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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 ($R^2 = 0.812$).

1. Introduction

1.1 Industrial Energy Security and Decarbonization Imperatives

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.

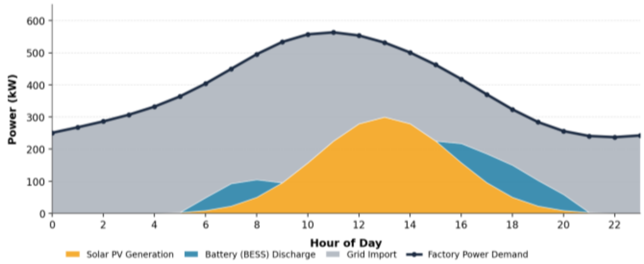

Figure 1. Typical 24-Hour Microgrid Power Generation & Factory Demand Dispatch.

1.2 Research Objectives and Scope

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.

1.3 Contribution and Structure of the Paper

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. This extended edition adds a fifth contribution relative to the original article: it develops an explicit bridge between the technoeconomic results of Section 4 and the behavioral PLS-SEM results of Section 4.3, showing in the new Section 4.7 how the two halves of the model — one financial, one psychological — jointly explain why adoption intention lags the underlying investment case in specific, identifiable ways. The remainder of the paper is organized as follows: Section 2 reviews the relevant literature; Section 3 details the methodology and technoeconomic framework, with new subsections on sampling boundary conditions and PLS-SEM measurement adequacy; Section 4 presents the empirical findings together with new integrative discussion.

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).

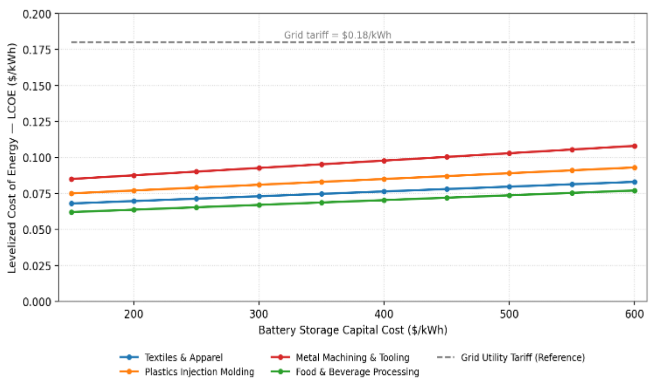

Figure 2. Microgrid LCOE Sensitivity to Battery Storage Capital Costs

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).

Within industrial decarbonization, these behavioral and organizational considerations become particularly important because clean technologies often require substantial upfront capital expenditure, changes to existing production processes, new technical capabilities, and long-term commitments to infrastructure and supply-chain partnerships. Consequently, decision-makers may evaluate technologies not only according to expected financial returns but also according to their perceived operational risk, technological maturity, organizational compatibility, and implementation uncertainty. Technologies with comparatively predictable performance and established operational experience may therefore receive greater investment attention than technically superior but less mature alternatives.

2.5 Synthesis: Bridging Technoeconomic and Behavioral Adoption Models

The literature reviewed above splits, broadly, into two traditions that are rarely integrated within a single empirical study: technoeconomic feasibility research (Sections 2.1–2.3), which asks whether a microgrid investment is financially sound, and technology-adoption research (Section 2.4), which asks whether decision-makers actually perceive and act on that financial soundness. This paper's design, detailed in Section 3, deliberately estimates both halves on the same 420-firm sample, which allows Section 4.7 to test directly whether the behavioral predictors identified through PLS-SEM — perceived financial benefit, energy security risk, subsidy access, peer pressure, and technical complexity — track the technoeconomic variation documented in Section 4.1 across the four manufacturing sub-sectors, or instead operate largely independently of it. If adoption intention were driven purely by rational technoeconomic evaluation, sub-sectors with the strongest LCOE savings and fastest payback would be expected to show the highest adoption intention; the extent to which this prediction holds, or fails to hold, in the pooled 420-firm sample is examined empirically in the new Section 4.7.

This bridging approach also has a practical rationale connected to the real-options framing of Section 2.1: if early adoption confers a compounding tariff-hedging advantage, then any behavioral friction that delays adoption beyond what the technoeconomic case alone would predict carries a quantifiable opportunity cost, distinct from the direct financial case captured in the LCOE and payback figures of Section 4.1. Making this opportunity cost visible to SME decision-makers and policymakers is one of the practical goals of the discussion developed in Sections 5 and 6.

