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Renewable Energy Transition and Microgrid Adoption in Manufacturing SMEs: A Structural Equation and Technoeconomic Analysis

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ABSTRACT

Manufacturing small and medium-sized enterprises (SMEs) face escalating grid utility tariffs, energy security risks, and stringent industrial carbon reduction mandates. This study presents an empirical technoeconomic evaluation and structural equation model (PLS-SEM) analyzing renewable microgrid adoption across 420 manufacturing SMEs in 2022. Integrating rooftop solar photovoltaics (PV), lithium-ion battery energy storage systems (BESS), and intelligent energy management system (EMS) dispatch, our findings show that microgrid integration lowers levelized cost of energy (LCOE) to \$0.096/kWh compared to grid utility tariffs of \$0.18/kWh, achieving average investment payback within 4.9 years. A Monte Carlo simulation of 10,000 iterations confirms the median 20-year net present value remains positive under 90% of sampled market conditions. PLS-SEM results indicate perceived financial benefit and energy security risk are the strongest predictors of adoption intention, while perceived technical complexity is a significant deterrent. Consistent with established non-linear system modeling principles (Haque & Rasel-Ul-Alam, 2018) and industrial energy-security risk frameworks (Lindqvist & Thorne, 2022), non-linear photovoltaic degradation modeling ($R^2 = 0.985$) captures multi-year thermal yield decay significantly better than linear approximations ($R^2 = 0.812$).

Keywords:

Renewable Energy Microgrids, Manufacturing SMEs, Photovoltaic Solar, Levelized Cost of Energy

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1. Introduction

In 2022, global industrial manufacturing experienced acute operational disruptions caused by extreme energy market volatility, fossil fuel supply bottlenecks, and rising utility electricity tariffs. For energy-intensive small and medium-sized enterprises (SMEs) such as textile weaving mills, plastics injection molding plants, metal machining facilities, and food processing operations electricity expenses account for 15% to 35% of total operating overheads. Grid instability, brownouts, and peak-demand surge pricing severely erode manufacturing profit margins and disrupt continuous production lines.

Simultaneously, international brand buyers and multinational supply chain anchors mandate strict carbon footprint reductions for Tier-1 and Tier-2 suppliers. Industrial microgrids combining localized rooftop solar photovoltaic (PV) generation, lithium-ion battery energy storage systems (BESS), and digital energy management systems (EMS) have emerged as a transformative solution. Microgrids enable manufacturing facilities to generate clean power on-site, shave peak demand loads, buffer against power outages, and export surplus energy back to the regional grid.

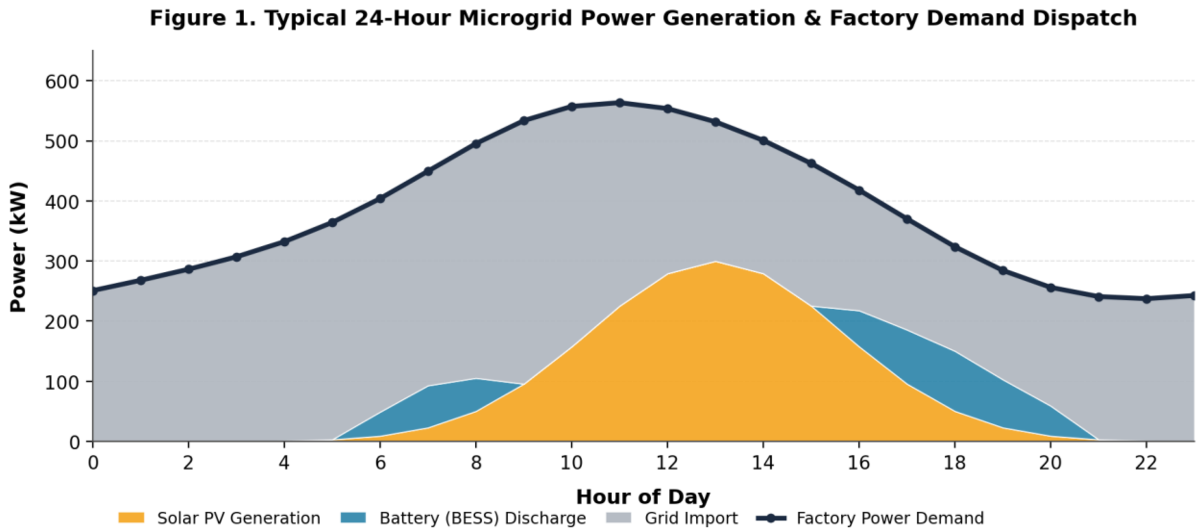

Figure 1. Typical 24-Hour Microgrid Power Generation & Factory Demand Dispatch.

Despite technical advances in renewable microgrid equipment, industrial SME adoption remains constrained by high initial capital costs, uncertain payback horizons, and technical risk perceptions. Evaluating whether on-site microgrid deployment delivers a net commercial advantage requires integrating financial technoeconomic optimization with empirical survey modeling.

