

Risk-Aware Electricity Procurement for Flexible Cement Plants: A Utility-Theoretic Approach in Multi-Electricity Markets

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Abstract— This study presents a decision-making framework for flexible cement plants participating in multiple electricity markets under uncertainty. A highly electrified plant with demand-side flexibility, hydrogen-based fuel switching, and carbon capture (CCS) is modeled to engage in long-term, day-ahead, and reserve markets. Using Expected Utility Theory (EUT), we evaluate electricity procurement strategies for decision-makers with varying risk preferences under five uncertainty scenarios. The plant selects the strategy offering the highest utility for its operator while also marketing operational flexibility for additional revenue. A post-decision risk analysis using Conditional Value at Risk (CVaR) is used to assess downside exposure. Results indicate that all decision-makers regardless of their risk preference, consistently favour a procurement strategy that blends long-term contracting with limited exposure to the day-ahead market. The proposed framework captures this trade-off and supports electricity procurement decisions that reflect both economic performance and individual risk attitudes.

Index Terms— Expected Utility Theory, Flexible Cement Plant, Electricity Procurement Strategy, Risk-Aware Decision-Making, Electricity Market

I. INTRODUCTION

The cement industry is among the most energy-intensive sectors globally, responsible for approximately 7–8% of total CO₂ emissions [1]. Traditionally seen as inflexible electricity consumers [2], cement plants are increasingly recognised for their flexibility potential when equipped with technologies like load shifting, energy storage, electrolysers, and carbon capture and storage (CCS) [3, 4]. As high-load industrial facilities, cement plants can respond to market signals and support system stability [5, 6].

Recent studies have proposed frameworks to assess and enhance such flexibility. For example, Rojas-Innocenti et al. (2024) highlight the role of distributed generation and storage

[5], while Golmohamadi (2022) reviews emerging flexibility strategies in energy-intensive sectors [3].

Agent-based modelling has become a common approach for analysing such market interactions, offering a way to simulate the bidding behaviour and market responses of industrial actors under various electricity market designs [7]. Krstevski et al. discuss how industrial flexibility providers, such as cement plants, can participate in electricity markets through innovative business models [8]. Borst et al. use agent-based simulation to evaluate electricity procurement strategies under dynamic pricing conditions [7].

However, most existing studies focus on technical feasibility or cost minimisation, and overlook the fact that real-world industrial decision-makers have different risk attitudes. In economics and finance, risk preference refers to the tendency to choose actions with higher variance in outcomes over safer but equally valuable options [9]. A risk-neutral operator maximises expected value by weighing outcomes based on probabilities. In contrast, risk-averse or risk-seeking agents evaluate decisions based on utility, a subjective measure of satisfaction or preference, rather than monetary outcomes alone [10].

Recent studies applying utility theory show that industrial operators' market participation decisions are shaped by their risk preferences [11]. Some firms prefer stable returns via long-term contracts, while others pursue higher (but riskier) profits through spot or reserve markets. To better quantify downside risk, Conditional Value at Risk (CVaR) is increasingly used to assess revenue exposure in worst-case market conditions. For example, Bohlayer et al. (2020) applied CVaR to evaluate bidding strategies and risk-adjusted returns in electricity markets [12, 13].

Building on these foundations, this study proposes a utility-theoretic framework for flexible cement plants participating in multiple electricity markets. We model a highly electrified plant with demand-side flexibility, hydrogen fuel switching, and

CCS, simulating participation in long-term, day-ahead, and control reserve markets. Using EUT, we assess how bidding strategies differ for operators with heterogeneous risk preferences under five market uncertainty scenarios. CVaR is then applied post-decision to quantify downside exposure and assess the robustness of each strategy. This framework supports risk-aware procurement and flexibility marketing for industrial consumers in evolving energy systems [14].