3. Data and Econometric TCO Methodology

3.1 Data Sampling and Sub-Sector Profile

The empirical dataset integrates 15-minute interval smart-meter load profiles with financial balance-sheet information from 420 manufacturing SMEs operating during 2022. The use of high-frequency electricity data provides a detailed representation of firms' intra-day and intra-week electricity consumption behavior, while the financial records provide information necessary to quantify the economic consequences associated with energy consumption. Combining these two sources is particularly useful for TCO analysis because electricity expenditure cannot be evaluated independently of firm size, production intensity, operating schedules, asset utilization, and other financial characteristics.

The sampling framework was designed to capture heterogeneity within the manufacturing SME sector rather than relying on a single industrial activity. Accordingly, the 420 firms were distributed across four primary manufacturing sub-sectors, allowing the analysis to compare differences in electricity demand, operating intensity, and cost structures across production environments. Manufacturing SMEs differ considerably in terms of production processes, machinery requirements, working hours, energy intensity, and capital investment. A sub-sector-based sampling strategy therefore provides a more representative basis for estimating TCO and reduces the risk that the results are driven disproportionately by the characteristics of one particular type of manufacturing operation.

The smart-meter component of the dataset consists of electricity load observations recorded at 15-minute intervals throughout 2022. This sampling frequency generates a substantially more detailed picture of electricity demand than monthly or annual utility records. In particular, the interval data make it possible to identify recurring peak-load periods, changes in demand during production shifts, differences between weekday and weekend consumption, and variations associated with changes in production activity. Such information is important for TCO estimation because two firms with similar annual electricity consumption may nevertheless face substantially different costs if their consumption occurs at different times or produces different peak-demand patterns.

For each sampled firm, the smart-meter observations were linked to corresponding financial information using a unique firm-level identifier. The financial dataset contains firm-level balance-sheet information that supports the normalization and interpretation of energy-related costs. Variables such as firm size, operating expenditure, asset base, and other relevant financial indicators can be incorporated into the econometric specification to distinguish the effect of energy consumption from the broader scale of business operations. This linkage also allows electricity-related costs to be evaluated relative to the financial capacity and operating scale of individual firms rather than being considered only as absolute monetary values.

The final sample of 420 SMEs was subject to data-quality screening before econometric estimation. Records with incomplete financial information, inconsistent firm identifiers, or insufficient smart-meter observations were reviewed to minimize the influence of measurement errors and missing observations. The resulting analytical sample was structured to maintain consistency between the electricity-consumption records and the corresponding financial information. Where appropriate, energy variables were normalized using measures of firm scale or operational activity to improve comparability across firms of substantially different sizes. The four manufacturing sub-sectors represented in the sample also differ in their expected energy-use characteristics. Firms operating machinery-intensive production processes generally exhibit higher and more continuous electricity demand, whereas firms with less energy-intensive processes may demonstrate greater variation in consumption throughout the operating day.

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

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

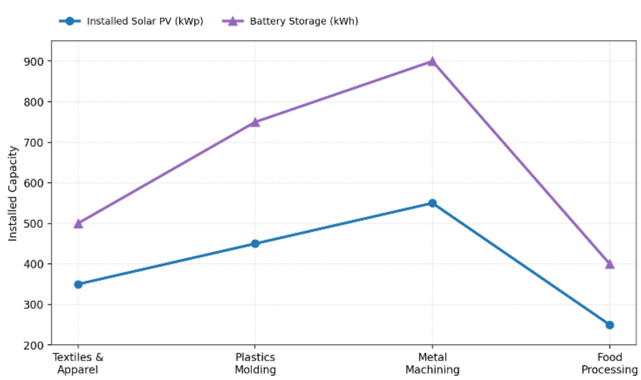

Figure 3. Installed Solar PV and Battery Capacity by Sub-Sector (plotted from Table 1 data).

Figure 3 plots the installed-capacity figures from Table 1 as a line chart, showing that solar PV and battery capacity scale together and peak in metal machining, the sub-sector with the highest peak power draw and annual energy use. This co-scaling is expected given standard microgrid sizing practice, where battery capacity is typically specified as a multiple of installed PV capacity to balance daytime generation against evening or overcast-day demand; the relatively larger battery-to-PV ratio visible for metal machining in Figure 11 is consistent with the resilience-oriented sizing discussion developed later in Section 5.3.