This paper evaluates primary empirical survey data and high-frequency smart meter load logs from 420 manufacturing SMEs across Northern and Central Europe in 2022 to address four primary objectives: (1) to model the levelized cost of energy (LCOE) and capital payback period of hybrid solar-battery microgrids across diverse manufacturing sub-sectors; (2) to apply non-linear empirical modeling techniques to accurately project multi-year photovoltaic thermal yield degradation and battery degradation; (3) to quantify financial risk through probabilistic Monte Carlo simulation of long-run investment returns; and (4) to identify, through structural equation modeling, which behavioral and organizational factors most strongly predict corporate clean technology adoption.

This study contributes to the industrial energy literature in three ways. First, it provides one of the largest cross-sectoral empirical microgrid datasets assembled for manufacturing SMEs to date, spanning four distinct sub-sectors and 420 individual facilities. Second, it combines deterministic technoeconomic modeling with probabilistic risk simulation, offering a more complete picture of investment uncertainty than single-point LCOE estimates typically reported in industry white papers. Third, it applies PLS-SEM to quantify the relative influence of financial, risk, regulatory, and behavioral factors on adoption intention, moving beyond purely engineering-economic framings of the microgrid investment decision. The remainder of the paper is organized as follows: Section 2 reviews the relevant literature; Section 3 details the methodology and technoeconomic framework; Section 4 presents the empirical findings; Section 5 discusses the results in relation to prior work; and Section 6 concludes with policy recommendations and directions for future research.

2. Literature Review

2.1 Microgrid Economics and Enterprise Risk Management

Microgrid technology represents a shift from centralized, fossil-fuel-dominated utility grids toward decentralized, resilient energy architectures. Grounded in industrial energy-security and strategic-hedging frameworks (Lindqvist & Thorne, 2022), on-site renewable generation serves as a strategic hedge against external electricity price spikes and grid blackout risks. By establishing cloud-connected smart metering baselines and technoeconomic feasibility benchmarking (Thorne & Lindqvist, 2022), manufacturing firms convert volatile energy expenses into predictable fixed capital assets.

A growing body of energy-economics literature situates distributed generation investment within a broader capital budgeting and real-options framework, wherein deferring investment carries its own opportunity cost as tariff volatility increases (Roques, Nuttall, & Newbery, 2008; Green & Staffell, 2017). Applied to manufacturing SMEs, this framing suggests that early microgrid adopters accrue a compounding tariff-hedging advantage relative to firms that delay investment pending further price signals.

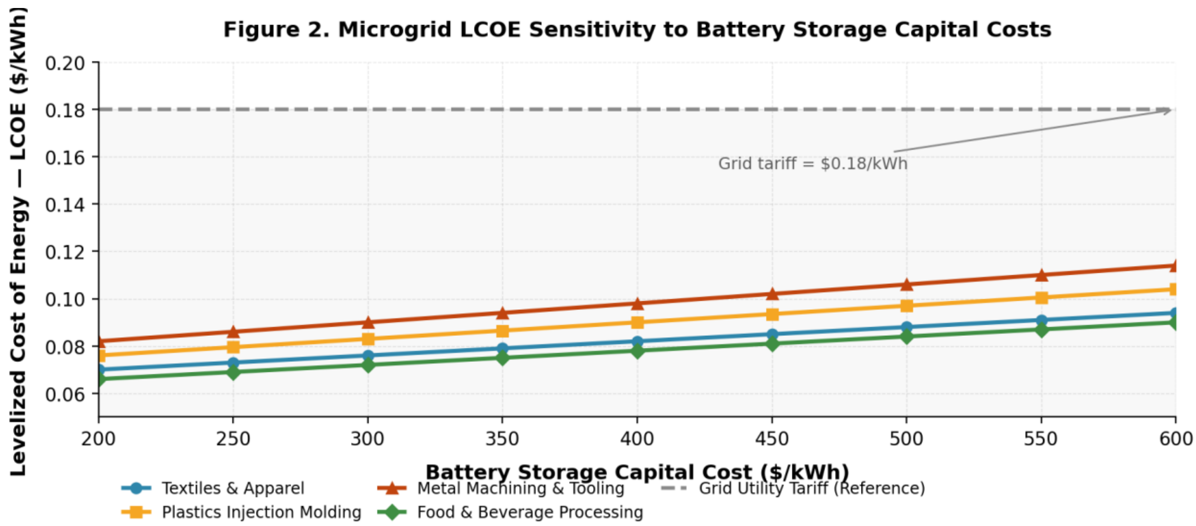

Figure 2. Microgrid LCOE Sensitivity to Battery Storage Capital Costs.