II. METHODOLOGY

This study integrates a utility-based decision-making framework with an agent-based electricity market simulation to evaluate how a flexible, electrified cement plant participates in multiple electricity markets under uncertainty. The approach combines three core components: a process-level model of a flexible cement plant, a multi-market simulation built using the ASSUME agent-based framework, and a risk-aware decision model based on EUT to reflect heterogeneous operator behavior. The plant acts as a demand-side agent that adapts its electricity consumption in response to market signals and offers flexibility as an ancillary service. Strategy selection is guided by the operator’s risk preference, and financial downside exposure is further assessed using CVaR.

A. Electricity Market Setup and Strategy Design

The electricity market environment is implemented using the ASSUME agent-based simulation framework, which enables the configuration of multiple electricity markets with realistic bidding, clearing, and delivery timelines. In this study, the flexible cement plant participates in three interconnected electricity markets: the Long-Term Market (LTM), which offers forward contracts for full-day energy procurement; the Energy-Only Market (EOM), which operates on a day-ahead hourly basis to handle deviations from long-term procurement; and the Control Reserve Market (CRM), where the plant can submit upward reserve offers in 4-hour blocks. These markets are cleared sequentially, starting with the LTM, followed by the EOM, and finally the CRM, reflecting temporal interactions between procurement opportunities.

The plant simulates operational decisions by selecting from five predefined bidding strategies. These range from fully inflexible long-term procurement to diversified market participation with active flexibility marketing. The strategies are briefly described in Table 1. These strategies reflect varying levels of market exposure and flexibility utilization, and serve as the decision options evaluated under uncertainty.

B. Cement Plant and Flexibility Model

The cement plant is modelled as a flexible, electrified industrial system composed of five interconnected subsystems: clinker production, grinding mills, electrolyser, CCS, and clinker inventory. Clinker production is the most energy- and emission-intensive unit, driven by both thermal and electrical input. Grinding mills represent raw material preparation and cement finishing, consuming electricity and operating under ramping and daily usage constraints. The electrolyser enables fuel switching by producing hydrogen from electricity, reducing dependence on fossil fuels. The CCS unit captures process emissions, storing or bypassing them based on

operational limits and cost signals. Finally, the clinker inventory acts as a buffer that temporally decouples production from grinding, enabling load shifting without affecting output targets.

TABLE 1 DEFINITION OF MARKETING STRATEGIES OF FLEXIBILITY

Strategies	Market Participation	Strategy
LTM_Inflex	LTM Only	100% of energy is procured as inflexible load in the LTM
LTM_Flex		100% of energy is procured as flexible load in the LTM
LTM_50_EOM	LTM and Day-Ahead (DA)	Energy is split between LTM and DA; up to 50% of the maximum load is procured in LTM, and the remaining energy is procured in the DA market.
LTM_80_EOM		Similar to LTM_50_EOM, but with an 80% threshold—80% of the maximum load is procured in LTM, while the remaining 20% is procured in the DA market.
LTM_EOM_Reserve	LTM, DA and Positive Control Reserve(P-CRM)	80% in LTM, 20% in DA, and the maximum potential reserve power is offered in the P-CRM market.

Each subsystem is implemented with technical constraints including ramp rates, energy efficiency, and availability profiles, shown in Table 4.

Flexibility is introduced through load shift variables, operating hour constraints, and reserve capacity declarations, allowing the plant to adjust consumption profiles in response to market prices. This structure enables the plant not only to optimise operational cost, but also maximise load shift to market its operational flexibility. This plant is model as a Mixed-Integer Linear Program (MILP) and embedded within the agent-based simulation, allowing each subsystem to respond dynamically to strategy selection and market outcomes.

The cement production process follows a stock-flow approach as detailed in [4].