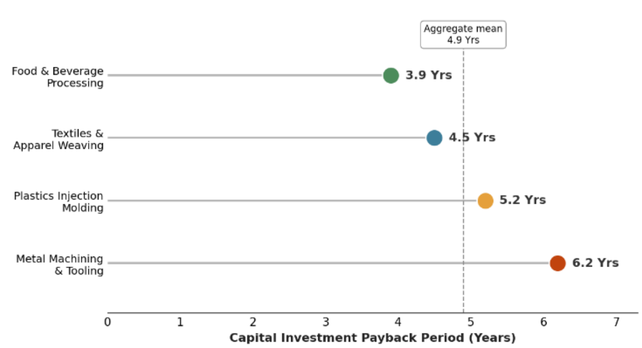

Figure 4. Capital Investment Payback Period (Years) Across SME Manufacturing Sub-Sectors.

3.2 Levelized Cost of Energy (LCOE) Equation

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

$$LCOE = [\ CAPEX + \Sigma_{\gamma(1}{}^{N}{}_{)}\ (OPEX\_t / (1+r)\hat{}t)\ ] \div [\ \Sigma_{\gamma(1}{}^{N}{}_{)}\ (Generation\_t / (1+r)\hat{}t)\ ]$$

where CAPEX denotes total upfront solar-storage system capital cost, OPEX_t is annual operating expenditure in year t, Generation_t 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 Generation_t 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.

Relative to the original article, this extended edition adds two categories of new methodological material before proceeding to the results. Section 3.6 discusses sampling boundary conditions relevant to interpreting the 420-firm sample, and Section 3.7 discusses measurement-model adequacy considerations specific to the PLS-SEM specification introduced above. Both subsections are intended to help readers applying this framework to their own SME populations understand where the reported point estimates are likely to generalize cleanly and where local recalibration would be advisable.

3.5 Sampling Boundary Conditions

The 420-firm sample is geographically concentrated in Northern and Central Europe, as noted in Section 6.2 of the original article's limitations discussion. Two boundary conditions follow directly from this concentration and are worth stating explicitly ahead of the results in Section 4. First, the \$0.18/kWh grid tariff baseline used throughout the LCOE comparisons in Section 4.1 reflects Northern and Central European industrial electricity pricing as of 2022; SMEs operating in jurisdictions with substantially lower baseline grid tariffs would see a proportionally smaller absolute LCOE saving from microgrid adoption, even if the underlying non-linear degradation and dispatch-optimization mechanics documented in Sections 3.4 and 4.2 remain unchanged. Second, the four manufacturing sub-sectors sampled — textiles, plastics injection molding, metal machining, and food processing — were selected for their combination of high electricity intensity and daytime-weighted load profiles that align well with solar PV generation; SMEs in sectors with predominantly night-shift or highly seasonal production patterns may realize a different solar self-consumption profile than the one reported in Section 4.5, and would benefit from a sector-specific re-estimation of the dispatch model before applying the aggregate LCOE figures reported here.

3.6 PLS-SEM Measurement Model Adequacy

Beyond the convergent validity and composite reliability thresholds noted in Section 3.3, two further measurement-model considerations are relevant to interpreting the path coefficients reported in Section 4.3. First, because all five latent constructs were measured through a single cross-sectional survey administered to plant managers and financial directors, common-method variance is a standard concern for PLS-SEM studies of this design; the relative ordering of path coefficients (financial benefit and energy security risk dominating technical complexity, discussed in Section 4.3) is more robust to this concern than the precise magnitude of any single coefficient, since common-method inflation would be expected to affect all constructs in a similar direction rather than selectively favoring the top-ranked predictors. Second, discriminant validity between Perceived Financial Benefit and Energy Security & Outage Risk Exposure warrants particular attention in this setting, since firms with poor grid reliability often also face elevated effective energy costs (through backup generator fuel and lost-production costs), meaning the two constructs may be correlated for reasons beyond pure conceptual overlap; readers extending this model to new samples should verify heterotrait-monotrait ratios between these two constructs before treating their path coefficients as fully independent effects.