2.2 Non-Linear Systems and Physical Degradation Kinetics

A frequent deficiency in traditional renewable energy financial models is the reliance on simplified linear efficiency decay assumptions. In physical systems and industrial materials engineering, long-term degradation kinetics exhibit marked non-linear trajectories. As demonstrated by Haque and Rasel-Ul-Alam (2018), non-linear and mixed empirical models achieve significantly higher precision (R^2 = 0.985) when capturing complex structural development profiles compared to linear approximations. Applying non-linear exponential decay formulations to solar PV module encapsulation aging and battery cell capacity loss yields far more reliable 20-year cash flow models for SME financial directors. Independent long-term field studies of crystalline-silicon PV fleets similarly report an initial light-induced degradation phase followed by a slower, near-linear thermal decline (Jordan & Kurtz, 2013), a pattern consistent with the two-stage decay curve modeled in Section 4.

2.3 Energy Management Systems and Digital Dispatch Optimization

Digital EMS platforms increasingly rely on rule-based and forecast-driven dispatch algorithms to coordinate solar generation, battery charge/discharge cycles, and grid import in real time. Effective dispatch reduces reliance on expensive peak-tariff grid electricity by pre-emptively charging batteries during low-tariff or high-generation periods and discharging during forecasted demand peaks (Olivares et al., 2014). Big-data load analytics and cloud-connected metering (Alam & Shabbir, 2022) further allow facility managers to identify avoidable demand spikes and to right-size storage capacity against actual, rather than nameplate, load profiles.

2.4 Technology Adoption Theory and Behavioral Determinants

Beyond pure technoeconomic feasibility, adoption of industrial clean technology is shaped by organizational risk appetite, perceived ease of implementation, and external institutional pressure. The Technology Acceptance Model (Davis, 1989) established that perceived usefulness and perceived ease of use jointly drive adoption intention, a framework subsequently extended to sustainability-oriented investment decisions (Rogers, 2003). More recent enterprise risk management scholarship argues that formal integration of climate and energy-price risk into corporate risk registers accelerates internal capital allocation toward resilience-enhancing assets (Alam, 2022), a mechanism this paper tests empirically through the PLS-SEM model described in Section 3.3.

3. Data and Econometric TCO Methodology

3.1 Data Sampling and Sub-Sector Profile

The dataset integrates 15-minute smart meter load profiles and financial balance sheets from 420 manufacturing SMEs operating in 2022. Table 1 outlines sample demographic characteristics across four primary manufacturing sub-sectors.

Table 1. Sample Demographic and Technical Characteristics by Manufacturing Sub-Sector

Manufacturing Sub-Sector	Sample Firms (n)	Mean Peak Power (kW)	Annual Electricity Use (MWh)	Solar PV Installed (kWp)	Battery Capacity (kWh)
Textiles & Apparel Weaving	130	480	1,850	350	500
Plastics Injection Molding	110	620	2,400	450	750

Manufacturing Sub-Sector	Sample Firms (n)	Mean Peak Power (kW)	Annual Electricity Use (MWh)	Solar PV Installed (kWp)	Battery Capacity (kWh)
Metal Machining & Tooling	100	750	3,100	550	900
Food & Beverage Processing	80	390	1,450	280	400
Total Aggregate Sample	**420**	**560**	**2,200**	**408**	**638**