1) *Clinker Production and Energy Demand*: The clinker production unit represents the most energy- and emission-intensive stage. Thermal and electrical demands are modelled based on specific energy intensities per unit of clinker produced. Let C_t be the clinker output at time t , then:

$$Q_{thermal,t} = q_{spec} \times C_t \quad (1)$$

$$P_{electricity,t} = E_{spec} \times C_t \quad (2)$$

$$E_t = \vartheta_{CO_2} \times C_t \quad (3)$$

These equations capture the direct link between operational intensity and energy/emission outputs, essential for coordinating with both fuel procurement and emission-reduction technologies.

2) *Carbon Capture and Storage (CCS)*: The CCS unit captures a portion of the process emissions using a time-coupled storage and processing model. Let η_{CCS} be the capture efficiency. The emissions are divided as:

$$E_{captured,t} = E_t \times \eta_{ccs} \quad (4)$$

$$E_{\{bypass,t\}} = E_t \times (1 - \eta_{ccs}) \quad (5)$$

$$S_t = S_{t-1} + E_{captured,t} - R_t \quad (6)$$

This setup allows emissions to be flexibly captured and stored, with processing governed by plant decisions rather than forced timing, enabling better alignment with electricity prices or CO₂ pricing signals.

3) *Demand-Side Flexibility*: The plant's operational flexibility is modelled using load shifting, characterised by positive and negative adjustments lsp_t and lsn_t , activated by binary variable SI_t :

$$lsp_t \leq (1 - SI_t) \times M \quad (7)$$

$$lsn_t \leq SI_t \times M \quad (8)$$

The total power input ($tp_{in,t}$), adjusted for flexibility, must match the aggregate consumption of all active units:

$$tp_{in,t} + lsp_t - lsn_t = \sum P_{unit,t} \quad (9)$$

This ensures that flexibility is realistically bounded and accurately reflected in market bidding behaviour.

C. Expected Utility-Based Decision Framework

To evaluate strategy selection under uncertainty, we apply EUT, a widely used framework for modeling decisions under risk. Unlike traditional cost-minimisation approaches, EUT allows each decision-maker to evaluate outcomes based on their individual risk preferences, not just expected monetary return. This reflects heterogeneous behavior, where some operators prioritise stable and predictable revenue while others pursue more aggressive, high-variance strategies. In electricity market participation, different plant operators exhibit varying attitudes toward financial risk [15].

According to the Von Neumann–Morgenstern utility theorem, if a decision-maker's preferences satisfy the rationality axioms, their behavior under uncertainty can be modeled using expected utility functions[16].

In this study, each electricity procurement strategy yields a distribution of financial outcomes across multiple simulated market scenarios. These outcomes are evaluated through a utility function $U(W)$, where W represents the monetary result (e.g., profit or revenue) under a given scenario. The operator selects the strategy that maximises expected utility, defined as:

$$EU = \sum_i P_i U(W_i) \quad (10)$$

where:

- P_i is the probability of outcome i ,
- W_i is the monetary outcome (e.g., profit or revenue),
- $U(W_i)$ is the utility associated with that outcome.

The utility function's shape varies according to the operator's attitude toward risk.

a) *Risk-Neutral*: This linear utility function implies that the operator evaluates strategies solely based on their expected

monetary outcome, with no sensitivity to risk. The marginal utility of wealth is constant, which reflects indifference to variability or volatility. Their utility function is:

$$U(W) = W \quad (11)$$

b) *Risk-Averse*: This concave function implies diminishing marginal utility of wealth. As wealth increases, each additional unit contributes less to perceived utility. This represents an operator who prefers stable outcomes and is willing to sacrifice potential gains to reduce uncertainty.

$$U(W) = \sqrt{W} \quad (12)$$

c) *Risk-Seeking*: his quadratic utility function represents a risk-seeking decision-maker who prefers outcomes with higher variability and is willing to accept greater downside risk for the possibility of larger gains. The function is convex, meaning the marginal utility of wealth increases as outcomes grow. Unlike risk-averse operators who prioritize stability, risk-seeking behavior emphasizes potential upside, making this profile more inclined to pursue aggressive strategies in volatile markets.

$$U(W) = W^2 \quad (13)$$

These utility forms are standard in economic decision theory and allow consistent modeling of operators with different risk attitudes. By using this structure, the same plant can show different electricity procurement behaviors depending solely on the assigned risk profile.