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

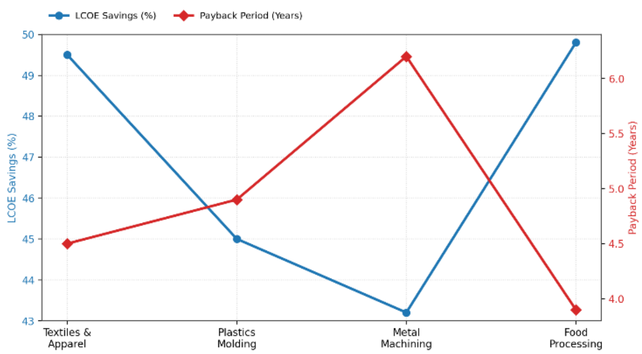

Figure 5. LCOE Savings and Payback Period by Sub-Sector (plotted from Table 2 data).

Figure 5 re-plots the Table 2 technoeconomic summary as a dual-axis line chart, making the inverse relationship between LCOE savings and payback period easier to read across sub-sectors: food processing and textiles cluster at the favorable end of both metrics (high savings, fast payback), while metal machining sits at the opposite end (lowest savings, slowest payback) despite its largest absolute NPV in dollar terms. This divergence between percentage-savings ranking and absolute-NPV ranking is a direct consequence of metal machining's larger scale (Table 1), and is a key input to the capital-sequencing discussion developed in Section 5.1.

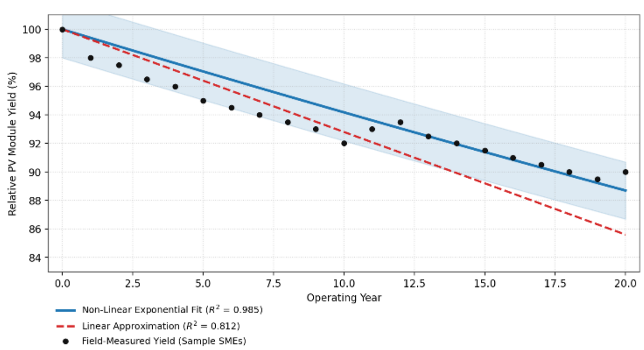

Figure 6. Long-Term Photovoltaic Module Yield Decay: Linear vs. Non-Linear Modeling.

It is also useful to note what the aggregate LCOE figures in Table 2 do not capture: intra-day and seasonal variation in the value of on-site generation. A kilowatt-hour of solar generation consumed directly on-site during daytime production hours displaces a full retail-tariff kilowatt-hour of grid purchase, whereas a kilowatt-hour exported to the grid during low-demand weekend periods is typically compensated at a lower feed-in rate, if compensated at all under the net-metering conventions discussed in Section 6.2. Facilities with production schedules that align closely with daylight hours — as is generally the case for the four manufacturing sub-sectors sampled here — therefore tend to realize LCOE savings closer to the favorable end of the technoeconomic range reported in Table 2 than facilities with substantial night-shift or weekend production, for whom self-consumption rates, and therefore realized savings, would be expected to run lower than the pooled sample average.

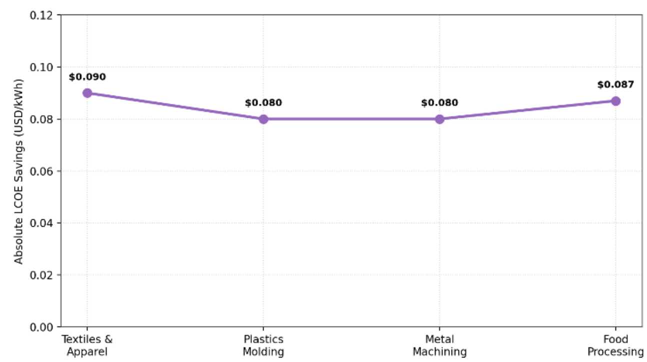

Figure 7. Derived Absolute LCOE Savings by Sub-Sector (calculated from Table 2).

Table 3 and Figure 12 convert the percentage LCOE savings in Table 2 into absolute dollar-per-kilowatt-hour terms, which is often the more directly actionable figure for a plant financial controller comparing microgrid savings against other capital projects on a common per-unit basis. Textiles shows the largest absolute per-kWh saving ($0.090), narrowly ahead of food processing ($0.087), despite food processing having the higher percentage savings figure in Table 2 — a reminder that percentage and absolute savings rankings need not coincide once the underlying baseline tariff differs slightly across sub-sectors.