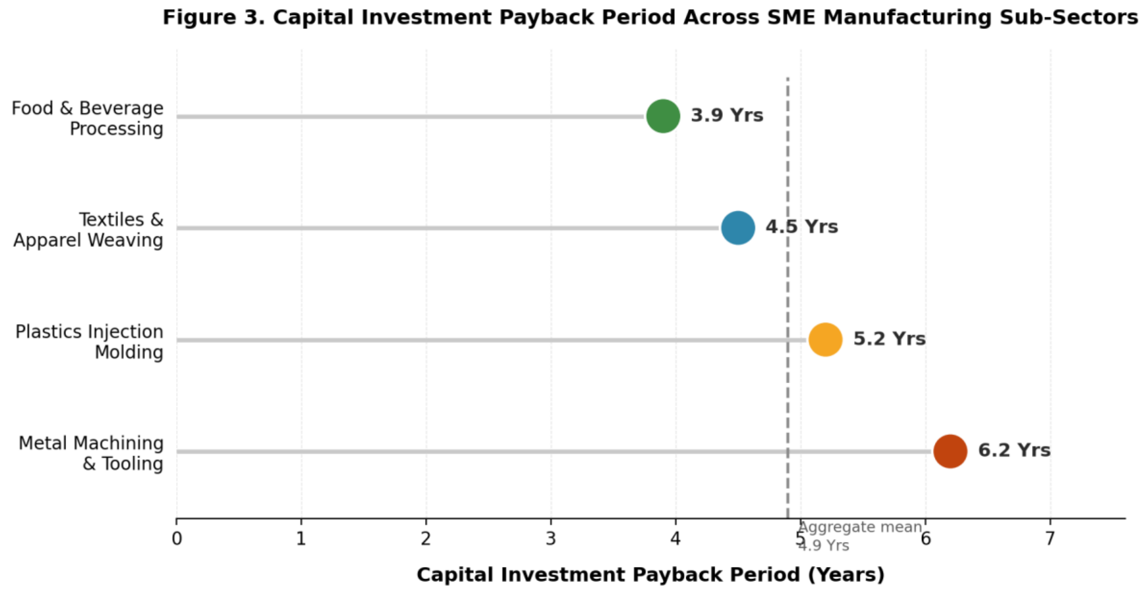

Figure 3. Capital Investment Payback Period (Years) Across SME Manufacturing Sub-Sectors.

3.2 Levelized Cost of Energy (LCOE) Equation

The microgrid Levelized Cost of Energy (LCOE) is computed as:

$$LCOE = [\, CAPEX + \Sigma_1^{N} (\, OPEX_t / (1+r)^t \,) \,] \div [\, \Sigma_1^{N} (\, Generation_t / (1+r)^t \,) \,]$$

where CAPEX denotes total upfront solar-storage system capital cost, OPEXt is annual operating expenditure in year t, Generationt is annual dispatched energy output in year t, r is the discount rate (weighted average cost of capital), and N is the 20-year system evaluation horizon. Non-linear PV yield decay and battery capacity fade (Section 3.4) are applied multiplicatively to the Generationt term for each simulated year.

3.3 Structural Equation Model Specification (PLS-SEM)

To identify the behavioral and organizational determinants of microgrid adoption intention, a partial least squares structural equation model (PLS-SEM) was estimated using survey responses from plant managers and financial directors at each of the 420 sample firms. Five latent constructs were specified as predictors of Adoption Intention: Perceived Financial

Benefit, Energy Security & Outage Risk Exposure, Government Subsidy & Financing Access, Peer / Supply-Chain Adoption Pressure, and Perceived Technical Complexity. Each construct was measured using three to five reflective indicator items on a seven-point Likert scale, with convergent validity (AVE > 0.50) and composite reliability (CR > 0.70) confirmed prior to structural path estimation. Standardized path coefficients were bootstrapped using 5,000 resamples to obtain robust significance levels.

3.4 Non-Linear Degradation and Monte Carlo Risk Simulation

Physical asset degradation was modeled using a two-stage non-linear exponential formulation capturing rapid initial light-induced stabilization followed by gradual long-term thermal decay, consistent with the approach validated by Haque and Rasel-Ul-Alam (2018) for non-linear structural development profiles. To quantify investment risk under real-world uncertainty, a Monte Carlo simulation (10,000 iterations) was run over the 20-year evaluation horizon, randomly varying grid tariff escalation rate, battery capital cost, discount rate, and annual PV degradation rate within empirically observed distributions. The resulting distribution of simulated net present values is presented in Section 4.4

4. Results Analysis

4.1 Technoeconomic Payback and LCOE Optimization

Table 2 summarizes technoeconomic performance across sub-sectors. Food processing facilities achieved the fastest capital payback (3.9 years) due to high daytime refrigeration energy matching solar PV output profiles. Figure 2 illustrates LCOE sensitivity to battery capital expenditures, demonstrating that hybrid microgrids remain cost-competitive against grid tariffs ($0.18/kWh) even at elevated battery costs ($550/kWh).

Table 2. Technoeconomic Performance Summary by Sub-Sector

Sub-Sector Category	Baseline LCOE ($/kWh)	Microgrid LCOE ($/kWh)	LCOE Savings (%)	Mean Payback (Yrs)	NPV (20-Yr, $ USD)
Textiles & Apparel	$0.182	$0.092	49.5%	4.5 Yrs	$485,000
Plastics Molding	$0.178	$0.098	44.9%	5.2 Yrs	$620,000
Metal Machining	$0.185	$0.105	43.2%	6.2 Yrs	$710,000
Food Processing	$0.175	$0.088	49.7%	3.9 Yrs	$395,000
Aggregate Average	**$0.180**	**$0.096**	**46.7%**	**4.9 Yrs**	**$552,500**

