, ambiguous probability beliefs, and downside risk.

2.3. Treatment of probability and risk in existing studies

A central distinction across investment studies in hard-to-abate sectors concerns how uncertainty is translated into probability assumptions and how risk is evaluated. While the literature widely acknowledges uncertainty in energy prices, policy trajectories, and technology costs, the treatment of probability and risk remains uneven. This subsection reviews how existing studies assign probabilities to future states, represent belief heterogeneity, and measure risk. It then highlights limitations that are particularly consequential for long-term, capital-intensive investments.

Scenario analysis and stochastic optimisation are widely used to evaluate decarbonisation options and investment strategies for hard-to-abate sectors. Table 1 summarises common approaches that provide useful structure for comparing pathways and identifying trade-offs under uncertainty. However, scenario sets are often discrete and limited. Stochastic formulations commonly require probability inputs that are assumed rather than inferred. This becomes problematic when long-run futures are disputed and evidence is sparse [35,37].

Where probabilities are used, they are often assigned through equal scenario weights or expert judgement [37,38]. This is pragmatic, but it can hide belief heterogeneity. Plausible futures may be weighted very differently by investors, firms, regulators, or system planners. Only a small share of the literature represents heterogeneous beliefs explicitly, for example in agent-based modelling contexts. Even there, this is more common in residential or broader energy investment settings than in heavy industry [40].

Most applied studies report expected values, levelised costs, or marginal abatement costs, and treat uncertainty through scenario spreads or sensitivity analysis [41]. These metrics are informative for central tendencies, but they do not directly quantify exposure to rare, adverse combinations of prices and policies that can drive investment non-viability [37,42]. Tail-focused risk metrics such as Value at Risk or Expected Shortfall are still uncommon in hard-to-abate investment assessments, despite their relevance for capital-intensive decisions with asymmetric downside exposure [37,42].

In the risk-measure literature, law-invariant evaluation depends only on the loss distribution under a fixed probability model [30,45]. Within coherent risk measures, Expected Shortfall is supported by axiomatic properties such as convexity and subadditivity, and is closely linked to tail functionals, whereas Value at Risk is not subadditive and can understate tail exposure [30,45–47]. From an implementation perspective, Expected Shortfall is commonly formulated using the Rockafellar–Uryasev approach, results in tractable convex optimisation problems that are widely used in risk-averse energy planning and operations under renewable and price uncertainty [23,48].

A persistent limitation in many energy applications, however, is the assumption of a single fixed probability distribution. Distributionally robust optimisation relaxes this assumption by evaluating risk against the worst-case distribution within an ambiguity set, and can embed law-invariant cores such as the mean or Expected Shortfall [49–51]. This provides a route to address probability ambiguity and tail risk jointly, but it has been less developed in the context of capital-intensive industrial investments where ambiguity is naturally expressed as a range of stakeholder belief sets rather than as a purely statistical confidence region [50,51].

This literature review shows how uncertainty is treated in investment decisions for hard-to-abate industries. Whilst uncertainty is commonly explored through scenarios, two critical aspects are rarely addressed explicitly. First, parameter uncertainties and divergent probability beliefs are seldom represented in a transparent way. Second, tail risk is rarely quantified in forms that directly support risk-averse investment choices. These gaps limit the usefulness of existing methods for decision support under deep uncertainty. Most applied studies use discrete scenario comparisons, sensitivity analysis, or expected-value metrics, which are informative for understanding average outcomes, but they offer limited support when investment viability is determined by adverse cases rather than average performance but provide limited guidance when adverse outcomes drive investment viability. Probability assumptions are often implicit, fixed, or based on equal weighting, even though long-term futures are disputed, and beliefs differ across stakeholders. At the same time, tail risks arising from unfavourable combinations of energy prices, policy conditions, and technology costs are rarely quantified in monetary terms that align with investor decision making.

Taken together, the literature provides strong motivation for scenario-based evaluation of industrial decarbonisation investments under deep uncertainty. However, two gaps remain particularly salient for the decision context studied here. First, uncertainty concerns not only outcomes but also the probability models used to weigh them. In practice, probability assignments may differ across stakeholders, expert assessments, scenario providers, or data-driven calibrations, and several probability views can be internally coherent. Yet many applications either impose a single probability vector, treat probabilities implicitly (e.g., uniform weights), or avoid probabilistic modelling altogether. Second, quantitative risk evaluation in capital budgeting is frequently organised around expected outcomes, while explicit measures of downside exposure and tail risk are used less systematically, despite the fact that adverse outcomes, rather than average performance, often determine investment viability for long-term, capital-intensive assets.

These limitations motivate a framework that moves beyond single-model expected-value evaluation and beyond purely qualitative robustness narratives. Such a framework should admit a set of plausible scenario-probability vectors for a discrete scenario set, transparently encode this plurality as an explicit ambiguity set, and evaluate investment performance using investor-relevant monetary risk measures with an explicit focus on downside and tail outcomes. Because scenarios are discrete representations of future states and the central uncertainty often lies in probability assignments rather than in scenario labels, the evaluation should be loss law invariant. Conclusions should depend on the implied distribution of economic losses rather than on scenario identifiers. This review therefore motivates the ambiguity-aware, loss law invariant framework developed in this paper, which combines parameter uncertainty with probability bounds induced by alternative probability views and evaluates technologies using worst-case mean and worst-case expected shortfall criteria.

3. Methodology

This section presents a general framework for evaluating capital-intensive investments under deep uncertainty. The framework is applicable across technologies and sectors and can be combined with standard capital budgeting metrics. In this paper, net present value (NPV) is used to illustrate the approach because it is widely used in industrial investment appraisal and directly reflects discounted cash flows. The framework defines scenario-level outcomes, represents multiple probability views through belief vectors, converts these views into an explicit ambiguity set, and then evaluates downside performance under probability ambiguity. Results are reported alongside conventional risk neutral benchmarks. The final subsection describes the application to a primary steel investment case.

3.1. Framework overview and workflow

Let $\mathcal{I}$ denote the set of technology options and $\mathcal{S}$ the set of scenarios. The decision framework consists of the following steps.

1. **Scenario design (parameter uncertainty).** A finite scenario set $\mathcal{S}$ is constructed to span plausible combinations of key uncertain drivers, such as electricity, hydrogen, and natural gas prices, carbon prices, policy and tariff regimes, and technology costs. Each scenario $s \in \mathcal{S}$ represents an internally consistent future state.
2. **Scenario outcomes.** For each technology option $i \in \mathcal{I}$ and scenario $s \in \mathcal{S}$, an economic outcome $X_{i,s}$ is computed using a selected capital-budgeting metric. In this paper, $X_{i,s} = \mathrm{NPV}_{i,s}$. The set $\{X_{i,s}\}_{s\in\mathcal{S}}$ characterises how each technology performs across parameter uncertainty without assigning probabilities.
3. **Belief sets (probability views).** A set of belief vectors $\{p^{(b)}\}_{b\in\mathcal{B}}$ is specified, where each $p^{(b)} \in \Delta^{|\mathcal{S}|}$ assigns probabilities to scenarios based on expert judgement, data, or structured narratives. The coexistence of multiple belief vectors explicitly captures probability ambiguity.
4. **Ambiguity-aware risk evaluation.** The belief vectors are translated into a tractable ambiguity set of admissible probability distributions. Robust, investor-relevant downside metrics are then computed using loss law–invariant criteria, namely the worst-case mean and the worst-case expected shortfall. These metrics provide performance guarantees that hold across all probability distributions consistent with the stated beliefs.
5. **Benchmarking and interpretation.** Compare ambiguity-aware rankings against standard risk-neutral benchmarks (e.g., scenario-wise outcomes without probabilities, expected values under fixed belief vectors, and belief-dependent distributional summaries) to clarify which conclusions are driven by probability assumptions versus downside risk protection.

3.2. Economic performance metric and scenario outcomes

Let $i \in \mathcal{I}$ index investment options and $s \in \mathcal{S}$ index scenarios representing alternative future states. A capital budgeting metric is required to evaluate the economic performance of each option in each scenario. While the framework is compatible with alternative measures such as internal rate of return or equivalent annual cost, this study uses net present value (NPV) because it is widely applied in industrial investment appraisal and directly reflects discounted cash flows.

For each technology option i and scenario s, an NPV value $\mathrm{NPV}_{i,s}$ is computed. At this stage, no probabilities are assigned to scenarios. The resulting matrix $\{\mathrm{NPV}_{i,s}\}$ provides a transparent benchmark that shows how each technology performs across alternative futures (an ex post comparison that does not constitute an ex ante decision rule). This step isolates outcome uncertainty from probability assumptions and allows scenario-wise comparisons without committing to a particular belief about likelihoods.

3.3. Belief sets and probability ambiguity

Investment decisions under deep uncertainty are characterised not only by uncertainty about outcomes, but also by ambiguity about which futures are more plausible. To represent this, the framework allows for multiple belief sets rather than a single probability distribution.

Let $p^{(b)} \in \Delta^{|\mathcal{S}|}$ denote a probability vector over scenarios associated with belief $b \in \mathcal{B}$. Each belief set reflects a coherent but subjective view about the future, informed by expert judgement, data, or narratives. These beliefs are not interpreted as estimates of a true data-generating process, but as plausible representations of how different decision-makers might assess scenario likelihoods.

From the collection of belief sets, per-scenario probability bounds are constructed as

$$L_s = \min_{b\in\mathcal{B}} p_s^{(b)}, \qquad U_s = \max_{b\in\mathcal{B}} p_s^{(b)}, \quad \forall s \in \mathcal{S}.$$

These bounds define a box-type ambiguity set

$$\mathcal{Q} = \left\{ p \in \mathbb{R}_+^{|\mathcal{S}|} : \sum_{s\in\mathcal{S}} p_s = 1,\ L_s \le p_s \le U_s \ \ \forall s \right\}. \tag{1}$$

The set $\mathcal{Q}$ captures probability ambiguity explicitly by allowing scenario probabilities to vary within bounds implied by the stated beliefs. Feasibility requires $\sum_s L_s \le 1 \le \sum_s U_s$, which is verified in the application.

3.4. Loss law–invariant risk evaluation

To evaluate investment performance under probability ambiguity, outcomes are assessed on the loss scale. For technology i and scenario s, define the loss

$$\ell_{i,s} = -\mathrm{NPV}_{i,s}. \tag{2}$$

Evaluation is *loss law–invariant*, meaning that risk depends only on the distribution of losses under a given probability vector, not on the labels of scenarios. For reporting, we convert all loss-based risk measures back to the NPV scale by sign reversal, so that higher reported values consistently indicate more favourable investment outcomes.

Following the model-set approach of Fadina, Liu, and Wang, ambiguity-aware evaluation is obtained by taking the worst-case value of a loss functional over all probability distributions in Q:

$$\Phi(\ell_i \mid Q) = \sup_{p\in Q} \Phi(\ell_i \mid p). \tag{3}$$

Two loss law–invariant risk measures are used.

3.4.1. Worst-case mean

The worst-case mean loss captures the most adverse expected performance consistent with the ambiguity set:

$$\text{WC Mean}_i = \sup_{p\in Q} \sum_{s\in S} p_s \ell_{i,s}. \tag{4}$$

This metric generalises expected value analysis by allowing probabilities to move adversarially within the specified bounds.

3.4.2. Worst-case expected shortfall

To capture tail risk, expected shortfall at confidence level α is used. For a fixed probability vector p, expected shortfall is defined as

$$\rho_{\text{ES},\alpha}(\ell_i \mid p) = \min_{\eta\in\mathbb{R}} \left\{ \eta + \frac{1}{1-\alpha} \sum_{s\in S} p_s(\ell_{i,s} - \eta)_+ \right\}. \tag{5}$$

Here, η is an auxiliary threshold variable defining the tail loss level and is unrelated to any time index used elsewhere in the paper.

The ambiguity-aware counterpart is obtained by maximising over Q:

$$\text{WC ES}_{\alpha,i} = \sup_{p\in Q} \rho_{\text{ES},\alpha}(\ell_i \mid p). \tag{6}$$

This quantity represents the mean loss in the worst $(1-\alpha)$ fraction of outcomes under the most adverse probability distribution allowed by the belief bounds. Both worst-case mean and worst-case expected shortfall can be computed efficiently as linear programmes when Q is a box set.

3.5. Benchmarks and performance comparison

The proposed framework evaluates investment options through a sequence of informative benchmarks. Each benchmark reflects a distinct assumption about how uncertainty is treated and corresponds to a commonly used decision logic in practice. Presenting these benchmarks side by side clarifies how investment rankings change as the analysis moves from parameter uncertainty alone to probability ambiguity and downside risk.

3.5.1. Benchmark 1: Scenario-wise outcomes without probabilities

As a first reference point, net present values are evaluated separately for each scenario without assigning probabilities. For each scenario $s \in S$, the technology option with the highest $\text{NPV}_{i,s}$ is identified. This benchmark illustrates how technology preferences would differ across future states under perfect foresight. It does not, however, constitute a decision rule, as it implicitly assumes that the investor can condition the choice on the realised scenario.

3.5.2. Benchmark 2 risk neutral expected values under fixed beliefs

This benchmark evaluates expected outcomes under each belief vector defined in Section 3.3. For each belief b, the expected net present value is

$$\text{EV}_i^{(b)} = \sum_{s\in S} p_s^{(b)} \, \text{NPV}_{i,s}. \tag{7}$$

Selecting the option with the highest expected value under a given belief corresponds to risk neutral decision making under a single subjective probability model. Reporting results across belief vectors shows how recommendations vary across probability views.