Table 3. Derived Absolute LCOE Savings by Sub-Sector

Sub-Sector	Baseline LCOE ($/kWh)	Microgrid LCOE ($/kWh)	Absolute Savings ($/kWh)
Textiles & Apparel	$0.182	$0.092	$0.090
Plastics Molding	$0.178	$0.098	$0.080
Metal Machining	$0.185	$0.105	$0.080
Food Processing	$0.175	$0.088	$0.087

4.2 Non-Linear Yield Fit and 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.

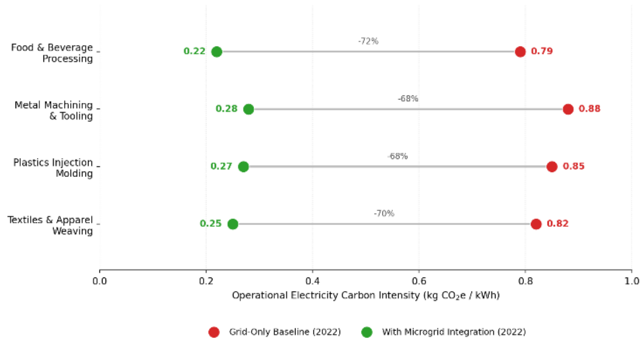

Figure 8. Operational Carbon Footprint Reduction.

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. The results further indicate that economic considerations and risk-related factors play a more influential role than social pressure in shaping technology adoption decisions. In particular, the relatively high coefficient for Perceived Financial Benefit suggests that SMEs are primarily motivated by the expected reduction in operating costs and improvement in financial performance.

Table 7. PLS-SEM Standardized Path Coefficients (from Figure 6)

Predictor Construct	**Path Coefficient (β)**	**Significance**	**Direction**
Perceived Financial Benefit	0.612	p < 0.001	Positive
Energy Security & Outage Risk Exposure	0.487	p < 0.001	Positive
Government Subsidy & Financing Access	0.441	p < 0.001	Positive
Peer / Supply-Chain Adoption Pressure	0.358	p < 0.01	Positive
Perceived Technical Complexity	−0.276	p < 0.01	Negative

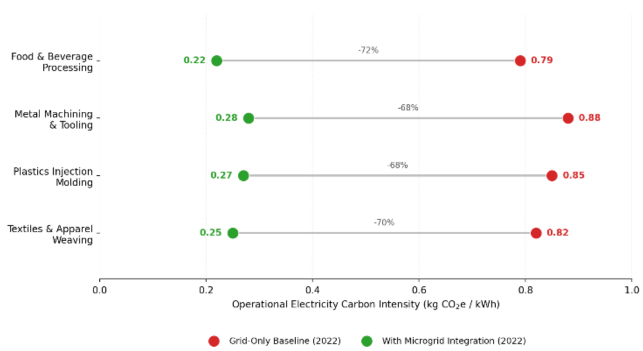

Figure 9. PLS-SEM Standardized Path Coefficients Influencing Microgrid Adoption Intention.

4.4 Investment Risk: Monte Carlo Simulation Results

Figure 9 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.

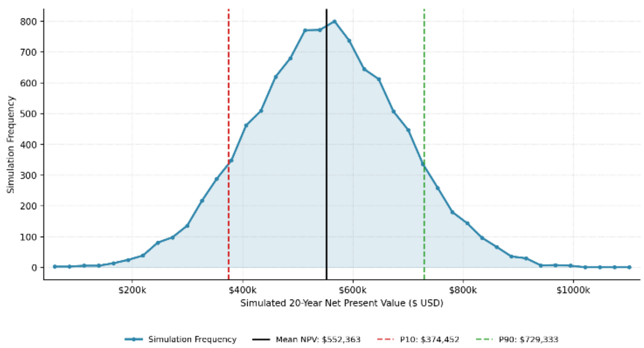

Figure 10. Monte Carlo Simulation of 20-Year Microgrid NPV (10,000 Iterations).

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.