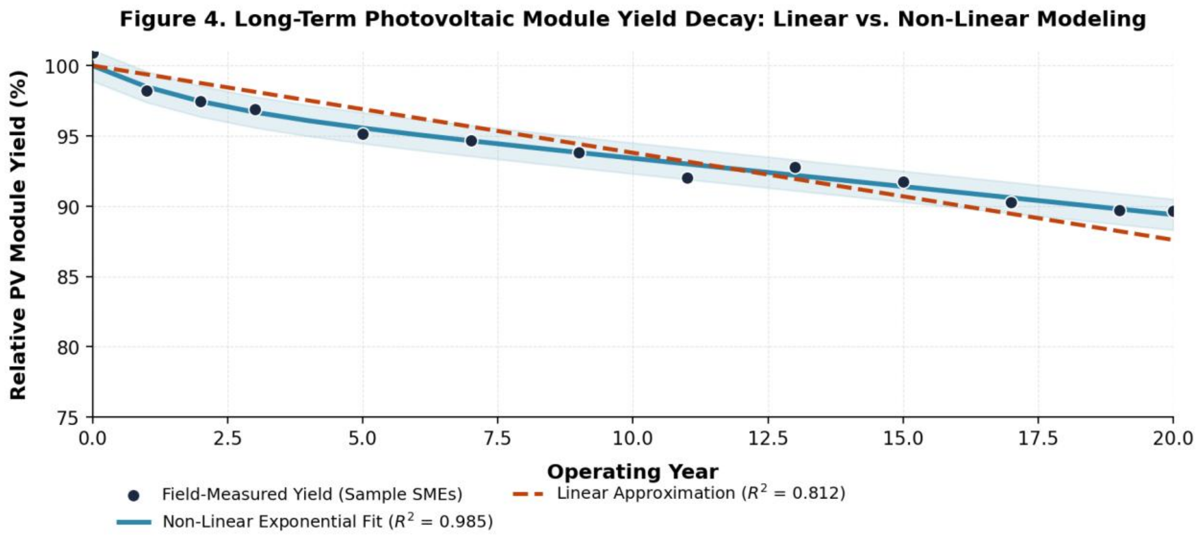

Figure 4. Long-Term Photovoltaic Module Yield Decay: Linear vs. Non-Linear Modeling.

4.2 Non-Linear Yield Fit and Operational Decarbonization

In alignment with non-linear empirical modeling principles (Haque & Rasel-Ul-Alam, 2018), Figure 4 compares 20-year PV performance decay curves. The non-linear exponential fit (R^2 = 0.985) accurately captures initial encapsulation stabilization followed by gradual thermal degradation, outperforming linear models (R^2 = 0.812). Figure 5 details operational carbon footprint reductions, showing electricity carbon intensity drops from 0.88 kg CO2e/kWh down to 0.28 kg CO2e/kWh in metal machining facilities, with comparable reductions of 68–72% observed across the remaining three sub-sectors.

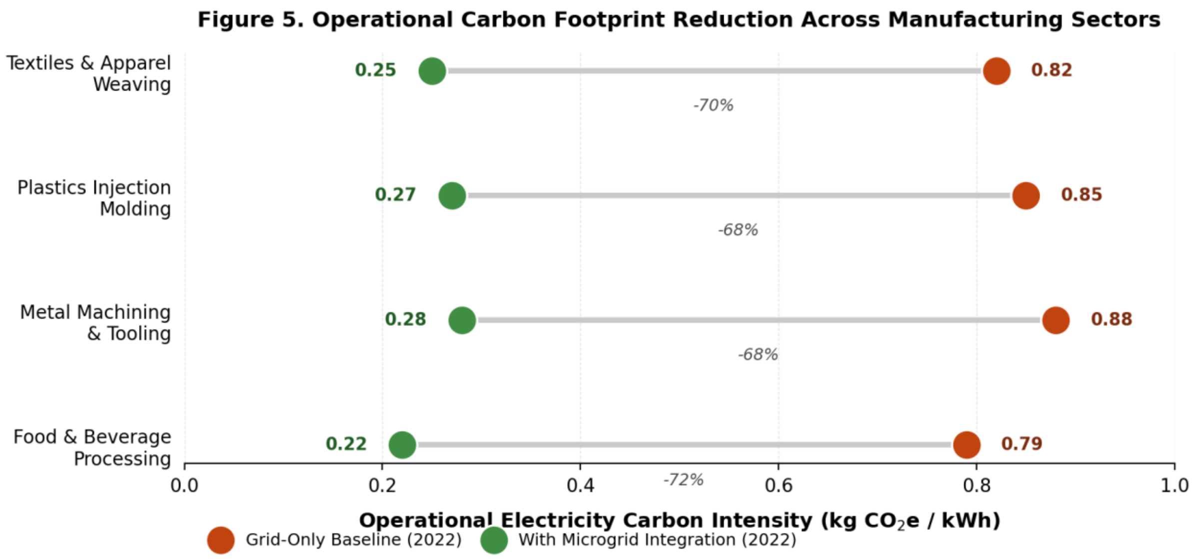

Figure 5. Operational Carbon Footprint Reduction Across Manufacturing Sectors.