3.5.3. Benchmark 3 distributional information within belief sets

To characterise belief dependent risk exposure, cumulative distribution functions of $\text{NPV}_{i,s}$ are constructed for each technology under each belief vector. These distributions show dispersion and downside exposure that are not visible from expected values alone. They also show when an option that maximises expected value under one belief still places substantial probability mass on unfavourable outcome ranges.

3.5.4. Benchmark 4 optimistic selection across beliefs

The maximum expected value across belief sets is reported as

$$\max_{b\in B} \text{EV}_i^{(b)}. \tag{8}$$

This criterion reflects optimistic belief selection, where the investor adopts the belief that is most favourable to a given technology. It does not reflect disagreement between beliefs and it provides no protection against adverse probability misspecification.

3.5.5. Benchmark 5: Ambiguity-aware evaluation under loss law invariance

This benchmark avoids selecting a single belief vector. Scenario probabilities are allowed to vary within the ambiguity set Q derived from all belief vectors. Performance is evaluated using loss law invariant criteria, namely the worst case mean loss and the worst case expected shortfall at confidence level α. These metrics quantify the largest expected loss and the largest tail loss that can occur under any probability distribution consistent with the stated beliefs.

3.5.6. Decision rule

The decision rule selects the technology with the smallest worst case mean loss. For investors with stronger downside aversion, a constraint can also be applied to the worst case expected shortfall. On the net present value scale, this corresponds to selecting the option with the largest worst case expected net present value, subject to a tail risk bound.

The framework is compatible with other decision theoretic approaches such as expected utility maximisation or prospect theory. Implementing these approaches requires specifying utility functions or reference dependent value functions and additional behavioural parameters. To maintain transparency and tractability, this study focuses on loss law invariant risk measures that directly characterise downside and tail outcomes under probability ambiguity.

3.6. Implementation: scenario inputs, market simulation, and plant-level cash flows

This subsection describes how scenario-specific inputs are generated and how net present values are computed for the use case. These elements operationalise the framework introduced above but are not intrinsic to it. The ambiguity-aware decision methodology can be applied with any capital-budgeting metric, scenario generator, or market model. Here, net present value is used as the evaluation metric, and scenario inputs are derived from an electricity market simulation combined with exogenous fuel and policy assumptions.

3.6.1. Electricity market simulation and procurement prices

Hourly day ahead prices for 2035 are generated with the open source ASSUME agent based electricity market framework [52,53]. In this study, only the day ahead market is simulated and the resulting price series is used to construct the electricity procurement price for the industrial case study. The model represents market participants as supply and demand agents with technology specific attributes and clears an hourly day ahead market under a standardised design. The market design follows current practice, including the clearing rule, trading windows, product durations, and bounds on bid volumes and prices. Supply consists of generation technologies and storage units.

Demand is represented by hourly load time series allocated to transmission nodes. Since Germany is modelled as a single bidding zone, this spatial allocation does not affect the clearing price.

The model represents bidding behaviour relevant for price formation, including renewable variability and storage operation. Bidding strategies follow Qussous et al. [54]. Renewable units bid available energy at very low prices. Thermal units submit a must-run block priced at marginal cost net of amortised start and stop costs, and an additional flexible block priced at marginal cost. Storage agents charge when expected prices are low and discharge when expected prices are high, subject to power limits, energy limits, and round-trip efficiency. Demand agents are price takers.

Technology portfolios and hourly demand profiles are taken from the *Langfristszenarien* project for 2035 for two system narratives, O45 Strom and O45 H_2 [55]. These narratives are derived from an integrated energy system modelling framework and therefore reflect sector coupling through the underlying assumptions on electrification, hydrogen supply, and electrolysis related electricity demand. O45 Strom represents a high electrification case with higher electricity loads. O45 H_2 represents a hydrogen rich case with substantial electricity demand for electrolysis. Both narratives include expanded wind and solar capacity. Scenario specific commodity inputs, including natural gas prices and CO_2 prices, parameterise thermal unit marginal costs in the market model. Cross border exchanges and renewable availability profiles are included based on historical profiles that are scaled to the 2035 capacity levels of each narrative.

Hydrogen prices used in the plant cash-flow model are treated as external inputs and do not enter the electricity-market clearing. This boundary applies to imported hydrogen prices. Electricity and hydrogen remain coupled through the scenario narratives, in particular through the electrolysis-related electricity demand embedded in the O45 H2 inputs. The exogenous hydrogen price affects only the steel plant economics and represents a delivered plant-gate price under the assumptions in Section 4. The resulting procurement price series provides a representative 2035 price level for each narrative. The aim is not to forecast multi-decade dynamics, but to test how the price level implied by a given 2035 system configuration affects investment viability under uncertainty.

The resulting procurement price series is used as a representative 2035 price level consistent with each system narrative. The objective is not to forecast multi decade price dynamics, but to evaluate how a long run price level implied by a given 2035 system configuration affects investment viability under uncertainty.

3.6.2. Industrial electricity prices

The all-in electricity price faced by the steel plant is constructed by adding regulated tariff components to the scenario-specific procurement price. These components include network charges, levies and surcharges, concession fees, metering and meter operation, and electricity tax, following the structure reported in the Monitoring Report 2024 [56].

Network charges are modelled as a two-part tariff consisting of a capacity-based component (€/kW·a) and a consumption-based component (€/MWh). The case study assumes a high voltage transmission-level grid connection, consistent with the plant's contracted capacity. In the discounted tariff regime, only the capacity-based network charge is reduced to 10% of the published value in accordance with §19 StromNEV for high-utilisation industrial consumers (≥ 8,000 full-load hours), while the consumption-based charge remains unchanged. No concession-fee reduction is applied, electricity tax is set to the industrial minimum of 0.50 €/MWh, and reductions in surcharges and levies reflect the maximum relief reported for large industrial consumers, subject to eligibility under the relevant legal provisions. Procurement prices are identical across tariff regimes.

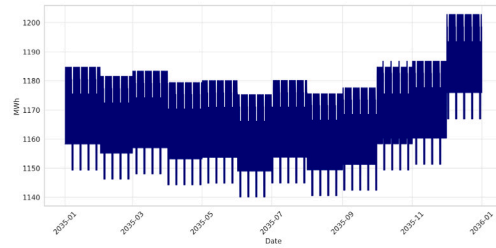

Fig. 1. Representative load profile for a European steel plant [57].

3.6.3. Other energy and policy inputs

Natural gas prices affect both the electricity-market simulation and the plant operating-cost calculation. The supply price follows the supplier-controlled component reported in the Monitoring Report, and network charges, taxes, and surcharges are added to obtain the net industrial gas price. Hydrogen prices are specified exogenously and affect only the operating costs of hydrogen-based routes. The CO_2 price is treated as a fixed policy parameter across scenarios.

3.6.4. Plant operations and operating costs

The case study considers a primary steel plant producing 3.8 Mt of crude steel per year. Hourly electricity demand follows representative iron-and-steel load profiles from the Hotmaps project, scaled to plant capacity (see Fig. 1). Three pathways are analysed: NG–DRI–EAF, H_2–DRI–EAF with imported hydrogen, and Electrolyser–DRI–EAF with on-site hydrogen production. For the electrolyser pathway, two capital-cost variants and two tariff regimes are examined. Plant operation is modelled as a cost-minimisation problem subject to technical constraints and minimum production requirements. Prices are scenario-specific and constant within a scenario. The operations model produces annual operating costs, emissions, and material inputs, which are aggregated into annual cash flows.

3.6.5. Scenario-level net present values

For each technology option i and scenario s, annual cash flows are assumed constant over the project lifetime and discounted using a fixed real discount rate. Net present value is computed as

$$NPV_{i,s} = -I_i + \sum_{y=1}^{T} \frac{CF_{i,s}}{(1+r)^y} + \frac{SV_i}{(1+r)^T},$$

where I_i is upfront investment cost, $CF_{i,s}$ the annual operating cash flow, T the project horizon, and SV_i a terminal value if applicable. The resulting set $\{NPV_{i,s}\}_{s\in S}$ forms the input to the risk-neutral and ambiguity-aware evaluations described in Sections 3.3–3.5.

By construction, the implementation separates parameter uncertainty across scenarios, belief-based probability ambiguity, and downside outcome risk. The modelling environment generates internally consistent scenario outcomes, while the decision framework determines how these outcomes are evaluated under alternative probability views and probability bounds.

4. Use case and assumptions

This section describes the application case and the assumptions used to generate net present values for each scenario. The purpose is to demonstrate how the framework combines parameter uncertainty, probability ambiguity, and downside risk evaluation. This is not intended as plant-specific investment advice. We consider a representative primary steel investment in Germany in 2035 and construct a discrete scenario space under two alternative energy-system narratives. For each scenario, an electricity market model produces an hourly day-ahead price. The annual average of this annual price series is

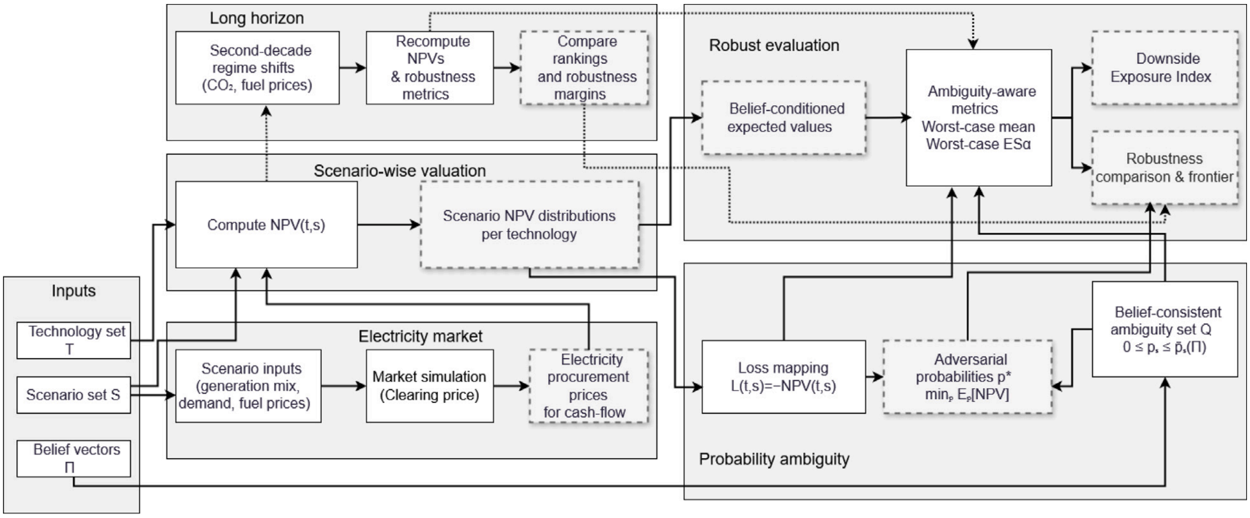

Fig. 2. Analytical workflow of the case-study implementation. Upper blocks generate scenario outcomes. Lower blocks evaluate these outcomes under belief-conditioned expected values and ambiguity-aware worst-case criteria. Imported hydrogen prices are specified exogenously and do not feed back into the electricity-market simulation.

used as the procurement component of the industrial electricity price. Regulated electricity-price components are then added transparently based on published tariffs and statutory minima, with any reductions modelled strictly as utilisation-based reductions under §19 StromNEV. Fig. 2 provides an overview of the workflow used in the steel case study. It shows how scenario inputs are mapped to scenario-level NPVs and how these outcomes are evaluated under belief vectors and probability distributions admissible under the belief bounds.

A metric is required that maps each technology option and scenario to a single financial outcome. In this application, net present value (NPV) is used. NPV is widely used in industrial capital budgeting and allows a transparent decomposition of revenues and costs within a cash-flow model. The framework is not limited to NPV and can be implemented with any capital budgeting metric, provided it is computed consistently across scenarios and technology options.

Two system narratives are used for Germany in 2035 that differ in electrification and hydrogen deployment. The high electrification case is ES (O45 Strom) with annual electricity demand of 730.04 TWh. The high hydrogen case is HS (O45 H_2) with annual electricity demand of 647.96 TWh. Both narratives assume 630.56 GW of renewable generation capacity. Under each narrative, natural gas and hydrogen prices are specified at three levels, resulting in 18 scenarios labelled ES1 to ES9 and HS1 to HS9 (Table 2). For each scenario, an agent-based model produces an hourly day-ahead price series. The annual average of this series is used as the procurement component of the industrial electricity price, and regulated tariff elements are added as described below. Hydrogen is treated as an exogenous energy carrier in the electricity market simulation and represents imports or production outside German electricity market clearing, so the three hydrogen price levels reflect uncertainty in international supply conditions. Natural gas prices affect both the day-ahead merit order and the operating costs of the natural gas-based pathway. The electricity market outcomes are simulated only for 2035, so the hourly price series represents a single-year snapshot of market conditions.

4.1. Technology pathways and decision variables

Decarbonising steel production requires moving away from the conventional blast furnace–basic oxygen furnace route (BF–BOF) towards alternative pathways with lower emissions. Electric arc furnaces (EAFs) can melt scrap, pig iron, or direct-reduced iron (DRI) using electricity and are therefore central to low-carbon steelmaking. In the direct reduction process, iron ore is reduced to sponge iron using a reducing gas before being melted in an EAF [41].