D. Scenario and Uncertainty Modeling

This study considers five distinct uncertainty scenarios to capture external factors that influence electricity procurement decisions: a base case with nominal forecasts, renewable energy (RE) variability, electricity demand fluctuation, and price volatility in natural gas and CO₂. Natural gas and CO₂ prices are modeled using autoregressive (AR(1)) processes to reflect market fluctuations with mean-reverting behavior. The variation in Renewable energy availability is simulated by introducing Gaussian noise, while demand uncertainty is introduced using smoothing filters applied to the baseline load profile.

These scenarios generate different electricity price trajectories, resulting in a range of financial outcomes for each procurement strategy. The expected utility of each strategy is then calculated using these outcome distributions. Scenario probabilities (shown in Table 2) differ by risk profile: risk-neutral decision-makers assign equal weights to all scenarios, while risk-averse operators place higher probability on more stable cases. These weighted preferences influence utility calculations and ultimately guide the selection of optimal bidding strategies.

TABLE 2. SCENARIOS AND ITS PROBABILITY DISTRIBUTION

	Base	RE	Demand	Natural gas price	CO ₂ price
<i>Risk Neutral</i>	0.2	0.2	0.2	0.2	0.2
<i>Risk Averse</i>	0.3	0.15	0.15	0.2	0.2
<i>Risk Seeking</i>	0.4	0.1	0.1	0.2	0.2

TABLE 3. EXPECTED RETURNS (IN M EUR).

	Base	RE	Demand	Natural Gas	CO ₂
LTM Inflex	1.522	1.597	1.504	1.558	1.600
LTM Flex	1.557	1.623	1.496	1.594	1.577
LTM 50 EOM	1.656	1.638	1.681	1.671	1.674
LTM 80 EOM	1.594	1.644	1.543	1.568	1.594
LTM_EOM_Reserve	1.307	1.313	1.307	1.312	1.308

E. Post-Decision Risk Assessment

While expected utility helps identify the strategy that aligns with an operator’s risk preference, it does not explicitly capture downside exposure in worst-case scenarios. To address this, we conduct a post-decision risk assessment using Conditional Value at Risk (CVaR), a widely used financial risk metric that quantifies the average loss in the worst α -percent of outcomes offering a more informative measure of tail risk than Value at Risk (VaR) alone. In this study, CVaR is calculated for the utility-optimal strategy of each risk profile using simulated monetary outcomes across five uncertainty scenarios. This reveals the vulnerability of each strategy to extreme market conditions, complementing expected utility analysis and supporting more robust risk-aware decision-making.

III. RESULTS

This section presents the outcomes of simulating electricity procurement strategies for a flexible, electrified cement plant participating in multiple electricity markets under uncertainty. Five bidding strategies are evaluated across three types of decision-makers—risk-neutral, risk-averse, and risk-seeking—using an expected utility framework. The simulation spans a four-month horizon, assuming a cement production target of 10,000 tonnes and corresponding electricity demand between 6.6 and 6.9 GWh, influenced by CCS operation. Electricity prices vary across five scenarios driven by changes in renewable generation, demand, and market volatility in natural gas and CO₂.

All monetary returns are based on an assumed cement selling price of 115 EUR per tonne, which defines the revenue baseline for profitability and utility evaluation. The monetary outcomes for each strategy under all five scenarios are summarised in Table 3. These scenario-based returns are then used to compute both expected outcome and expected utility, with each scenario weighted according to the decision-maker’s risk profile. Risk-neutral operators assign equal probability (0.20) to each scenario. Risk-averse operators give higher weight to stable outcomes like the base and natural gas scenarios, while risk-seeking operators emphasize volatile cases such as demand and RE uncertainty.