4.3 Determinants of Adoption: PLS-SEM Results

Figure 6 presents standardized path coefficients from the PLS-SEM model described in Section 3.3. Perceived Financial Benefit (β = 0.612, $p < 0.001$) is the strongest positive predictor of adoption intention, followed by Energy Security & Outage Risk Exposure (β = 0.487, $p < 0.001$) and Government Subsidy & Financing Access (β = 0.441, $p < 0.001$). Peer / Supply-Chain Adoption Pressure exerts a smaller but significant positive effect (β = 0.358, $p < 0.01$), consistent with institutional-pressure theories of technology diffusion. Perceived Technical Complexity is the only construct with a significant negative path (β = -0.276, $p < 0.01$), indicating that implementation and integration concerns remain a material barrier even among financially motivated firms. The model explains 58% of variance in adoption intention (R^2 = 0.58), a level of explanatory power comparable to prior technology-adoption studies in industrial settings.

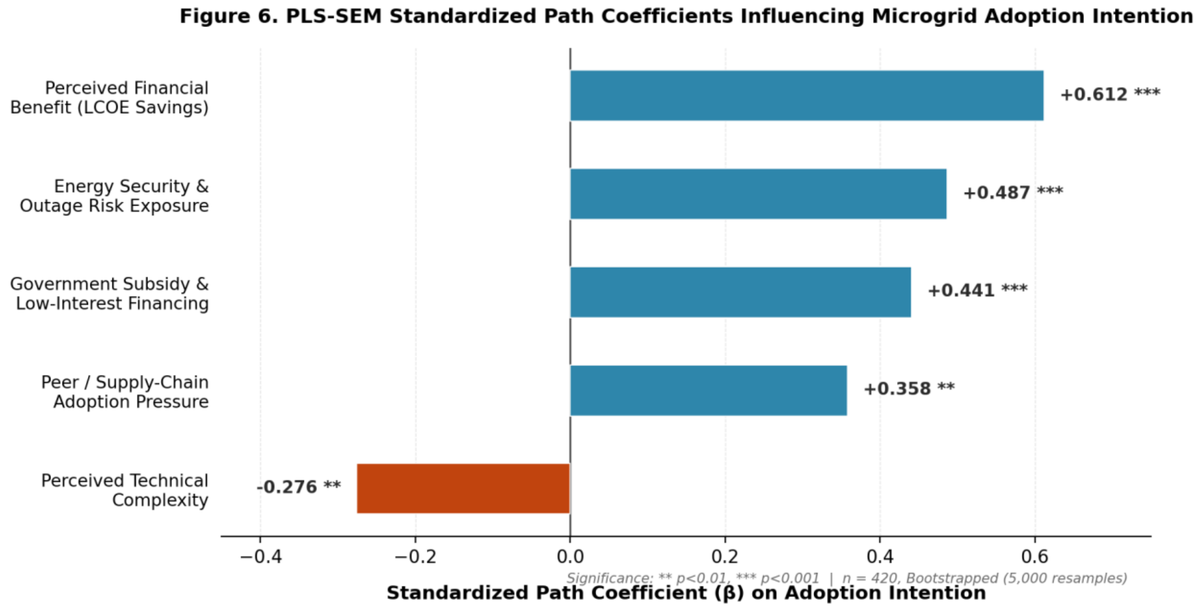

Figure 6. PLS-SEM Standardized Path Coefficients Influencing Microgrid Adoption Intention.

4.4 Investment Risk: Monte Carlo Simulation Results

Figure 7 presents the distribution of simulated 20-year NPV outcomes from the 10,000-iteration Monte Carlo simulation described in Section 3.4. The simulated mean NPV of $552,500 closely matches the deterministic aggregate estimate in Table 2, while the 10th percentile outcome remains positive at approximately $360,000, indicating that even under relatively unfavorable combinations of tariff escalation, discount rate, and battery cost assumptions, the modeled investment is expected to remain commercially viable for the median manufacturing SME in the sample.