Three archetypal technology pathways are analysed. The first uses natural gas as the reducing agent (NG–DRI–EAF). The second uses hydrogen from external sources (H_2–DRI–EAF). The third produces hydrogen on-site through water electrolysis powered by electricity (Electrolyser–DRI–EAF).

For the electrolyser-based pathway, two dimensions are varied that strongly affect investment economics. Electrolyser capital costs are examined at two levels, 1500 €/kW to represent current costs and 500 €/kW to reflect 2035 cost expectations based on reported ranges and learning effects [58,59]. Electricity tariffs are examined under two treatments that differ in whether selected regulated price components are reduced. The procurement component of the electricity price is given by the scenario-specific average day-ahead market price from the electricity market model and remains identical across tariff treatments. Any tariff reductions are not linked to operational flexibility. They reflect utilisation-based reductions under §19 StromNEV for high-utilisation industrial consumers.

4.2. Scenario set and inputs

Table 2 summarises the scenario set and key price inputs. The ES and HS narratives differ in annual demand while renewable capacity is held constant. Within each narrative, natural gas and hydrogen prices are specified at three levels each, resulting in 18 scenarios that reflect fuel-cost uncertainty. For each scenario, the electricity market model produces an hourly day-ahead price series. Its annual average is listed as the average market-clearing price (Avg MCP) and is used as the procurement component of the industrial electricity price. Consistent with the single-year market simulation, this procurement component is held constant over the investment horizon in the cash-flow model.

Table 2 lists both a natural gas supply price and a net industrial end-user price (NG net) based on the structure in the Monitoring Report 2024 [56]. The supply price represents the supplier-controlled component, while NG net adds non-supply components such as network-related charges, metering, and statutory taxes and levies, accounting for industrial reductions where applicable. In the cash-flow model, operating costs for NG–DRI–EAF use the NG net price from Table 2.

Hydrogen prices are specified exogenously at 45, 70, and 105 €/MWh, corresponding to 1.5, 2.3, and 3.5 €/kg when converted using

Table 2
Scenario set and key price inputs. Average market-clearing prices (procurement) are produced by the agent-based simulation. All prices in €/MWh and CO_2 in €/t.

Scenario	Energy system	NG supply	NG net (with reduction)	CO_2	Avg MCP	Elec (w/o disc.)	Elec (with disc.)	H_2
ES1	O45-Strom	20.41	30.95	129.36	34.76	75.46	46.86	45
ES2	O45-Strom	20.41	30.95	129.36	34.76	75.46	46.86	70
ES3	O45-Strom	20.41	30.95	129.36	34.76	75.46	46.86	105
ES4	O45-Strom	18.70	29.24	129.36	34.06	74.76	46.16	45
ES5	O45-Strom	18.70	29.24	129.36	34.06	74.76	46.16	70
ES6	O45-Strom	18.70	29.24	129.36	34.06	74.76	46.16	105
ES7	O45-Strom	13.75	24.29	129.36	32.00	72.70	44.10	45
ES8	O45-Strom	13.75	24.29	129.36	32.00	72.70	44.10	70
ES9	O45-Strom	13.75	24.29	129.36	32.00	72.70	44.10	105
HS1	O45-H2	20.41	30.95	129.36	24.16	64.86	36.26	45
HS2	O45-H2	20.41	30.95	129.36	24.16	64.86	36.26	70
HS3	O45-H2	20.41	30.95	129.36	24.16	64.86	36.26	105
HS4	O45-H2	18.70	29.24	129.36	23.56	64.26	35.66	45
HS5	O45-H2	18.70	29.24	129.36	23.56	64.26	35.66	70
HS6	O45-H2	18.70	29.24	129.36	23.56	64.26	35.66	105
HS7	O45-H2	13.75	24.29	129.36	22.16	62.86	34.26	45
HS8	O45-H2	13.75	24.29	129.36	22.16	62.86	34.26	70
HS9	O45-H2	13.75	24.29	129.36	22.16	62.86	34.26	105

the lower heating value [60]. These values are interpreted as plant-gate delivered prices for hydrogen supplied via pipeline and are consistent with published 2030 cost ranges for pipeline supply in Germany, which span 4.5 to 12.8 ct/kWh and correspond to 45 to 128 €/MWh [61]. In addition, an explicit capacity-based network charge for pipeline delivery is included using the regulated ramp-up tariff for the German hydrogen core network [62]. This charge is converted into an equivalent volumetric adder based on booked capacity and annual offtake. Hydrogen used as reducing agent in the DRI process is modelled without an energy tax adder, consistent with the current treatment discussed for metallurgical and chemical reduction uses [63]. In the Electrolyser–DRI–EAF route, hydrogen is produced endogenously via electricity-to-hydrogen conversion with efficiency η_{ely} as listed in Table 4.

4.3. Electricity-price components and tariff treatment

The industrial electricity price in each scenario is modelled as the sum of the procurement component and regulated components. The procurement component is the scenario-specific annual average day-ahead price (Avg MCP). Regulated components include network charges, metering, concession fees, levies and surcharges, and electricity tax. Procurement costs vary across scenarios, while regulated components follow published values and statutory minima.

A transmission-level connection at high voltage is assumed for the modelled site, corresponding to 220 to 380 kV. This assumption is used only to select the applicable published tariff levels. It does not affect electricity-market clearing in the day-ahead simulation.

Table 3 lists regulated tariff components for a large industrial consumer and distinguishes a case without discounts and a case with discounts. In the case without discounts, published values from the Monitoring Report 2024 are applied [56]. In the case with discounts, reductions are implemented strictly as utilisation-based reductions for high-utilisation industrial consumers under §19 StromNEV. Only the capacity-based network charge is reduced to 10% of its published level, while the consumption-based network charge remains unchanged [65]. Concession fees are identical across both cases because §2 KAV does not provide a statutory discount. In the discounted case, electricity tax is set to the industrial minimum of 0.50 €/MWh. Surcharges and levies reflect the maximum relief levels described for large industrial consumers, subject to eligibility under the relevant legal provisions [56]. The total electricity price used in the cash-flow model equals the scenario-specific procurement price (Avg MCP) plus the regulated components associated with the selected tariff case.

Table 3
Decomposition of industrial electricity tariff components for a large industrial consumer in Germany.[a]

Component	Without discounts	With discounts
Network capacity price [€/kW·a]	53.06	5.31
Network consumption price [€/MWh]	6.9	6.9
Metering and operation [€/MWh]	2.0	2.0
Concession fees [€/MWh]	1.1	1.1
Surcharges and levies [€/MWh]	10.2	1.6
Electricity tax [€/MWh]	20.5	0.5

[a] Procurement costs (market clearing price, MCP) are excluded and treated as scenario-specific. Network charges are modelled as a two-part tariff consisting of a capacity-based component (€/kW·a) and a consumption-based component (€/MWh) [64]. In the discounted case, only the capacity-based network charge is reduced to 10% of the published tariff in accordance with §19 StromNEV [65] for high-utilisation industrial consumers (≥ 8000 full-load hours), while the consumption-based charge remains unchanged. Concession fees are assumed to be identical in both cases, as no statutory reduction applies under §2 KAV. Electricity tax is set to the industrial minimum of 0.50 €/MWh. Reductions in surcharges and levies reflect maximum allowable relief for large industrial consumers as reported in the Monitoring Report 2024 [56], subject to eligibility under the respective legal provisions.

4.4. Cost and technical input parameters

Table 4 summarises the technical and economic inputs used in the scenario-level cash-flow and net present value calculation. Unit CAPEX assumptions for DRI and EAF are taken from [66], and additional operating-cost and process parameter values follow [67]. Electrolyser CAPEX varies by Variant 1 and Variant 2 as described above.

4.5. Probability views over scenarios

Four probability views over the 18 scenarios capture differing assessments of plausibility. These views serve two roles. First, they provide risk-neutral expected values as benchmarks. Second, they define the per-scenario probability bounds used to form the ambiguity set in Section 3.3. Table 5 lists the views, and each column sums to one.

The *Base* belief assigns equal probability of 1/18 to all scenarios and serves as an uninformative benchmark. The *Electricity-based* belief places probability weight on ES1–ES9 and reflects a view in which electrification dominates system evolution. The *Hydrogen-based* belief places probability weight on HS1–HS9 and reflects a view in which

Table 4
Consolidated input parameters [66–68].

Parameter	Unit	Value
Material and emission factors		
Iron ore	t/t	1.40
Lime	t/t	0.05
Lime CO_2 factor	t CO_2/t	0.10
Natural gas CO_2 factor	t CO_2/t	0.40
Specific energy consumptions (SEC)		
DRI SEC	MWh/t	0.09
EAF SEC	MWh/t	0.44
DRI specific NG	MWh/t	2.44
DRI specific H_2	MWh/t	2.25
Steel-plant capacity parameters		
DRI plant capacity	MW	167
EAF plant capacity	MW	250
Electrolyser capacity	MW	1270.5
DRI inventory	t	73
Capacity utilisation (DRI/EAF/Ely)	%	80.0
Electrolyser efficiency	–	0.86
Economic parameters		
Steel sales price (2023–2024 avg)	€/t	720
Depreciation period	years	20
Cost components		
Iron ore cost	€/t	225
Lime cost	€/t	100
CO_2 emission price	€/t	100
Labour costs	€/t	38
Maintenance costs	€/t	2.37
Capital expenditures per component (CAPEX)		
DRI (all tech)	€/t	230
EAF (all tech)	€/t	184
Electrolyser (Variant 1)	€/kW	1500
Electrolyser (Variant 2)	€/kW	500
Total CAPEX each technology configuration		
NG–DRI–EAF	Bill.€	1.57
H_2–DRI–EAF	Bill.€	1.57
Electrolyser–DRI–EAF (Variant 1)	Bill.€	3.37
Electrolyser–DRI–EAF (Variant 2)	Bill.€	2.17

Table 5
Probability views (belief vectors) over the 18 scenarios.

Scenario	Base	Electricity	Hydrogen	Conservative
ES1	0.055	0.111	0	0
ES2	0.055	0.111	0	0.25
ES3	0.055	0.111	0	0.25
ES4	0.055	0.111	0	0
ES5	0.055	0.111	0	0
ES6	0.055	0.111	0	0
ES7	0.055	0.111	0	0
ES8	0.055	0.111	0	0
ES9	0.055	0.111	0	0
HS1	0.055	0	0.111	0
HS2	0.055	0	0.111	0.25
HS3	0.055	0	0.111	0.25
HS4	0.055	0	0.111	0
HS5	0.055	0	0.111	0
HS6	0.055	0	0.111	0
HS7	0.055	0	0.111	0
HS8	0.055	0	0.111	0
HS9	0.055	0	0.111	0

hydrogen plays the dominant role. The *Conservative* belief assigns probability only to a small set of stress cases (ES2, ES3, HS2, and HS3) at 0.25 each.

Let $p^{(b)}$ denote a belief vector. The per-scenario bounds for the ambiguity set Q in Section 3.3 are $L_s = \min_b p_s^{(b)}$ and $U_s = \max_b p_s^{(b)}$.

In this dataset the bounds are

$$L_s = 0 \quad \forall s, \qquad U_s = \begin{cases} 0.25 & \text{for } s \in \{\text{ES2, ES3, HS2, HS3}\}, \\ 0.11 & \text{for all other scenarios.} \end{cases}$$

This choice is feasible because the lower bounds sum to zero and the upper bounds sum to at least one, i.e.

$$4 \times 0.25 + 14 \times \frac{1}{9} \geq 1.$$

These bounds are used in the linear optimisation for worst-case mean and worst-case expected shortfall in Section 3.4.

5. Results

5.1. Scenario-wise investment outcomes under parameter uncertainty

This section analyses the scenario-wise economic outcomes for all technology options under parameter uncertainty, without imposing any probability distribution over futures. The resulting net present values therefore reflect deterministic outcomes based on scenario assumptions, rather than expected values or risk-adjusted measures. The complete scenario-level NPVs are provided in Appendix B. Here, we focus on comparative patterns and the range of outcomes across technologies.

5.1.1. Capital efficiency across scenarios

Fig. 3 shows the capital efficiency of each technology pathway across scenarios using the ratio of net present value to upfront investment cost (NPV/I). This metric indicates how much value is created for every euro invested. By scaling NPVs with capital expenditure, the figure enables a direct comparison between options with very different investment levels while keeping the analysis scenario based and without assigning probabilities to the scenarios.

Natural Gas–DRI–EAF shows consistently high capital efficiency across all 18 scenarios, with NPV/I between 6.84 and 8.14. The spread is comparatively small, and the technology remains in a narrow performance band across both electricity- and hydrogen-system narratives. In other words, capital efficiency for the natural gas route is relatively stable with respect to the scenario variations considered.

H_2–DRI–EAF shows substantially greater dispersion and a clear clustered structure, with NPV/I ranging from 2.62 to 7.10. The results group into three bands that align with the three hydrogen price levels in the scenario design. Under low hydrogen prices, capital efficiency approaches the natural gas benchmark, for example 6.75 to 6.83 in ES1, ES4, ES7 and 7.04 to 7.10 in HS1, HS4, HS7. Under medium hydrogen prices, NPV/I declines to around 5.03 to 5.38 in ES2, ES5, ES8 and HS2, HS5, HS8. Under high hydrogen prices, it falls further to 2.62 to 2.96 in ES3, ES6, ES9 and HS3, HS6, HS9. This stepwise pattern indicates that hydrogen price assumptions are the primary driver of capital efficiency for the hydrogen import pathway.