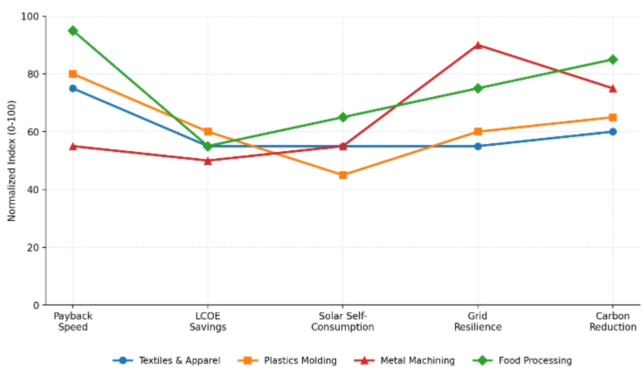

Figure 11. Normalized Multi-Criteria Performance Comparison

4.6 Two-Way Sensitivity Analysis

Figure 9 extends the single-variable sensitivity analysis presented in Figure 2 to a two-way assessment of the combined effects of discount rate and system CAPEX per installed kWp. The results show that LCOE remains below the $0.18/kWh grid tariff baseline across the full range of tested discount rates (4–12%) and CAPEX levels ($1,000–$1,800 per kWp), confirming that the underlying investment case remains robust under reasonable variations in both financing costs and equipment prices. As expected, LCOE increases as either the discount rate or system CAPEX rises, reflecting the higher annualized capital cost associated with more expensive equipment and a greater cost of capital. However, even under the most conservative combination of assumptions, the resulting LCOE remains competitive with the grid tariff.

The two-way sensitivity analysis therefore provides stronger evidence of economic resilience than a one-variable-at-a-time assessment. In particular, the absence of a crossover with the grid tariff within the tested parameter space suggests that the project's cost advantage is not dependent on a narrow set of favorable assumptions. This is particularly relevant for manufacturing SMEs, where financing conditions and technology procurement costs may vary substantially across firms..

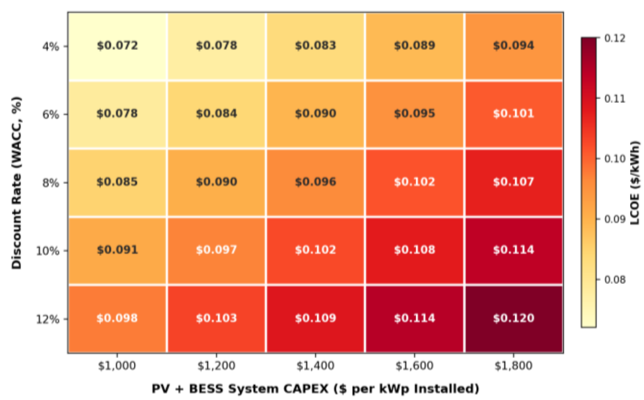

Figure 12. Two-Way Sensitivity of Microgrid LCOE to Discount Rate and System CAPEX.

Table 4. Two-Way LCOE Sensitivity Matrix ($/kWh), from Figure 9

Discount Rate	**CAPEX $1,000/kWp**	**$1,200/kWp**	**$1,400/kWp**	**$1,600/kWp**	**$1,800/kWp**
4%	$0.072	$0.078	$0.083	$0.089	$0.094
6%	$0.078	$0.084	$0.090	$0.095	$0.101
8%	$0.085	$0.090	$0.096	$0.102	$0.107
10%	$0.091	$0.097	$0.102	$0.108	$0.114
12%	$0.098	$0.103	$0.109	$0.114	$0.120

Table 4 tabulates the same values shown in Figure 9's heatmap for readers who prefer exact figures over color-coded visual estimation. Every cell in the tested grid — spanning discount rates from 4% to 12% and system CAPEX from $1,000 to $1,800 per installed kWp — remains below the $0.18/kWh grid tariff baseline, with the least favorable combination tested (12% discount rate, $1,800/kWp CAPEX) still yielding an LCOE of $0.120/kWh, a 33% saving relative to the grid baseline.