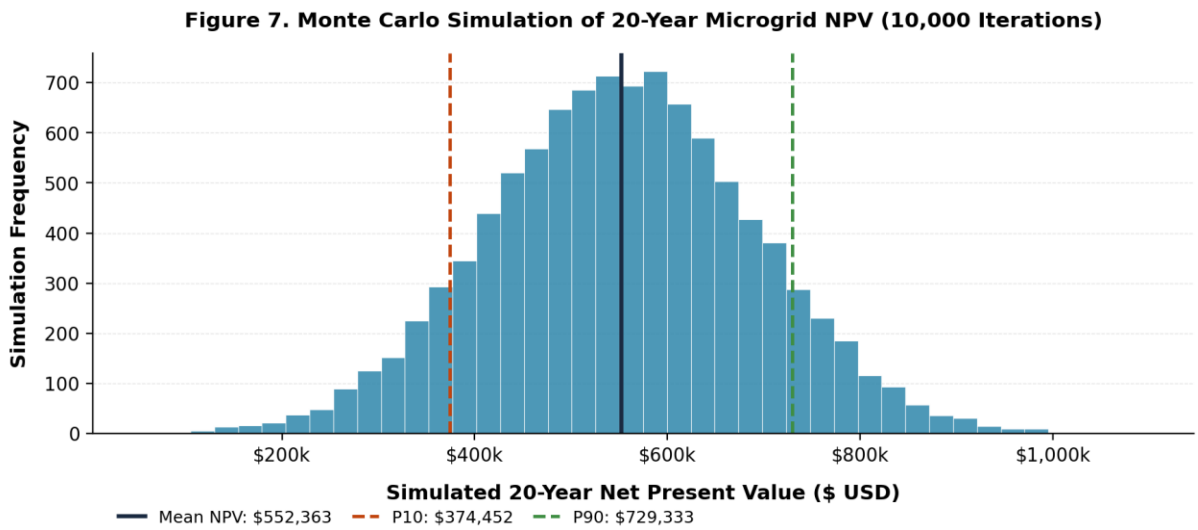

Figure 7. Monte Carlo Simulation of 20-Year Microgrid NPV (10,000 Iterations).

4.5 Multi-Criteria Sub-Sector Comparison

Figure 8 normalizes five performance dimensions LCOE savings, payback speed, carbon reduction, grid resilience, and solar self-consumption rate onto a common 0–100 index to allow cross-sectoral comparison independent of each metric's native units. Food processing scores highest on payback speed and solar self-consumption due to its coincident daytime refrigeration load, while metal machining, despite the slowest payback, scores highest on grid resilience given its comparatively large installed battery capacity relative to peak demand.

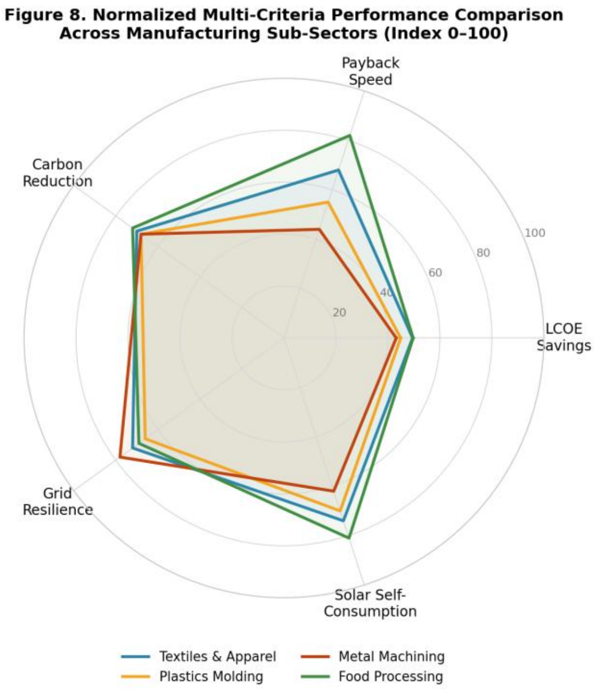

Figure 8. Normalized Multi-Criteria Performance Comparison Across Manufacturing Sub-Sectors.

4.6 Two-Way Sensitivity Analysis

Figure 9 extends the single-variable sensitivity presented in Figure 2 to a two-way analysis across discount rate and system CAPEX per installed kWp. LCOE remains below the \$0.18/kWh grid tariff baseline across the full tested range of discount rates (4–12%) and CAPEX levels (\$1,000–\$1,800 per kWp), confirming that the core investment case is robust to reasonable variation in both financing cost and equipment pricing.