For the electrolyser based routes, the main differences come from the tariff regime and the electrolyser capex variant, while variation within each variant remains moderate. Without tariff discounts, Electrolyser–DRI–EAF (Variant 1) stays at a low level, with NPV/I between 1.25 and 1.90. This indicates that high upfront costs constrain capital productivity even when NPVs are positive. With discounted electricity tariffs, Variant 1 increases to 2.64 to 3.29, which is roughly a doubling relative to the undiscounted case. Lower electrolyser capex in Variant 2 improves results further. Variant 2 without discounts reaches 2.54 to 3.56, and Variant 2 with discounts rises to 4.74 to 5.76. Across both variants, tariff relief shifts NPV/I upward in a consistent way. This underlines the role of regulated electricity price components for capital efficiency in electricity intensive steelmaking routes.

Across the scenario set, the electrolyser options perform better in the hydrogen energy system narrative scenarios (HS) than in the electricity energy system narrative scenarios (ES) for the same capex and tariff setting. This reflects differences in the electricity price inputs used in

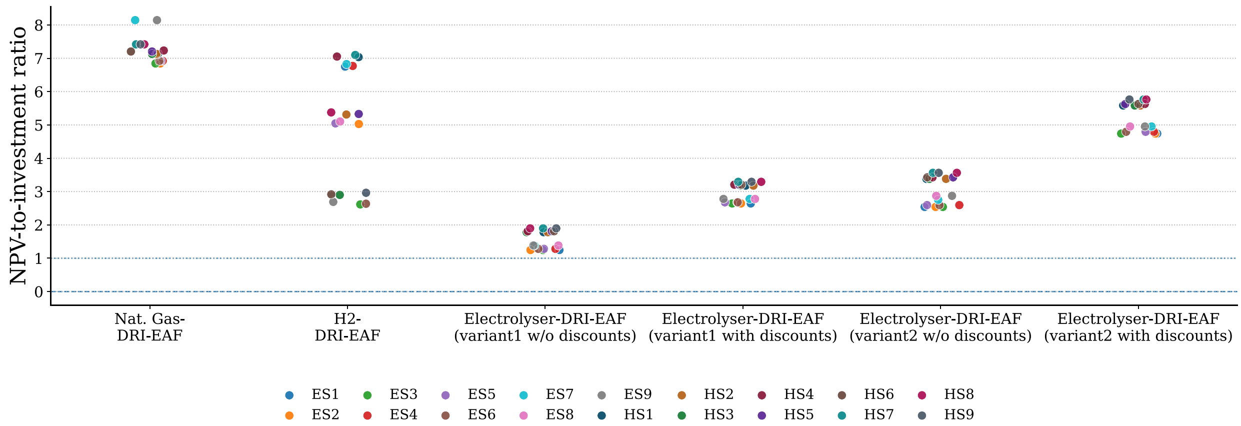

Fig. 3. NPV to Investment ratio.

the cash flow model. Natural Gas–DRI–EAF remains the benchmark for capital efficiency. Electrolyser–DRI–EAF in Variant 2 with discounted tariffs narrows the gap substantially and outperforms H_2–DRI–EAF under medium and high hydrogen price conditions. Overall, the NPV/I results offer a concise view of capital productivity under parameter uncertainty and provide a natural transition to the next step of the analysis, where probability beliefs and probability ambiguity are introduced.

5.1.2. Absolute profitability

Fig. 4 summarises absolute net present values across the 18 scenarios using boxplots with overlaid scenario points. The boxes report the interquartile range, and the whiskers show the spread across the scenario set. This view makes it straightforward to compare both typical outcomes and downside cases for each technology under parameter uncertainty, without assigning probabilities.

Natural Gas–DRI–EAF shows consistently high NPVs in all scenarios, ranging from €10.77 bn in ES1 to ES3 up to €12.81 bn in ES7 and ES9. The distribution is narrow, with most outcomes concentrated around €11 to €12 bn, and the lowest values still above €10 bn. This indicates robust profitability for the gas based route across the full scenario set and limited sensitivity to the scenario drivers within this modelling setup.

H_2–DRI–EAF shows the largest spread in absolute profitability, spanning €4.11 bn in ES3 to €11.17 bn in HS7. The outcomes fall into distinct clusters that track the hydrogen price tiers in the scenario design. Under low hydrogen prices, NPVs are close to the gas benchmark, for example €10.62 to €10.74 bn in ES1, ES4, ES7 and €11.07 to €11.17 bn in HS1, HS4, HS7. Under the medium tier, NPVs decline to roughly €7.91 to €8.46 bn in ES2, ES5, ES8 and HS2, HS5, HS8. Under the high tier, NPVs fall further to €4.11 to €4.66 bn in ES3, ES6, ES9 and HS3, HS6, HS9. The lower tail therefore reflects pronounced exposure to hydrogen price stress, even though the technology remains NPV positive in all scenarios.

For Electrolyser–DRI–EAF without tariff discounts, profitability is clearly lower than for the natural gas route and also below the more favourable hydrogen import cases. Variant 1 ranges from €4.34 bn in ES1 to ES3 to €6.60 bn in HS7 to HS9. Variant 2 ranges from €5.61 bn in ES1 to ES3 to €7.87 bn in HS7 to HS9. The shift from Variant 1 to Variant 2 is visible across the full scenario set, which indicates that lower electrolyser capex raises profitability in a broadly uniform way.

Discounted electricity tariffs move the electrolyser based distributions upward. Variant 1 with discounts ranges from €9.20 to €11.46 bn, which places it within the range of the incumbent benchmark in several scenarios. Variant 2 with discounts reaches the highest NPVs across all options, ranging from €10.47 bn in ES1 to ES3 to €12.73 bn in HS7 to HS9. In the hydrogen system scenarios, Variant 2 with discounts remains above €12.3 bn throughout. It also performs strongly in the electricity system scenarios, staying above €10.4 bn across the board. Relative to the undiscounted cases, tariff relief therefore improves both typical outcomes and the lower end of the distribution.

Three comparative patterns stand out. The natural gas route combines high profitability with limited dispersion. The hydrogen import route remains profitable, but outcomes vary widely and the lower tail is driven by hydrogen price assumptions. The electrolyser based routes depend strongly on the cost and tariff regime. Without discounts they remain well below the natural gas benchmark. With lower electrolyser capex in Variant 2 and tariff relief, they become consistently competitive and often higher in absolute NPV. These scenario wise distributions motivate the next step of the analysis, where the same outcomes are evaluated under alternative probability beliefs and then under probability ambiguity.

5.2. Expected outcomes of the belief sets

This section extends the scenario-wise analysis by introducing probability beliefs over future states. Rather than assuming a single objective probability distribution, we consider multiple belief sets that reflect alternative, internally coherent views of which scenarios are plausible. These beliefs are not treated as forecasts, instead they are used to examine how conventional expected value based investment appraisal depends on subjective probability assignments. The complete results for all scenarios and technologies under each belief set are provided in Appendix C. The appendix shows how scenario level NPVs are converted to belief specific expected outcomes.

5.2.1. Distributional effects of belief sets

Fig. 5 shows empirical cumulative distribution functions (CDFs) of NPV for each technology under the four belief sets. For a given belief vector, the CDF gives the probability that NPV is at or below a given threshold. Because the analysis is based on a discrete scenario set, the curves are stepwise; each step corresponds to probability mass placed on scenarios with similar NPV values.

Under the Base belief with equal weights on all scenarios, Natural Gas–DRI–EAF and Electrolyser–DRI–EAF (Variant 2 with discounts) sit furthest to the right. This corresponds to the highest NPV levels and little probability mass at low NPVs. For the gas route, probability mass remains above about €10.7 bn. Variant 2 with discounts covers a broader high NPV range and reaches its highest values in hydrogen system scenarios, with the upper tail above €12 bn. H_2–DRI–EAF covers a much wider range. The CDF shows pronounced jumps at low NPV levels, which reflect the hydrogen price tiers. A non trivial share of probability lies around €4 to €5 bn, while low hydrogen price cases overlap with the incumbent range. The undiscounted electrolyser variants remain clearly to the left of the other options, with most probability mass below €8 bn, consistent with their lower NPVs across

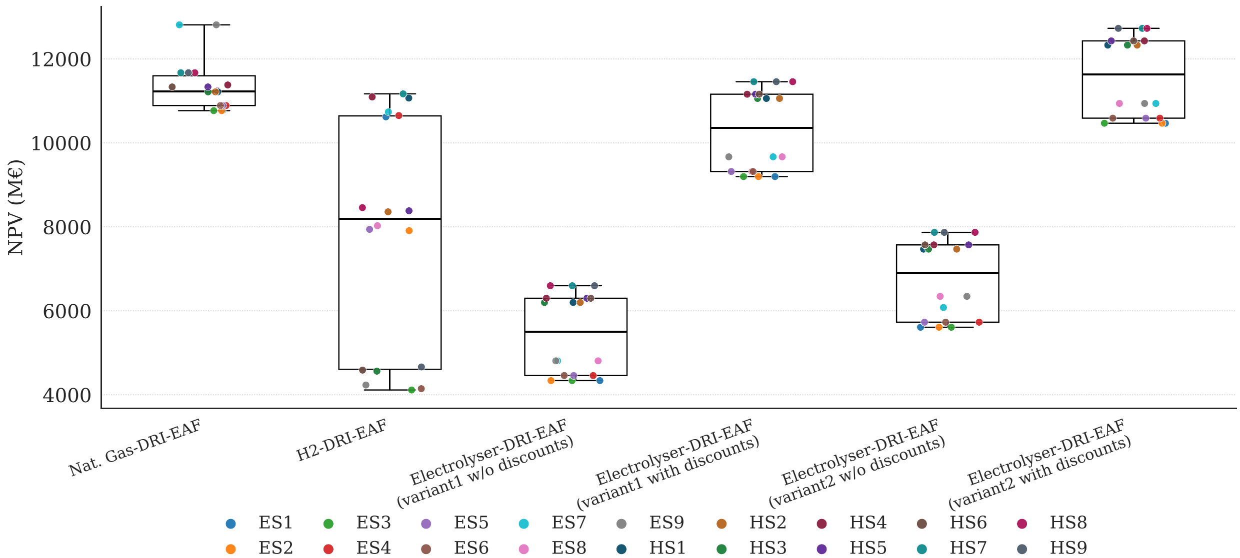

Fig. 4. Scenario NPV distribution by technology with scenario points.

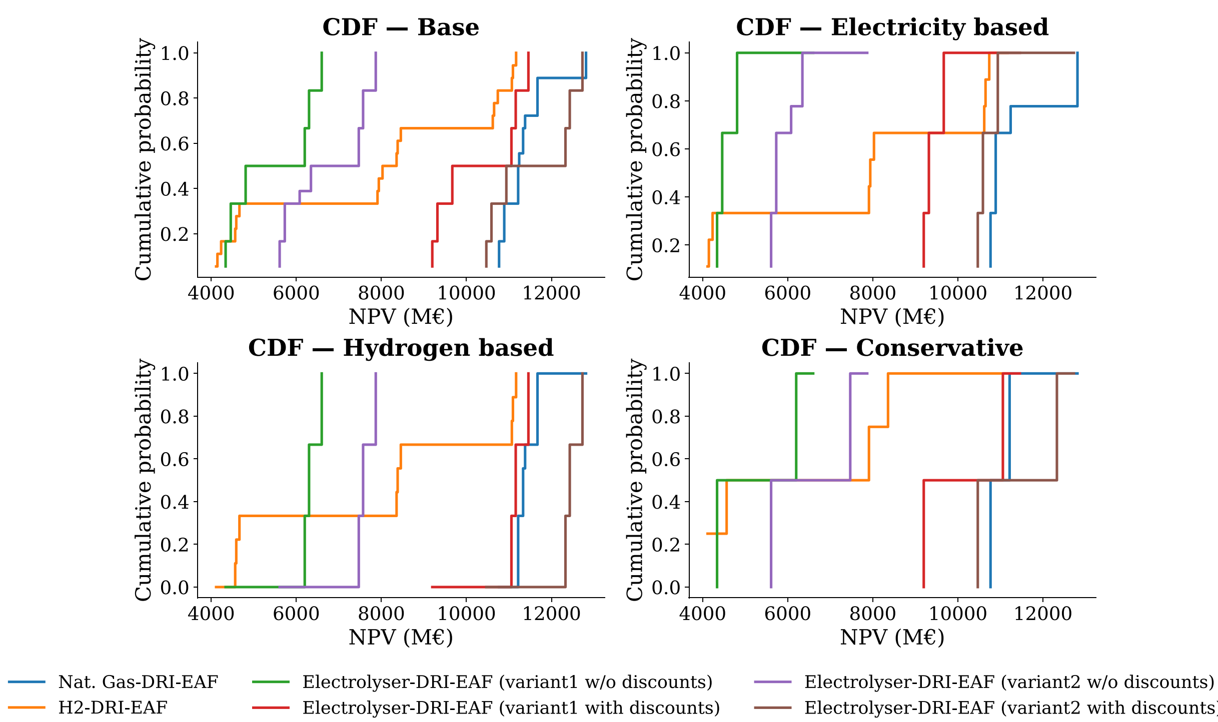

Fig. 5. Empirical CDFs of NPVs by belief vector (Base, Electricity-based, Hydrogen-based, Conservative).

the scenario set. Under the electricity based belief, where probability is assigned only to electricity system scenarios, Natural Gas–DRI–EAF changes little relative to the Base belief. H_2–DRI–EAF becomes more clearly segmented. One part of the probability mass remains in the higher NPV range under low hydrogen prices, while another part shifts to the low NPV range around €4 to €5 bn under high hydrogen prices. The discounted electrolyser variants remain to the right of their undiscounted counterparts. Variant 2 with discounts still stays in the higher NPV region within the electricity system subset.