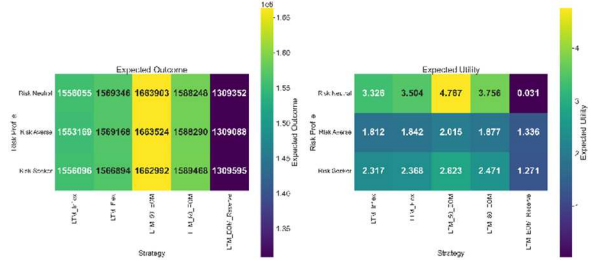
B. Expected Utility Analysis

Figure 1 compares expected monetary outcomes and expected utilities for each strategy across the three risk profiles. The heatmap on the left shows that LTM_50_EOM consistently delivers the highest expected returns (~1.66 million EUR), followed by LTM_80_EOM. However, when utility is considered, preferences shift based on risk profile. Risk-neutral and risk-seeking decision-makers prefer LTM_50_EOM, while risk-averse operators show a slight inclination toward LTM_Flex, reflecting their desire for stable, predictable returns. The poor performance of LTM_EOM_Reserve across all profiles indicates that added complexity and uncertainty from reserve participation do not compensate with adequate returns.

C. Behavioral Implications of Utility Functions

Figure 2 illustrates how different utility functions transform rescaled outcomes for each electricity procurement strategy across three risk profiles: risk-neutral, risk-averse, and risk-seeking. To improve interpretability of curvature and highlight behavioral differences, all monetary outcomes were rescaled by subtracting the global minimum outcome (1.307 Mill. EUR). This standardisation compressed the domain and enabled clearer visualization of marginal utility dynamics across strategies.

FIGURE 1 EXPECTED OUTCOME AND EXPECTED UTILITY



A. Simulation of Flexibility and Bidding Strategies

The plant’s operational flexibility is expressed through its ability to shift electricity demand across time while maintaining production. Depending on the chosen strategy and subsystem configuration, the total shiftable load ranges from approximately 0.18 MW to 0.44 MW. Strategies that include participation in day-ahead and reserve markets enable more dynamic scheduling, unlocking higher flexibility.

In the risk-neutral case, utility increases linearly with outcome, indicating constant marginal utility and no sensitivity to variability. For risk-averse operator, the concave curve reveals diminishing marginal utility, making these operators more responsive to downside protection than to potential gains. Conversely, the risk-seeking profile shows convex utility, with increasing marginal utility that strongly favors strategies offering higher variability and upside.

FIGURE 2 UTILITY VS OUTCOME

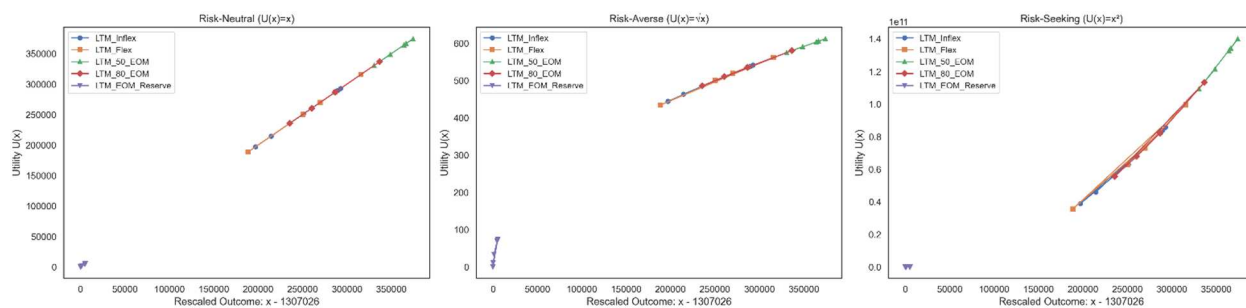


TABLE 4 TECHNICAL PARAMETERS FOR THE CEMANT PLANT PLANT [4, 5]