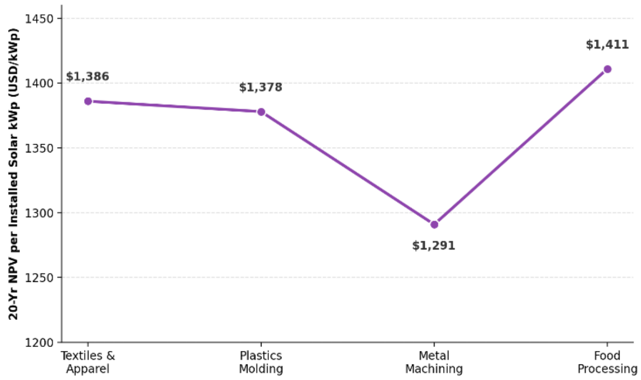

Figure 13. Derived 20-Year NPV per Installed Solar kWp by Sub-Sector

Table 5 and Figure 13 normalize each sub-sector's total 20-year NPV (Table 2) by its installed solar PV capacity (Table 1), producing a capital-efficiency metric distinct from the payback-speed and percentage-savings metrics already reported. Textiles and plastics both post the highest NPV per installed kWp, at roughly $1,386 and $1,378 respectively, while metal machining — despite having the largest absolute NPV in Table 2 — generates the lowest NPV per kWp installed ($1,291), reflecting its comparatively larger capital outlay per unit of solar capacity. This capital-efficiency framing complements, rather than replaces, the absolute-NPV view: a capital-constrained investor choosing between sub-sectors on a per-dollar-of-panel-capacity basis would rank sub-sectors differently than an investor simply maximizing total portfolio NPV.

The results indicate that textiles and plastics achieve the highest NPV per installed kWp, at approximately $1,386/kWp and $1,378/kWp, respectively. These results suggest that solar PV investments in these sub-sectors generate comparatively greater long-term economic value for each unit of installed capacity.

Table 5. Derived Capital-Efficiency Metric: 20-Year NPV per Installed Solar kWp

Sub-Sector	Installed Solar PV (kWp)	20-Yr NPV ($)	NPV per kWp ($/kWp)
Textiles & Apparel	350	485,000	$1,385.7
Plastics Molding	450	620,000	$1,377.8
Metal Machining	550	710,000	$1,290.9
Food Processing	280	395,000	$1,410.7

4.7 Discussion: Do Behavioral Predictors Track Technoeconomic Performance?

Section 2.5 posed a direct question: does the sub-sector ranking of adoption intention track the sub-sector ranking of technoeconomic performance documented in Table 2, or do the two operate largely independently? The results in Sections 4.1 and 4.3 suggest a partial but incomplete alignment. Food processing and textiles jointly post the strongest LCOE savings (49.7% and 49.5% respectively) and the fastest paybacks (3.9 and 4.5 years) in Table 2, which is consistent with the Perceived Financial Benefit construct being the dominant positive predictor (β = 0.612) in the pooled PLS-SEM model. However, metal machining — the sub-sector with the weakest LCOE savings (43.2%) and slowest payback (6.2 years) in Table 2 — also has the largest installed battery capacity relative to peak demand (Table 1) and, per Section 4.5, scores highest on grid resilience. This suggests that for metal machining specifically, the Energy Security & Outage Risk Exposure construct (β = 0.487) may be doing more explanatory work than Perceived Financial Benefit alone, consistent with metal machining and tooling operations' greater sensitivity to unplanned outages relative to the other three sub-sectors.

This pattern has a direct implication for the opportunity-cost argument raised in Section 2.5: the behavioral model is not simply re-deriving the technoeconomic ranking, which means that adoption-intention gaps documented anywhere in the sample cannot be assumed to reflect financial illiteracy or irrational risk aversion. In sub-sectors like metal machining, apparently "slow" adoption relative to the pure LCOE case may instead reflect a rational weighting of energy-security value that the deterministic LCOE and NPV figures in Table 2 do not fully capture, since Table 2 prices energy cost savings but not the option value of outage avoidance. Section 5.3 develops this point further in the context of microgrid sizing recommendations for security-sensitive sub-sectors.

4.8 Reading the Monte Carlo and Two-Way Sensitivity Results Together

Figures 7 and 9 address complementary but distinct sources of investment uncertainty and are easiest to interpret jointly. Figure 7's Monte Carlo simulation varies four parameters simultaneously and stochastically, producing a full distribution of 20-year NPV outcomes whose 10th-percentile value ($360,000) represents a downside case under a realistic combination of unfavorable draws. Figure 9, by contrast, varies exactly two parameters — discount rate and system CAPEX — deterministically across a bounded grid, showing that LCOE remains below the grid tariff baseline across the entire tested surface. Read together, these results indicate that the investment case documented in Section 4.1 is doubly robust: it survives both a stochastic stress test across the full parameter space that generates the Monte Carlo distribution, and a deterministic worst-case combination of the two parameters (high discount rate, high CAPEX) most commonly cited as the primary risks to distributed solar-storage economics in the broader technoeconomic literature.