Under the hydrogen based belief, Electrolyser–DRI–EAF (Variant 2 with discounts) shifts further to the right and remains the strongest performer in distributional terms. H_2–DRI–EAF improves in the upper part of its distribution under favourable hydrogen prices, but the lower part remains substantial because high hydrogen price states still lead to much lower NPVs. The ordering among electrolyser configurations does not change. Tariff relief shifts distributions to the right, and Variant 2 remains above Variant 1 within each tariff regime. Under the conservative belief, probability is concentrated on a small set of adverse scenarios, so the curves show fewer but larger steps. In this setting, Natural Gas–DRI–EAF remains in the high NPV range. Electrolyser–DRI–EAF (Variant 2 with discounts) also remains relatively far to the right, indicating that it retains strong profitability under stress weighted conditions. H_2–DRI–EAF shifts left because the stress states include hydrogen price penalty cases that reinforce its lower tail.

Overall, the CDFs show that technology ranking depends on the probability view, most visibly for H_2–DRI–EAF, where outcomes move in discrete steps with the hydrogen price tiers. They also show that tariff relief and lower electrolyser capex move the electrolyser routes into a higher NPV range across all belief sets, not only under electricity favourable narratives.

5.2.2. Expected NPVs under alternative beliefs

Belief specific expected NPVs are calculated by weighting the scenario NPVs with the belief vectors in Table 5 and summing across scenarios. While the CDF panels in Fig. 5 describe the full belief dependent distributions, expected values provide the standard risk neutral ranking for a given belief set. A detailed overview is given in Appendix C, which lists belief specific expected NPVs for each technology.

Under the Base belief with uniform weights across all 18 scenarios, the highest expected NPV is obtained for Electrolyser–DRI–EAF (Variant 2 with discounts) at 11,579.8 M€ (11.58 bn€), followed by Natural Gas–DRI–EAF at 11,363.0 M€ (11.36 bn€). Electrolyser–DRI–EAF (Variant 1 with discounts) reaches 10,309.4 M€ (10.31 bn€). The undiscounted electrolyser cases remain much lower at 5450.5 M€ and 6750.4 M€. H_2–DRI–EAF reaches 7817.7 M€ (7.82 bn€), which reflects the weight placed on the lower NPV hydrogen price states that are visible in the Base CDF.

Under the electricity based belief, where probability mass is restricted to electricity system scenarios, the ranking changes. Natural Gas–DRI–EAF becomes the expected value leader at 11,314.7 M€ (11.31 bn€), while Electrolyser–DRI–EAF (Variant 2 with discounts) decreases to 10,664.9 M€ (10.66 bn€). Electrolyser–DRI–EAF (Variant 1 with discounts) reaches 9394.4 M€ (9.39 bn€). This change is consistent with the electricity based CDF panel, where the gas route remains concentrated at high NPVs, while electrolysis routes retain higher fixed cost exposure even under electricity centred futures.

Under the hydrogen based belief, where probability mass is restricted to hydrogen system scenarios, expected NPVs increase for options that benefit from the HS narrative. Electrolyser–DRI–EAF (Variant 2 with discounts) remains the top option with an expected NPV of 12,494.9 M€ (12.49 bn€). Natural Gas–DRI–EAF follows at 11,411.4 M€ (11.41 bn€), and Electrolyser–DRI–EAF (Variant 1 with discounts) reaches 11,224.4 M€ (11.22 bn€). H_2–DRI–EAF reaches 8038.0 M€ (8.04 bn€) and stays well below the leading options because the hydrogen price tiers continue to dominate its outcomes, even when the system narrative is favourable to hydrogen.

Under the conservative belief, where probability mass is concentrated on the four stress scenarios ES2, ES3, HS2, and HS3, expected NPVs move closer to the lower tail of each distribution. Even in this pessimistic view, Electrolyser–DRI–EAF (Variant 2 with discounts) remains highest at 11,397.9 M€ (11.40 bn€), with Natural Gas–DRI–EAF close behind at 10,991.5 M€ (10.99 bn€). Electrolyser–DRI–EAF (Variant 1 with discounts) stays competitive at 10,127.5 M€ (10.13 bn€). H_2–DRI–EAF declines to 6236.3 M€ (6.24 bn€), consistent with the conservative CDF panel, where much of the probability mass lies in the low NPV region associated with hydrogen price stress.

Two implications follow from these view-specific expected values. First, the expected value ranking depends on the probability view. Natural Gas–DRI–EAF ranks first under the electricity-based view, while the discounted electrolysis route in Variant 2 ranks first under the Base, hydrogen-based, and conservative views. Second, H_2–DRI–EAF is never the expected value leader, even when probability mass is restricted to hydrogen-system scenarios, because high hydrogen-price cases drive down its expected performance. These patterns motivate the ambiguity-aware evaluation in the next section, which does not rely on a single probability view and instead evaluates performance across all distributions admissible under the probability bounds.

5.2.3. Maximum expected NPV under alternative belief sets

Fig. 6 summarises belief specific expected NPVs for all technology pathways. For each belief set, the ranking reflects a risk neutral comparison based on expected values under that probability view.

Across all belief sets, Natural Gas–DRI–EAF remains at a consistently high level, with expected NPVs between 10.99 and 11.41 bn€. Electrolyser–DRI–EAF (Variant 2 with discounts) is similarly strong and ranks first in three of the four belief sets. Under the Base belief, it reaches 11.58 bn€, above the gas route at 11.36 bn€. Under the hydrogen based belief, it reaches 12.49 bn€, which is the highest expected NPV across all belief sets, compared with 11.41 bn€ for the gas route. Under the conservative belief, it remains ahead at 11.40 bn€, while the gas route reaches 10.99 bn€.

The exception is the electricity based belief. In this case, Natural Gas–DRI–EAF becomes the expected value leader at 11.31 bn€, while Electrolyser–DRI–EAF (Variant 2 with discounts) declines to 10.66 bn€. This change matches the distributional patterns in Fig. 5. Restricting probability mass to electricity system scenarios changes the relative advantage of tariff supported electrolysis compared with the incumbent route.

For H_2–DRI–EAF, expected NPVs range from 6.24 to 8.04 bn€, with the highest value under the hydrogen based belief at 8.04 bn€. It remains below both the gas route and the discounted electrolyser pathways under every belief set, reflecting persistent sensitivity to the hydrogen price tiers embedded in the scenario design. The undiscounted electrolyser variants also remain materially lower. Variant 1 without discounts ranges from 4.54 to 6.37 bn€, and Variant 2 without discounts from 5.86 to 7.64 bn€. Introducing tariff discounts shifts both variants upward. Variant 1 with discounts ranges from 9.39 to 11.22 bn€, which brings it close to the gas benchmark under the hydrogen based and conservative beliefs.

Overall, the expected value ranking is not invariant to the probability view. The leading option switches between the gas route and discounted electrolysis depending on the belief set. This dependence motivates the ambiguity aware evaluation that follows, where the analysis avoids selecting a single belief and instead evaluates performance across all belief consistent probability distributions.

5.3. Ambiguity-aware evaluation under loss law invariance

The previous sections showed that technology rankings depend strongly on the assumed probability distribution over future scenarios. Any evaluation based on a single distribution, whether uniform or belief specific, therefore reflects a normative choice that is difficult to defend under deep uncertainty. To reduce this dependence, we evaluate investment performance under probability ambiguity by allowing scenario probabilities to vary within admissible under the probability bounds, as shown in Fig. 7. The assessment adopts a loss law invariant perspective and focuses on worst case mean performance and worst case tail outcomes. All ambiguity aware risk measures are defined on the loss scale, with $\ell_{i,s} = -\mathrm{NPV}_{i,s}$. Results are then presented on the NPV scale by reversing the sign to keep an investment oriented interpretation, where higher values indicate better outcomes. To make robustness penalties transparent in a non negative metric, Fig. 8 also reports a Downside Exposure Index that separates the gap between average expected NPV, worst case mean, and worst case expected shortfall.

5.3.1. Worst-case mean under probability ambiguity

Allowing scenario probabilities to vary within the admissible bounds changes what an expected NPV represents. Under the box type ambiguity set with zero lower bounds, the optimiser can shift probability mass towards unfavourable scenarios, constrained only by the upper bounds of the ambiguity set shown in Fig. 7. The worst case mean therefore captures the lowest expected NPV that is still compatible with the family of probability views encoded in these bounds.

For Natural Gas–DRI–EAF, the adversarial distribution places most weight on electricity system scenarios with comparatively lower NPVs while respecting the caps. In particular, ES2 and ES3 are set at their

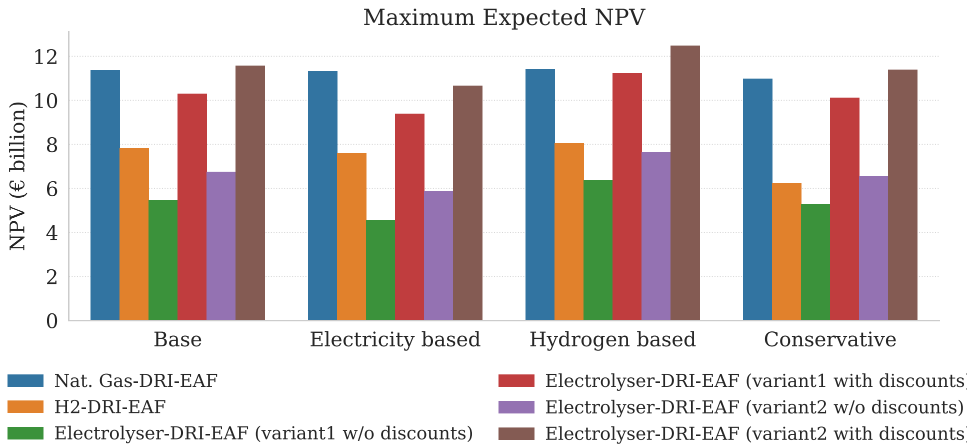

Fig. 6. Maximum Expected NPV.

upper bounds of 0.25 each, and additional mass is assigned to ES1, ES4, ES5, and ES6 up to their respective caps. Hydrogen system scenarios receive little or no weight, apart from a small allocation allowed by the bounds, for example HS2. Under this allocation, the worst case mean NPV is €10.83 bn, compared with the uniform Base expected value of €11.36 bn. The reduction of €0.53 bn, around 5%, indicates limited sensitivity to probability ambiguity. This is consistent with the narrow dispersion of NPVs for this pathway across the scenario set.

For H_2–DRI–EAF, the optimiser reallocates probability mass towards hydrogen stress outcomes that form the lower tail of the scenario wise NPV distribution. In the resulting allocation, ES3 and HS3 are set at their caps of 0.25 each, with additional weight assigned to other low performing states permitted by the bounds, such as ES6, ES9, HS6, and HS9. The worst case mean NPV therefore declines to €4.57 bn from the Base expected value of €7.82 bn. This is a drop of €3.25 bn, around 42%. The size of this robustness penalty indicates that the hydrogen import pathway performs well only if adverse hydrogen price states are given low probability, an assumption that is difficult to maintain once probability ambiguity is allowed.

The electrolyser based pathways show similar probability reallocations across variants. Probability mass concentrates on electricity system scenarios where their NPVs are lowest and where the upper bounds permit strong concentration, most notably ES2 and ES3. Differences in worst case mean outcomes are therefore mainly explained by the cost and tariff structure, rather than by changes in which scenarios become binding. Without tariff reductions, worst case mean NPVs are €4.40 bn for Variant 1 and €5.68 bn for Variant 2. With tariff reductions, worst case mean NPVs increase to €9.26 bn for Variant 1 and €10.53 bn for Variant 2. For Variant 2 with discounts, the remaining gap to the gas based benchmark under worst case mean evaluation is €0.30 bn, around 3%, which indicates near parity in robustness within the pessimistic, belief consistent region of the ambiguity set.

5.3.2. Worst-case tail outcomes

Worst case tail performance is evaluated using worst case expected shortfall at confidence level $\alpha = 0.11$. In the discrete scenario setting and under the box type ambiguity set with zero lower bounds, the tail criterion concentrates admissible probability mass on the most adverse outcomes, up to the probability caps. The worst case expected shortfall therefore acts as an extreme downside protection measure. It approaches the lowest NPV among the scenarios that can be made sufficiently likely under the admissible probability bounds. Fig. 8 summarises the implied downside exposure by separating two components. The first is the drop from the Base expected NPV to the worst case mean. The second is the additional drop from the worst case mean to the worst case expected shortfall.

For Natural Gas–DRI–EAF, the worst case expected shortfall is €10.77 bn, only €0.07 bn below the worst case mean of €10.83 bn. This narrow gap indicates that even when the evaluation focuses on the tail region under adversarial probabilities, outcomes remain close to the worst case mean benchmark.

For H_2–DRI–EAF, the worst case expected shortfall drops to €4.11 bn, compared with a worst case mean of €4.57 bn. The additional tail penalty is €0.45 bn, which is large relative to the pathway's remaining value under ambiguity and points to pronounced exposure to extreme downside states. Fig. 8 is consistent with this. Most of the downside exposure is concentrated in the gap between average performance and the ambiguity aware metrics, and the tail component is visibly larger than for the other routes.