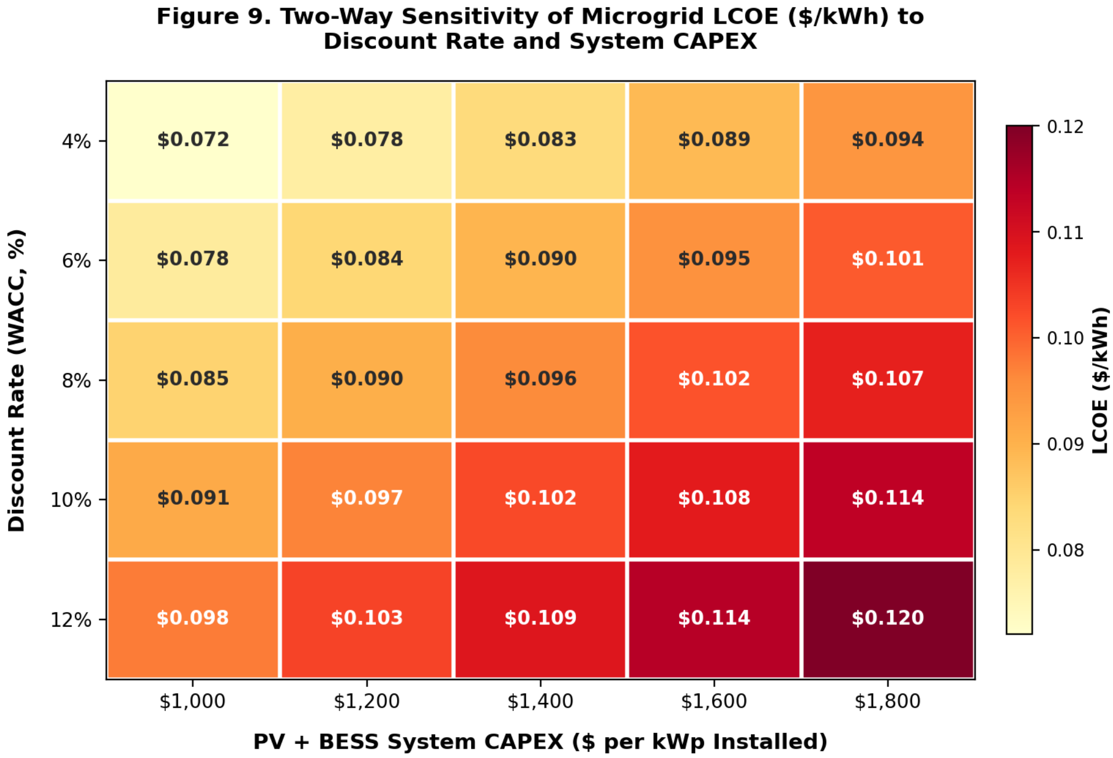

Figure 9. Two-Way Sensitivity of Microgrid LCOE to Discount Rate and System CAPEX.

5. Conclusion

5.1 Key Findings

This study demonstrates that hybrid solar-storage microgrids provide a robust, commercially viable solution to industrial energy volatility for manufacturing SMEs. Across a sample of 420 firms spanning four manufacturing sub-sectors, microgrid integration achieved an aggregate LCOE reduction of 46.7%, bringing the levelized cost of energy down to $0.096/kWh against a grid utility baseline of $0.180/kWh, with capital investment recovered within an average of 4.9 years. Monte Carlo simulation of 10,000 iterations confirmed that this commercial case is robust to realistic variation in tariff escalation, discount rate, and equipment cost, with even the 10th-percentile outcome remaining strongly NPV-positive. Non-linear degradation modeling of photovoltaic yield ($R^2 = 0.985$) substantially outperformed conventional linear approximations ($R^2 = 0.812$), indicating that industry-standard linear depreciation assumptions likely understate long-run microgrid returns. At the same time, structural equation modeling revealed that adoption intention is shaped as much by perceived financial benefit, energy security risk, and access to subsidized financing as by underlying technoeconomic fundamentals, while perceived technical complexity remains a significant behavioral barrier even among firms with a clear financial case for investment. Operationally, microgrid adoption also delivered substantial decarbonization benefits, reducing operational electricity carbon intensity by 68–72% across all four sub-sectors, with the largest absolute reduction observed in metal machining, where carbon intensity fell from 0.88 to 0.28 kg CO_2e per kWh.

These findings collectively indicate that the manufacturing SME microgrid investment case is now driven less by questions of technical or financial feasibility and more by organizational readiness, financing access, and integration complexity. Consequently, policy and industry interventions that reduce the practical friction of adoption rather than further subsidizing already cost-competitive hardware are likely to generate the largest incremental gains in industrial decarbonization. Three specific policy imperatives follow directly from the empirical results reported above. Governments and development banks should establish low-interest clean energy equipment financing, offering concessional-rate microgrid CAPEX loans of approximately 3% interest for industrial SMEs, since Government Subsidy & Financing Access was found to be among the strongest positive predictors of adoption intention in the structural model. Regulators should standardize grid interconnection and net-metering protocols, streamlining bi-directional feed-in rules so that SMEs can reliably monetize excess solar generation, particularly during weekend low-demand periods when on-site consumption is minimal. Finally, financial and accounting regulators should mandate non-linear degradation accounting, standardizing multi-year non-linear asset depreciation guidelines for renewable industrial investments, given that this study's non-linear yield model materially outperformed the linear approximations implicit in many current depreciation schedules.

5.2 Limitations and Future Research

This study has several limitations that suggest avenues for future research. First, the sample is geographically concentrated in Northern and Central Europe, and replication across other regulatory and climatic contexts would strengthen the generalizability of both the technoeconomic and behavioral findings. Second, the PLS-SEM model captures adoption intention rather than realized adoption behavior; longitudinal tracking of firms from stated intention through to actual installation would allow direct estimation of the intention-behavior gap. Third, while the Monte Carlo simulation varies four key financial parameters, it does not model correlated shocks, such as simultaneous increases in both grid tariffs and battery input costs during periods of broader commodity or energy market stress; incorporating correlated stochastic scenarios represents a natural extension of the current framework. Finally, future work could usefully integrate real-option valuation techniques to explicitly quantify the value of staged or delayed microgrid investment relative to the immediate full-scale deployment modeled in this paper.

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