Component	Max Power (MW)	Ramp Rates (MW/h)	Efficiency η (%)	Specific Thermal Energy (MWh/t)	Specific Electrical Energy (MWh/t)	Storage Size (t)	Max. Operating hours/day
Clinker System	0.2	Up: 0.02, Down: 0.02	-	0.97	0.025	-	24
Cement Mill	0.27	Up: 0.026, Down: 0.026	100	-	0.026	-	20
Electrolyser	6.5	Up: 6.5, Down: 6.5	80	-	-	-	24
CCS System	40	Up: 40, Down: 40	100	0.1	-	40	24
Clinker Inventory	-	-	-	-	24	1000	24

Despite these differing perceptions, LTM_50_EOM consistently appears as the most desirable strategy across all profiles. Its combination of long-term stability and day-ahead responsiveness delivers both high returns and behavioral appeal, whereas LTM_EOM_Reserve remains the least favorable, exhibiting low utility regardless of the decision-maker's risk preference.

D. Post-Decision Risk Assessment

While the expected utility framework identifies the most preferred strategy based on a decision-maker's risk attitude, it does not capture the full extent of downside financial exposure under adverse market conditions. To complement the utility-based assessment, we conduct a post-decision risk evaluation using CVaR. CVaR quantifies the expected return in the worst-performing scenarios, providing insight into potential losses beyond the Value at Risk (VaR) threshold.

For the optimal strategy selected by the risk-neutral operator, LTM_50_EOM, the VaR is estimated at approximately 1.547 M EUR, while the corresponding CVaR is 1.542 M EUR. The narrow gap between VaR and CVaR (around 4,942 EUR) indicates limited exposure to extreme downside outcomes, suggesting that this strategy remains robust even in the least favorable scenarios. In contrast, more volatile strategies such as LTM_EOM_Reserve shows lower expected returns and greater variability across scenarios, resulting in considerably lower CVaR values. This makes them less desirable for operators concerned with financial resilience.

IV. CONCLUSION AND DISCUSSION

This paper developed a decision-making framework based on EUT to evaluate electricity procurement strategies for a

flexible, electrified cement plant operating under uncertainty. The model incorporates demand-side flexibility and low-carbon technologies, including hydrogen-based fuel switching and CCS, and simulates market participation across long-term, day-ahead, and control reserve markets under five future scenarios. The goal was to assess how decision-makers with different risk preferences choose among predefined bidding strategies to maximise perceived utility while monetising operational flexibility.

A key contribution lies in integrating behavioral modeling through EUT to capture heterogeneous risk preferences. Rather than relying solely on cost minimisation, the framework evaluates strategies based on utility functions aligned with risk-neutral, risk-averse, and risk-seeking attitudes. The analysis revealed that LTM_50_EOM, a strategy blending long-term contracts with partial short-term exposure, consistently provided the highest expected utility across profiles. Post-decision risk evaluation using CVaR further confirmed its robustness, showing limited downside risk compared to more volatile strategies such as LTM_EOM_Reserve.

The framework contributes to the broader discourse on risk-aware industrial participation in electricity markets, particularly amid increasing volatility and uncertainty. By explicitly modeling how risk preferences shape bidding behavior, it provides a more realistic foundation for strategic electricity procurement under uncertainty.

Future research should explore the integration of additional sources of uncertainty, including regulatory shifts, policy incentives (e.g., carbon pricing frameworks or flexibility remuneration schemes), and changes in market design.