The electrolyser based pathways show a different pattern. For all electrolyser configurations, the gap between worst case mean and worst case expected shortfall is small, around €0.07 bn. This implies that once probabilities are shifted towards adverse scenarios, additional tail protection does not change the evaluation in a significant way. Differences across electrolyser variants are therefore driven mainly by the level of the robust outcomes, not by extra tail penalties. Without tariff reductions, worst case expected shortfall is €4.34 bn for Variant 1 and €5.61 bn for Variant 2. With tariff reductions, the corresponding values increase to €9.20 bn for Variant 1 and €10.47 bn for Variant 2. The resilience heatmap in Fig. 8 reflects this pattern. Discounted electrolyser options retain high normalised scores under both ambiguity aware metrics, while undiscounted variants remain substantially less resilient.

5.3.3. Robustness comparison and decision implications

Fig. 9 contrasts four evaluation lenses. These are the scenario average NPV without probabilities, the average expected NPV across belief sets, the worst case mean under probability ambiguity, and the worst case expected shortfall. Moving from average based evaluation to ambiguity aware metrics affects both the level of NPVs and the relative distance of low carbon pathways to the incumbent benchmark.

Natural Gas–DRI–EAF remains the most robust option under all criteria. Its scenario average NPV is €11.36 bn and declines only moderately under probability ambiguity to a worst case mean of €10.83 bn and a worst case expected shortfall of €10.77 bn. The small spread between these metrics indicates that performance is not driven by a small set of favourable scenarios. Instead, outcomes remain close to the central tendency even when probabilities are shifted towards adverse states.

The hydrogen import pathway shows the opposite pattern. Its scenario average NPV is €7.82 bn, but ambiguity aware evaluation reduces this to €4.57 bn under the worst case mean and €4.11 bn

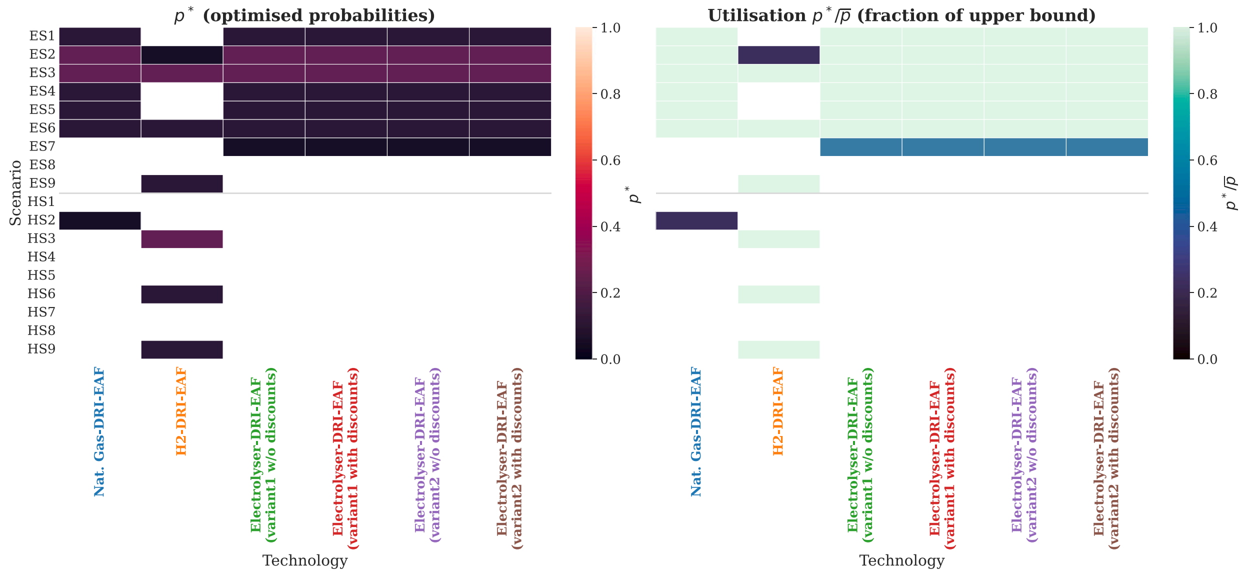

Fig. 7. Optimised scenario probability allocations under the box-type ambiguity set used for worst-case mean evaluation. The left panel shows the adversarial probability distributions (p^*) that minimise expected net present value for each technology, subject to belief-consistent upper bounds. The right panel shows the corresponding utilisation ratios ($p^*/\bar{p}$), indicating which scenario probability constraints are binding. Scenarios with utilisation close to one dominate the worst-case evaluation and therefore drive robustness outcomes under probability ambiguity.

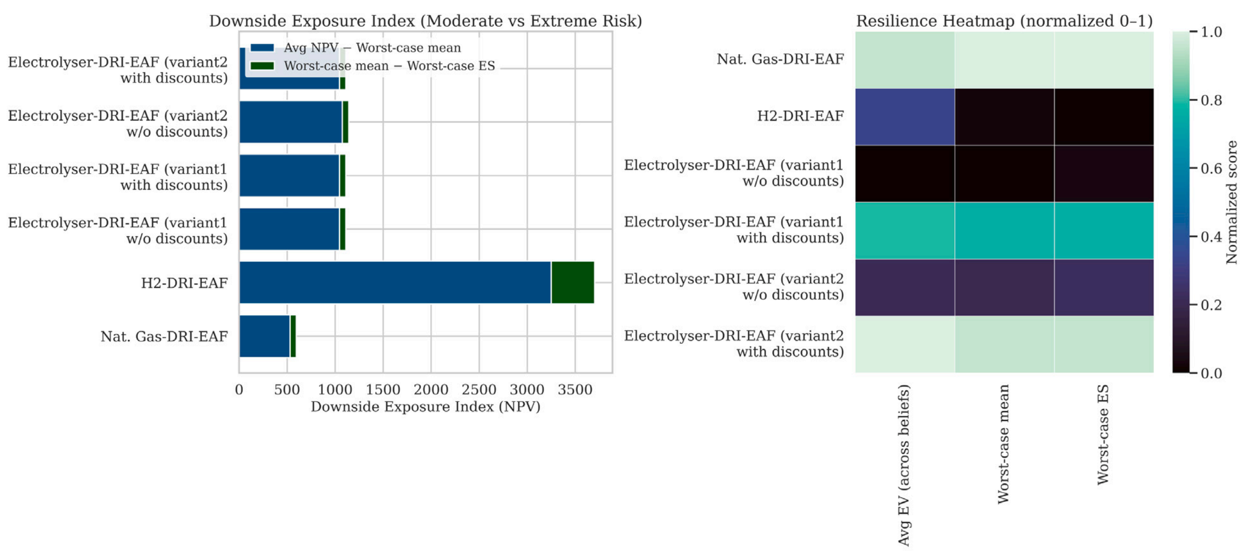

Fig. 8. Downside exposure and resilience under probability ambiguity. The left panel shows the Downside Exposure Index (non-negative by construction), decomposing the gap between average expected NPV, worst-case mean NPV, and worst-case expected shortfall, thereby distinguishing moderate from extreme downside risk. The right panel reports a normalised resilience heatmap (0–1) across technologies for average expected value, worst-case mean, and worst-case expected shortfall. Higher values indicate greater robustness against probability ambiguity and extreme downside outcomes.

under the worst case expected shortfall. In Fig. 9 in the left panel, this appears as the largest separation between average and robust metrics across all pathways. Fig. 8 supports this interpretation by showing that downside exposure is dominated by the drop from average performance to the ambiguity aware criteria. This indicates that the attractiveness of H_2–DRI–EAF depends on assigning low probability to adverse hydrogen price states, an assumption that is difficult to sustain once multiple probability views are allowed.

Electrolyser based routes fall between these extremes, and the tariff regime determines whether they move close to the robust benchmark. Without electricity tariff reductions, Electrolyser–DRI–EAF reaches worst case mean NPVs of €4.40 bn for Variant 1 and €5.68 bn for Variant 2. The corresponding worst case expected shortfalls are €4.34 bn and €5.61 bn. With tariff reductions, robust performance improves strongly. Variant 1 with discounts reaches €9.26 bn under the worst case mean and €9.20 bn under the worst case expected shortfall. Variant 2 with discounts reaches €10.53 bn and €10.47 bn. In the robust frontier view in Fig. 9 on the right panel, discounted Variant 2 sits closest to Natural Gas–DRI–EAF, which indicates near parity under both ambiguity aware metrics.

Two decision implications follow for the stated objective of ambiguity aware investment evaluation. First, rankings based only on belief

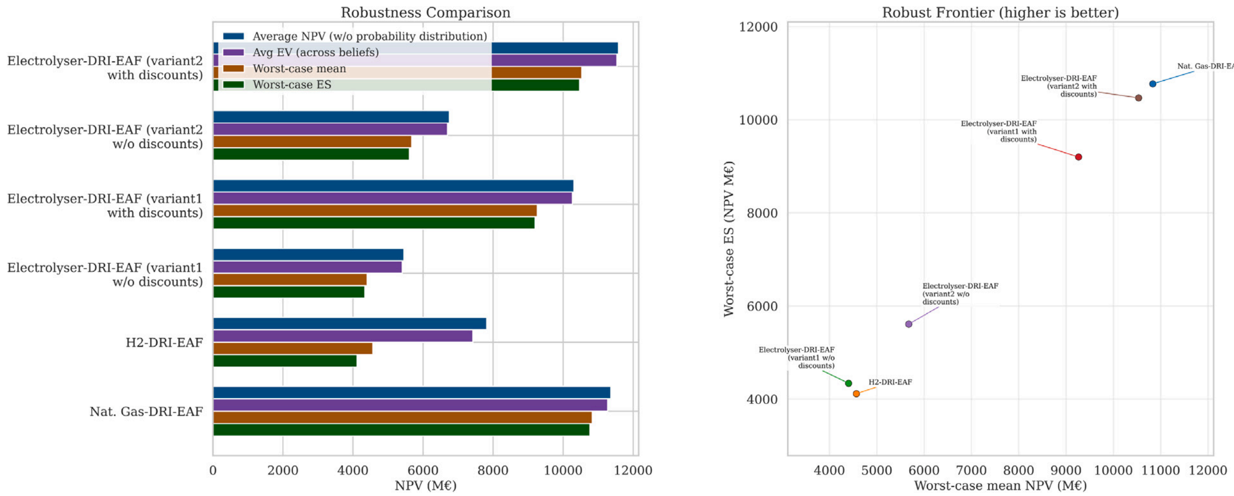

Fig. 9. Robustness comparison across technology pathways under probability ambiguity. The left panel compares Base expected NPVs, worst-case mean NPVs, and worst-case expected shortfalls for all technologies. The right panel shows the robustness frontier using worst-case mean and worst-case expected shortfall *reported on the NPV scale* (i.e., sign-reversed from the corresponding loss-based risk measures). Technologies closer to the upper-right region exhibit higher robustness against both adverse probability shifts and extreme downside outcomes.

specific expected values remain fragile because they depend on the selected probability view. By contrast, the ambiguity aware metrics provide a stable ordering once probability disagreement is treated as part of the problem. Second, policy related cost components matter mainly through their effect on robustness, not only through average performance. The discounted electrolyser pathways improve most in the adverse regions that drive the worst case evaluation, which moves them closer to the robust benchmark. In contrast, the hydrogen import pathway remains exposed to severe downside risk and is dominated by discounted electrolysis under both the worst case mean and the worst case expected shortfall. Overall, the ambiguity aware comparison shifts attention away from maximising expected value and towards identifying technology options whose investment case remains defensible under contested probability assignments and explicit protection against extreme downside outcomes.

5.4. Sensitivity analysis: non-stationary price in the second half of the investment horizon

Fig. 10 shows how the robustness ranking changes when key cost drivers shift in the second half of the project life. The baseline analysis assumes stationary annual conditions based on the representative 2035 setting. Here, years 11–20 are adjusted to reflect long horizon regime changes. The aim is not to produce a multi decade forecast, but to test whether the ambiguity aware ranking remains stable under plausible second decade changes in climate policy and fuel market conditions.

In the baseline, Natural Gas–DRI–EAF remains slightly stronger under both robustness criteria, with a worst case mean NPV of €10.83 bn and a worst case expected shortfall of €10.77 bn. The policy supported electrification option, Electrolyser–DRI–EAF Variant 2 with discounts, reaches €10.53 bn and €10.47 bn, respectively. The two options are therefore close in level, while the natural gas route maintains a small and consistent robustness margin.

5.4.1. Case 1: Elevated CO_2 price trajectory in years 11–20

Case 1 increases the CO_2 price used in the cash flow model by a factor of 1.2 in years 11–20, representing tighter climate policy over time. Under this assumption, both options remain robustly profitable and the ranking does not change. Natural Gas–DRI–EAF reaches a worst case mean NPV of €10.88 bn and a worst case expected shortfall of €10.82 bn. The discounted electrolyser pathway reaches €10.64 bn and €10.57 bn. The robustness gap therefore stays close to the baseline level, which indicates that the second decade CO_2 increase considered here is not sufficient to change the ambiguity aware ordering.