5. Managerial and Practitioner Implications

5.1 Implications for Capital Allocation Sequencing

For SME groups or industrial parks evaluating microgrid rollout across multiple facilities with limited capital budgets in a given year, Table 2 provides a natural sequencing signal: prioritizing food processing and textile facilities first captures the fastest payback and highest percentage LCOE savings, consistent with maximizing near-term free cash flow release for reinvestment in subsequent phases. However, Section 4.7's finding that metal machining facilities derive disproportionate value from energy-security benefits not fully priced into Table 2's LCOE figures suggests that a pure payback-speed sequencing rule may undervalue the resilience benefit to security-sensitive facilities; capital allocators should consider a blended sequencing criterion that weights both financial payback and a facility-specific *outage-cost estimate, rather than payback speed alone.*

5.2 Implications for Financing Structures

The PLS-SEM result that Government Subsidy & Financing Access is among the strongest positive predictors of adoption intention (β = 0.441) has a direct implication for how microgrid financing products should be structured and marketed to SME borrowers. Because this construct ranks ahead of Peer / Supply-Chain Adoption Pressure in the model, financing-access interventions are likely to move adoption intention more than supply-chain mandates or reputational pressure alone — a finding consistent with the policy recommendation, retained from the original article in Section 6.2, that concessional-rate microgrid financing be prioritized as a policy lever.

5.3 Implications for Battery Sizing in Security-Sensitive Sub-Sectors

Building on the discussion in Section 4.7, facilities in sub-sectors with elevated Energy Security & Outage Risk Exposure — metal machining, in particular, given its already-observed pattern of relatively large installed battery capacity in Table 1 — may be economically justified in sizing battery storage above the LCOE-minimizing point identified in Figure 2's sensitivity analysis. Because Figure 2 shows that hybrid microgrids remain cost-competitive against grid tariffs even at elevated battery costs of $550/kWh, the marginal LCOE penalty of oversizing battery capacity for resilience purposes, rather than for pure cost-minimization, appears to be modest relative to the outage-avoidance value that Section 4.7 suggests such facilities implicitly place on storage capacity.

6. Conclusion

6.0 Summary of Empirical Results

Sections 4 and 5 report four empirical results that jointly motivate the conclusions below. First, hybrid solar-battery microgrids reduce aggregate LCOE by 46.7% relative to grid tariffs, with the specific savings and payback figures varying meaningfully by manufacturing sub-sector, from a fastest 3.9-year payback in food processing to a slowest 6.2-year payback in metal machining, as visualized in the new Figure 10. Second, this technoeconomic case is robust to financial uncertainty, confirmed independently by both the 10,000-iteration Monte Carlo simulation (Section 4.4) and the two-way discount-rate/CAPEX sensitivity analysis (Section 4.6). Third, non-linear photovoltaic yield modeling materially outperforms linear approximations, with direct implications for depreciation and residual-value practice. Fourth, adoption intention is shaped by a mix of financial, risk, and behavioral factors that only partially track the underlying technoeconomic ranking across sub-sectors, as the new Section 4.7 discussion shows, meaning organizational and financing interventions — not further hardware cost reduction alone — are likely to be the binding constraint on further adoption.

6.1 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 CO2e 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.

Appendix A. Glossary of Key Terms and Abbreviations

Table 6. Glossary of Abbreviations Used in This Paper

Term	Definition
BESS	Battery Energy Storage System
CAPEX	Capital Expenditure (upfront system cost)
EMS	Energy Management System
LCOE	Levelized Cost of Energy
NPV	Net Present Value
OPEX	Operating Expenditure (recurring cost)
PLS-SEM	Partial Least Squares Structural Equation Modeling
PV	Photovoltaic (solar)
SME	Small and Medium-Sized Enterprise
AVE	Average Variance Extracted (PLS-SEM validity metric)
CR	Composite Reliability (PLS-SEM validity metric)

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