V. REFERENCES

- [1] A. Kanerva, "Flexibility Potential of Energy Intensive Industrial Processes," Faculty of Information Technology and Communication Sciences, Tampereen yliopisto, Finland, 2024.
- [2] European Commission - JRC IPTS European IPPC Bureau, *Best available techniques (BAT) reference document for the production of cement, lime and magnesium oxide: Industrial Emissions Directive 2010/75/EU (integrated pollution prevention and control)*. Luxembourg: Publications Office, 2013.
- [3] H. Golmohamadi, R. Keypour, B. Bak-Jensen, J. R. Pillai, and M. H. Khooban, "Robust Self-Scheduling of Operational Processes for Industrial Demand Response Aggregators," *IEEE Trans. Ind. Electron.*, vol. 67, no. 2, pp. 1387–1395, 2020, doi: 10.1109/TIE.2019.2899562.
- [4] M. Rombouts, "Flexible electricity use in the cement industry: Laying the foundation for a not so concrete future: A scenario analysis about the flexibility potential of European cement plants in 2050 to estimate the potential electricity costs savings and the impact on the electricity grid," Utrecht University, Utrecht University, Utrecht, 2021.
- [5] S. Rojas-Innocenti, E. Baeyens, A. Martín-Crespo, S. Saludes-Rodil, and F. Frechoso-Escudero, "Electrical Consumption Flexibility in the Cement Industry," *ArXiv*, abs/2403.06573, 2024, doi: 10.48550/arXiv.2403.06573.
- [6] S. Løbbe, A. Hackbarth, H. Hagenlocher, and U. Ziegler, "Chapter 16 - Industrial demand flexibility: A German case study," in *Variable Generation, Flexible Demand*, F. Sioshansi, Ed.: Academic Press, 2021, pp. 371–389. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/B9780128238103000091>
- [7] F. Borst, N. Strobel, T. Kohne, and M. Weigold, "Investigating the Electrical Demand-Side Management Potential of Industrial Steam Supply Systems Using Dynamic Simulation," *Energies*, vol. 14, no. 6, p. 1533, 2021, doi: 10.3390/en14061533.
- [8] P. Krstevski, A. K. Mateska, and S. Borozan, "Models for Integration of Flexibility Sources in Regional Electricity Markets," in *2022 57th International Scientific Conference on Information, Communication and Energy Systems and Technologies (ICEST)*, Ohrid, North Macedonia, 2022, pp. 1–4.
- [9] H. Markowitz, "PORTFOLIO SELECTION*," *The Journal of Finance*, vol. 7, no. 1, pp. 77–91, 1952, doi: 10.1111/j.1540-6261.1952.tb01525.x.
- [10] J. W. Pratt, "Risk Aversion in the Small and in the Large," *Econometrica*, vol. 32, 1/2, p. 122, 1964, doi: 10.2307/1913738.
- [11] J. C. Richstein and S. S. Hosseinioun, "Industrial demand response: How network tariffs and regulation (do not) impact flexibility provision in electricity markets and reserves," *Applied Energy*, vol. 278, p. 115431, 2020, doi: 10.1016/j.apenergy.2020.115431.
- [12] M. Bohlayer, M. Fleschutz, M. Braun, and G. Zöttl, "Energy-intense production-inventory planning with participation in sequential energy markets," *Applied Energy*, vol. 258, p. 113954, 2020, doi: 10.1016/j.apenergy.2019.113954.
- [13] L. Serpe, T. Fürmann, R. Qussous, and A. Weidlich, "Demand-side flexibility of the German steel industry: A case study," in *2023 19th International Conference on the European Energy Market (EEM)*, Lappeenranta, Finland, 2023, pp. 1–6.
- [14] R. T. Rockafellar and S. Uryasev, "Optimization of conditional value-at-risk," *JOR*, vol. 2, no. 3, pp. 21–41, 2000, doi: 10.21314/JOR.2000.038.
- [15] R. Aïd, G. Chemla, A. Porchet, and N. Touzi, "Hedging and Vertical Integration in Electricity Markets," *Management Science*, vol. 57, no. 8, pp. 1438–1452, 2011, doi: 10.1287/mnsc.1110.1357.
- [16] J. von Neumann and O. Morgenstern, *Theory of games and economic behavior*, 60th ed. Princeton N.J., Woodstock: Princeton University Press, 1944.