5.4.2. Case 2: Elevated CO_2 price trajectory with reduced natural gas supply prices in years 11–20

Case 2 combines the CO_2 increase with a 5% reduction in natural gas supply prices in years 11–20. In this sensitivity, robustness levels decrease for both pathways. Natural Gas–DRI–EAF falls to a worst case mean NPV of €10.33 bn and a worst case expected shortfall of €10.26 bn. The discounted electrolyser pathway decreases more strongly to €9.92 bn and €9.86 bn. The gas route therefore retains the higher robustness metrics, and the robustness gap increases relative to the baseline.

Across both cases, the ambiguity aware ranking between the two leading options remains stable. Natural Gas–DRI–EAF remains preferred under both worst case mean and worst case expected shortfall. At the same time, the sensitivities show how second decade regime shifts change robustness levels and margins, which are the key decision inputs under probability ambiguity.

6. Conclusion and discussion

This study develops an ambiguity-aware, loss law–invariant investment evaluation framework for capital-intensive industrial decarbonisation decisions under deep uncertainty. The approach combines scenario-level outcomes with probability bounds implied by multiple probability views and quantifies robustness using worst-case mean and worst-case expected shortfall criteria. This supports investment decision making under probability ambiguity using monetary downside metrics that are directly relevant for capital budgeting and for assessing the risk-mitigating effect of policy instruments.

In the primary steel application for Germany, Natural Gas–DRI–EAF, H_2–DRI–EAF with imported hydrogen, and Electrolyser–DRI–EAF configurations are compared, including two electrolyser CAPEX variants and two tariff treatments with and without utilisation-based electricity tariff reductions. Three findings are central. First, Natural Gas–DRI–EAF is the most robust pathway within the scenario and ambiguity sets analysed. Its average NPV across scenarios (without probabilities) is €11.36 bn. Under probability ambiguity, the worst-case

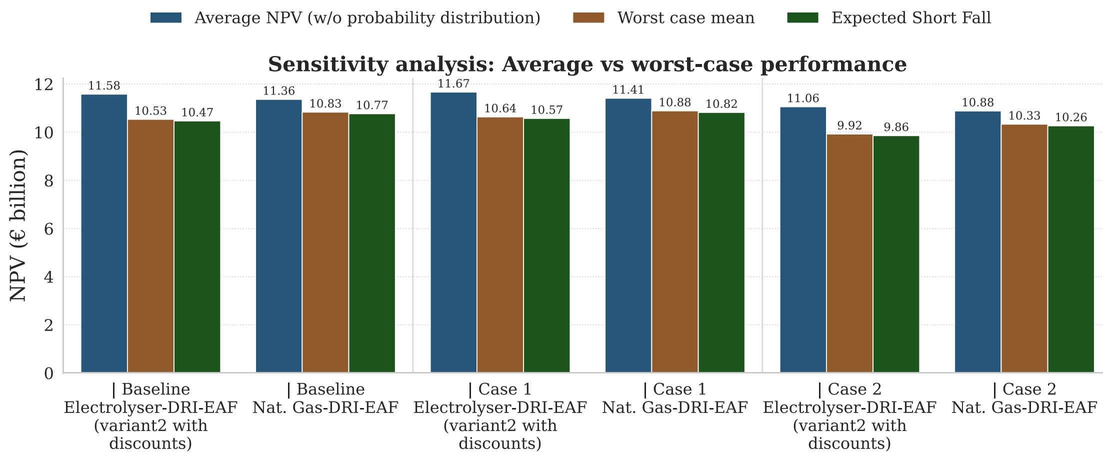

Fig. 10. Average NPV (without a probability distribution), worst-case mean NPV, and worst-case expected shortfall NPV under baseline conditions and two second-decade sensitivities (years 11–20): higher CO_2 prices, and higher CO_2 prices combined with lower natural gas supply prices. Worst-case mean and expected shortfall are reported on the NPV scale (by sign reversal from the underlying loss-based definitions) so that higher values consistently indicate more favourable outcomes.

mean NPV remains €10.83 bn and worst-case expected shortfall is €10.77 bn, implying a robustness penalty of €0.53 bn from the Base expected value to the worst-case mean (about 4.7%). Second, the strongest low-carbon option under ambiguity-aware criteria is Electrolyser–DRI–EAF (Variant 2 with discounts). Its average and Base expected NPV are €11.58 bn, while its worst-case mean and worst-case expected shortfall are €10.53 bn and €10.47 bn. Relative to Natural Gas–DRI–EAF, the baseline robustness gap is €0.30 bn on both worst-case metrics. The tariff instrument matters primarily through robustness. Without discounts, Variant 2 falls to €5.68 bn (worst-case mean) and €5.61 bn (worst-case expected shortfall), so tariff relief raises ambiguity-aware performance by about €4.9 bn in worst-case mean terms. Third, H_2–DRI–EAF remains ambiguity-fragile. Its Base expected NPV is €7.82 bn, but its worst-case mean declines to €4.57 bn and worst-case expected shortfall to €4.11 bn. This corresponds to a reduction of €3.25 bn from Base expected value to worst-case mean (about 41%) and €3.71 bn from Base expected value to worst-case expected shortfall (about 47%), indicating substantial exposure to hydrogen-price stress states admissible under the probability bounds implied by the probability views.

These results have different implications for industrial and policy decision makers. For industrial investors, the ambiguity-aware metrics separate options that are attractive on average from those that remain acceptable under pessimistic probability weighting and tail protection. Natural Gas–DRI–EAF provides the largest robustness buffer under the stated bounds, while the discounted Electrolyser pathway approaches parity but does not fully close the worst-case gap. In contrast, the hydrogen-import pathway is sensitive to adverse probability shifts admissible under the bounds, which indicates exposure to hydrogen-price risk that may require contractual hedging or staged commitment strategies. For policy and regulatory actors, the remaining robustness gap even under tariff relief is informative. The €4.9 bn uplift in worst-case mean for the discounted electrolyser configuration shows that instruments can shift performance in the adverse states that drive ambiguity-aware evaluation. At the same time, the residual gap relative to the gas benchmark indicates that existing measures do not fully protect low-carbon pathways against downside outcomes. Support design should therefore be assessed not only by average cost competitiveness but also by its capacity to protect pathways under adverse but admissible probability weightings.

Robustness in this study is conditional on the scenario set and on the ambiguity set Q constructed from the stated probability views. The worst-case mean and worst-case expected shortfall therefore provide guarantees only with respect to these sets. The long-horizon sensitivity tests whether conclusions persist under second-decade regime shifts. Across the baseline and two sensitivity cases (Fig. 10), Natural Gas–DRI–EAF remains ahead of Electrolyser–DRI–EAF (Variant 2 with discounts) on robustness criteria, but margins vary. In the baseline, the worst-case mean is €10.83 bn versus €10.53 bn, and the worst-case expected shortfall is €10.77 bn versus €10.47 bn. In Case 1, higher CO_2 prices in years 11–20 raise robustness levels for both options. The worst-case mean is €10.88 bn versus €10.64 bn, and the worst-case expected shortfall is €10.82 bn versus €10.57 bn. In Case 2, higher CO_2 prices combined with reduced natural gas prices in years 11–20 reduce robustness levels and widen the gap. Under the worst-case mean, the Natural Gas–DRI–EAF outcome falls from €10.33 bn to €9.92 bn. Under worst-case expected shortfall, it falls from €10.26 bn to €9.86 bn. These sensitivity results refine the interpretation. The ambiguity-aware ordering remains stable under the regime shifts, but robustness margins vary with long-horizon assumptions.

Across all analysed scenarios, the investment options considered have positive NPVs. The results reflect stylised plant-level operating economics within the modelling scope. They do not include several factors that often shape investment decisions for irreversible, including construction and ramp-up risk, supply-chain constraints, financing conditions, and the option value of waiting. These factors can delay or deter investment even when discounted operating cash flows appear favourable. Positive NPVs can also coincide with fragility under probability ambiguity when scenario probabilities are uncertain. In the ambiguity-aware evaluation, H_2–DRI–EAF illustrates this clearly. Its Base expected NPV is €7.82 bn, but the worst-case mean falls to €4.57 bn and the worst-case expected shortfall to €4.11 bn. The gap captures exposure to adverse but admissible probability shifts within the stated bounds. From a policy perspective, this matters because many instruments are intended to improve bankability in adverse states rather than to raise average returns. In this case study, utilisation-based tariff reductions raise Electrolyser–DRI–EAF (Variant 2) from €5.68 bn to €10.53 bn in worst-case mean terms. This improvement reflects stronger performance in the scenarios that drive the worst-case evaluation, not a marginal change in average outcomes.

6.1. Strengths and limitations

A first strength is that the evaluation remains meaningful when scenario probabilities differ across decision makers. The analysis does not commit to a single probability distribution. Instead, it uses several probability views and then evaluates performance against probability bounds implied by these views. This makes the role of probability assumptions explicit and keeps the robustness criteria aligned with the paper objective. A second strength is that the ambiguity-aware step provides more than a ranking. By solving for the worst-case probability allocations admissible under the bounds, the method identifies which scenarios drive the worst-case mean and the tail metrics. This supports interpretation of why a technology is robust or fragile and indicates where risk-mitigation measures would need to improve outcomes to matter under ambiguity. A third strength is generality. The analysis requires only scenario-wise NPVs $NPV_{i,s}$, so the same ambiguity-aware evaluation can be applied to other hard-to-abate investment problems once scenario outcomes are available.

The results are conditional on the scenario set and on the ambiguity set implied by the stated probability views. The robustness claims therefore apply within these sets and do not constitute guarantees outside the modelled futures. The sensitivity analysis tests whether the ordering is stable under structured long-horizon regime shifts. A second boundary concerns time dynamics. In the baseline, each scenario is represented by a single 2035 price and policy configuration applied over the full project lifetime. The sensitivity cases introduce second-decade shifts in CO_2 and fuel prices within the cash-flow model. Electricity prices are not re-simulated year by year, so feedbacks from changing fuel and CO_2 costs into market clearing and procurement prices over time are not captured. Third, the price of externally supplied hydrogen is specified as a plant-gate input. This represents hydrogen procurement under given import price assumptions rather than endogenous modelling of hydrogen price formation and delivery chains. Extending the setup to an explicit hydrogen supply module that covers imports, domestic production, delivery options, and infrastructure constraints would allow the robustness results for the hydrogen-import pathway to be tested under alternative hydrogen market representations. Finally, the probability views are stylised. They represent plausible disagreements about which scenario families are more likely, but they are not based on formal elicitation or a comprehensive synthesis of empirical evidence. The ambiguity set is therefore a transparent modelling choice rather than a measured representation of stakeholder beliefs. Future work should ground probability views more systematically, for example through structured stakeholder elicitation combined with evidence from scenario providers and market outlooks. A richer set of probability views would allow tighter probability bounds and would strengthen the credibility of the ambiguity-aware results.

6.2. Outlook

Future work should extend the case study along three directions. First, multi-year operational dynamics and staged investment could be included to represent learning, timing flexibility, and option value. Second, alternative ambiguity representations and tail functionals could be evaluated to test how robustness margins depend on the representation of probability ambiguity and on the chosen downside metric. Third, extending the option set to include incumbent BF–BOF continuation and retrofit pathways would allow direct comparison between maintaining conventional production and switching to DRI-based routes under the same ambiguity-aware evaluation logic. The steel application illustrates the central message that rankings based on any single probability view can be unstable when probability assignments are disputed. Ambiguity-aware worst-case mean and tail criteria provide a defensible basis for comparing technologies under explicitly stated probability bounds. The results also indicate that policy instruments should be assessed by their effect on downside and tail exposure in adverse futures, not only by their effect on average outcomes.

CRediT authorship contribution statement

Manish Gaebelein-Khanra: Conceptualisation, Methodology, Modelling, Data collection, Formal analysis, Writing – original draft, Writing – review & editing. **Marian Klobasa:** Formal analysis, Writing – review & editing. **Parag Patil:** Data collection & curation, Editing.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used AI tools in order to improve the readability and the language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Manish Gaebelein-Khanra reports article publishing charges was provided by Fraunhofer Institute for Systems and Innovation Research ISI. Manish Gaebelein-Khanra reports a relationship with Fraunhofer Institute for Systems and Innovation Research ISI that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Steel-plant operations model

This appendix documents the plant-level operations model used to generate scenario-specific operating costs and cash flows. The model is deterministic and solved independently for each scenario (see Table A.6).

The plant is represented as a demand-side agent whose electricity use depends on the steelmaking route. Three routes are analysed: NG–DRI–EAF, H_2–DRI–EAF with imported hydrogen, and Electrolyser–DRI–EAF with on-site hydrogen. For the electrolyser route, two tariff regimes are considered. Discounts apply only to regulated components. The procurement component, equal to the scenario-specific annual average day-ahead price, is identical across regimes.

Let $\mathcal{T}$ index hours in the year. For technology i, the operating schedule minimises variable cost:

$$\min \sum_{t\in\mathcal{T}} C_t^{\mathrm{op}}. \tag{A.1}$$

The operating cost is

$$C_t^{\mathrm{op}} = c^{\mathrm{elec}}\, P_t^{\mathrm{elec}} + c^{\mathrm{ng}}\, G_t^{\mathrm{in}} + c^{\mathrm{H_2}}\, H_t^{\mathrm{imp}} + c^{\mathrm{CO_2}}\left(E_t^{\mathrm{CO_2,DRI}} + E_t^{\mathrm{CO_2,EAF}}\right) + c^{\mathrm{ore}}\, Q_t^{\mathrm{ore}} + c^{\mathrm{lime}}\, Q_t^{\mathrm{lime}}. \tag{A.2}$$

Prices are scenario-specific constants within a scenario. We use the annual average MCP for c^{elec} and then add regulated components as described in Section 4. The hydrogen purchase term $c^{\mathrm{H_2}} H_t^{\mathrm{imp}}$ is active only in the imported-hydrogen route. In the electrolyser route hydrogen is produced endogenously.

Table A.6
Notation for the steel-plant operations model.

Symbol	Type	Description
P_t^{ely}, H_t^{ely}	variable	Electrolyser power input and hydrogen output at time t
H_t^{imp}, H_t^{in}	variable	Imported hydrogen and hydrogen fed to DRI at time t
G_t^{in}	variable	Natural gas input to DRI at time t
Q_t^{dri}, Q_t^{steel}	variable	DRI output and crude steel output at time t
P_t^{dri}, P_t^{eaf}, P_t^{elec}	variable	Electricity use of DRI, EAF, and total plant at time t
Q_t^{ore}, Q_t^{lime}	variable	Iron ore and lime inputs at time t
$E_t^{CO_2,DRI}$, $E_t^{CO_2,EAF}$	variable	Process CO_2 emissions from DRI and EAF at time t
C_t^{op}	variable	Variable operating cost at time t
c^{elec}, c^{ng}, c^{H_2}, c^{CO_2}, c^{ore}, c^{lime}	parameter	Prices that are scenario-specific and time-invariant within a scenario
η^{ely}	parameter	Electrolyser efficiency measured as hydrogen per MWh
$\lambda_{H_2}^{dri}$, λ_{ng}^{dri}, λ_{elec}^{dri}, λ_{ore}^{dri}	parameter	Specific consumptions for the DRI unit
λ_{dri}^{steel}, λ_{elec}^{steel}, λ_{lime}^{steel}	parameter	Conversion and specific consumptions for the EAF unit
d_t^{steel}	parameter	Exogenous minimum steel demand at time t

Table B.7
Scenario-wise outcomes for all technology pathways.

Scenario	Nat. Gas-DRI-EAF	H_2-DRI-EAF	Electrolyser-DRI-EAF (v1, w/o discounts)	Electrolyser-DRI-EAF (v1, with discounts)	Electrolyser-DRI-EAF (v2, w/o discounts)	Electrolyser-DRI-EAF (v2, with discounts)
ES1	10 767.25	10 619.42	4338.42	9197.32	5608.87	10 467.77
ES2	10 767.25	7909.24	4338.42	9197.32	5608.87	10 467.77
ES3	10 767.25	4114.99	4338.42	9197.32	5608.87	10 467.77
ES4	10 889.10	10 650.10	4459.04	9317.94	5729.49	10 588.39
ES5	10 889.10	7939.93	4459.04	9317.94	5729.49	10 588.39
ES6	10 889.10	4145.68	4459.04	9317.94	5729.49	10 588.39
ES7	12 811.48	10 737.34	4809.02	9667.91	6079.47	10 938.36
ES8	11 240.25	8027.16	4809.02	9667.91	6344.50	10 938.36
ES9	12 811.48	4232.91	4809.02	9667.91	6344.50	10 938.36
HS1	11 215.70	11 067.87	6198.73	11 057.63	7469.18	12 328.08
HS2	11 215.70	8357.69	6198.73	11 057.63	7469.18	12 328.08
HS3	11 215.70	4563.44	6198.73	11 057.63	7469.18	12 328.08
HS4	11 378.99	11 093.07	6299.82	11 158.71	7570.27	12 429.16
HS5	11 332.07	8382.90	6299.82	11 158.71	7570.27	12 429.16
HS6	11 332.07	4588.65	6299.82	11 158.71	7570.27	12 429.16
HS7	11 670.68	11 167.77	6597.98	11 456.87	7868.43	12 727.32
HS8	11 670.68	8457.59	6597.98	11 456.87	7868.43	12 727.32
HS9	11 670.68	4663.35	6597.98	11 456.87	7868.43	12 727.32

Electricity-to-hydrogen conversion is linear:

$$H_t^{ely} = \eta^{ely} P_t^{ely} \quad \forall t \in \mathcal{T}. \tag{A.3}$$

Hydrogen fed to the DRI can come from the electrolyser and from imports:

$$H_t^{in} = H_t^{ely} + H_t^{imp} \quad \forall t \in \mathcal{T}. \tag{A.4}$$

The DRI plant can run on natural gas, on hydrogen, or on blends. Output is

$$Q_t^{dri} = \frac{H_t^{in}}{\lambda_{H_2}^{dri}} + \frac{G_t^{in}}{\lambda_{ng}^{dri}} \quad \forall t \in \mathcal{T}. \tag{A.5}$$

Electricity and ore inputs scale with output:

$$P_t^{dri} = \lambda_{elec}^{dri} Q_t^{dri}, \qquad Q_t^{ore} = \lambda_{ore}^{dri} Q_t^{dri} \quad \forall t \in \mathcal{T}. \tag{A.6}$$

Direct process emissions from natural gas use are

$$E_t^{CO_2,DRI} = \phi^{ng} G_t^{in} \quad \forall t \in \mathcal{T}. \tag{A.7}$$

DRI is melted to steel in an EAF:

$$Q_t^{steel} = \frac{Q_t^{dri}}{\lambda_{dri}^{steel}}, \qquad P_t^{eaf} = \lambda_{elec}^{steel} Q_t^{steel}, \qquad Q_t^{lime} = \lambda_{lime}^{steel} Q_t^{steel} \quad \forall t \in \mathcal{T}. \tag{A.8}$$

Process emissions from lime usage are

$$E_t^{CO_2,EAF} = \phi^{lime} Q_t^{lime} \quad \forall t \in \mathcal{T}. \tag{A.9}$$

Total plant electricity demand equals the sum of unit loads:

$$P_t^{elec} = P_t^{ely} + P_t^{dri} + P_t^{eaf} \quad \forall t \in \mathcal{T}. \tag{A.10}$$

Steel production must meet the exogenous minimum demand derived from the load profile:

$$Q_t^{steel} \geq d_t^{steel} \quad \forall t \in \mathcal{T}. \tag{A.11}$$

Aggregate emissions used in (A.2) are given by $E_t^{CO_2} = E_t^{CO_2,DRI} + E_t^{CO_2,EAF}$. Technical limits such as unit capacities, ramping, and electrolyser nameplate ratings are imposed as simple bounds. Numerical values are reported in Section 4.

Appendix B. Scenario-wise outcomes for all technology pathways (values are reported in million euros)

See Table B.7.

Appendix C. Belief set wise outcomes for all technology pathways (values are reported in million euros)

See Tables C.8–C.11.

Data availability

Data will be made available on request.

Table C.8
Belief-conditioned expected NPVs under the Base belief set (Appendix). All values in million euros.

Scenario	Nat. Gas-DRI-EAF	H_2-DRI-EAF	Electrolyser-DRI-EAF (v1, w/o discounts)	Electrolyser-DRI-EAF (v1, with discounts)	Electrolyser-DRI-EAF (v2, w/o discounts)	Electrolyser-DRI-EAF (v2, with discounts)
ES1	598.18	589.97	241.02	510.96	311.60	581.54
ES2	598.18	439.40	241.02	510.96	311.60	581.54
ES3	598.18	228.61	241.02	510.96	311.60	581.54
ES4	604.95	591.67	247.72	517.66	318.31	588.24
ES5	604.95	441.11	247.72	517.66	318.31	588.24
ES6	604.95	230.32	247.72	517.66	318.31	588.24
ES7	711.75	596.52	267.17	537.11	337.75	607.69
ES8	624.46	445.95	267.17	537.11	352.47	607.69
ES9	711.75	235.16	267.17	537.11	352.47	607.69
HS1	623.09	614.88	344.37	614.31	414.95	684.89
HS2	623.09	464.32	344.37	614.31	414.95	684.89
HS3	623.09	253.52	344.37	614.31	414.95	684.89
HS4	632.17	616.28	349.99	619.93	420.57	690.51
HS5	629.56	465.72	349.99	619.93	420.57	690.51
HS6	629.56	254.92	349.99	619.93	420.57	690.51
HS7	648.37	620.43	366.55	636.49	437.13	707.07
HS8	648.37	469.87	366.55	636.49	437.13	707.07
HS9	648.37	259.07	366.55	636.49	437.13	707.07

Table C.9
Belief-conditioned expected NPVs under the Electricity-based belief set (Appendix). All values in million euros.

Scenario	Nat. Gas-DRI-EAF	H_2-DRI-EAF	Electrolyser-DRI-EAF (v1, w/o discounts)	Electrolyser-DRI-EAF (v1, with discounts)	Electrolyser-DRI-EAF (v2, w/o discounts)	Electrolyser-DRI-EAF (v2, with discounts)
ES1	1196.36	1179.94	482.05	1021.92	623.21	1163.09
ES2	1196.36	878.80	482.05	1021.92	623.21	1163.09
ES3	1196.36	457.22	482.05	1021.92	623.21	1163.09
ES4	1209.90	1183.34	495.45	1035.33	636.61	1176.49
ES5	1209.90	882.21	495.45	1035.33	636.61	1176.49
ES6	1209.90	460.63	495.45	1035.33	636.61	1176.49
ES7	1423.50	1193.04	534.34	1074.21	675.50	1215.37
ES8	1248.92	891.91	534.34	1074.21	704.94	1215.37
ES9	1423.50	470.32	534.34	1074.21	704.94	1215.37
HS1	0.00	0.00	0.00	0.00	0.00	0.00
HS2	0.00	0.00	0.00	0.00	0.00	0.00
HS3	0.00	0.00	0.00	0.00	0.00	0.00
HS4	0.00	0.00	0.00	0.00	0.00	0.00
HS5	0.00	0.00	0.00	0.00	0.00	0.00
HS6	0.00	0.00	0.00	0.00	0.00	0.00
HS7	0.00	0.00	0.00	0.00	0.00	0.00
HS8	0.00	0.00	0.00	0.00	0.00	0.00
HS9	0.00	0.00	0.00	0.00	0.00	0.00

Table C.10
Belief-conditioned expected NPVs under the Hydrogen-based belief set (Appendix). All values in million euros.

Scenario	Nat. Gas-DRI-EAF	H_2-DRI-EAF	Electrolyser-DRI-EAF (v1, w/o discounts)	Electrolyser-DRI-EAF (v1, with discounts)	Electrolyser-DRI-EAF (v2, w/o discounts)	Electrolyser-DRI-EAF (v2, with discounts)
ES1	0.00	0.00	0.00	0.00	0.00	0.00
ES2	0.00	0.00	0.00	0.00	0.00	0.00
ES3	0.00	0.00	0.00	0.00	0.00	0.00
ES4	0.00	0.00	0.00	0.00	0.00	0.00
ES5	0.00	0.00	0.00	0.00	0.00	0.00
ES6	0.00	0.00	0.00	0.00	0.00	0.00
ES7	0.00	0.00	0.00	0.00	0.00	0.00
ES8	0.00	0.00	0.00	0.00	0.00	0.00
ES9	0.00	0.00	0.00	0.00	0.00	0.00
HS1	1246.19	1229.76	688.75	1228.63	829.91	1369.79
HS2	1246.19	928.63	688.75	1228.63	829.91	1369.79
HS3	1246.19	507.05	688.75	1228.63	829.91	1369.79
HS4	1264.33	1232.56	699.98	1239.86	841.14	1381.02
HS5	1259.12	931.43	699.98	1239.86	841.14	1381.02
HS6	1259.12	509.85	699.98	1239.86	841.14	1381.02
HS7	1296.74	1240.86	733.11	1272.99	874.27	1414.15
HS8	1296.74	939.73	733.11	1272.99	874.27	1414.15
HS9	1296.74	518.15	733.11	1272.99	874.27	1414.15

Table C.11
Belief-conditioned expected NPVs under the Conservative belief set (Appendix). All values in million euros.

Scenario	Nat. Gas-DRI-EAF	H_2-DRI-EAF	Electrolyser-DRI-EAF (v1, w/o discounts)	Electrolyser-DRI-EAF (v1, with discounts)	Electrolyser-DRI-EAF (v2, w/o discounts)	Electrolyser-DRI-EAF (v2, with discounts)
ES1	0.00	0.00	0.00	0.00	0.00	0.00
ES2	2691.81	1977.31	1084.61	2299.33	1402.22	2616.94
ES3	2691.81	1028.75	1084.61	2299.33	1402.22	2616.94
ES4	0.00	0.00	0.00	0.00	0.00	0.00
ES5	0.00	0.00	0.00	0.00	0.00	0.00
ES6	0.00	0.00	0.00	0.00	0.00	0.00
ES7	0.00	0.00	0.00	0.00	0.00	0.00
ES8	0.00	0.00	0.00	0.00	0.00	0.00
ES9	0.00	0.00	0.00	0.00	0.00	0.00
HS1	0.00	0.00	0.00	0.00	0.00	0.00
HS2	2803.92	2089.42	1549.68	2764.41	1867.30	3082.02
HS3	2803.92	1140.86	1549.68	2764.41	1867.30	3082.02
HS4	0.00	0.00	0.00	0.00	0.00	0.00
HS5	0.00	0.00	0.00	0.00	0.00	0.00
HS6	0.00	0.00	0.00	0.00	0.00	0.00
HS7	0.00	0.00	0.00	0.00	0.00	0.00
HS8	0.00	0.00	0.00	0.00	0.00	0.00
HS9	0.00	0.00	0.00	0.00	0.00	0.00

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