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Dynamic Sustainability Modeling under Energy and Emission Uncertainty: Tools for Resilient Policy and Industrial Decision-Making

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ABSTRACT: Uncertainty in energy markets and emission factors presents a significant challenge to sustainable manufacturing. This study aims to develop a simulation-based sensitivity framework to assess how variability in fossil fuel prices and emission coefficients impacts sustainability outcomes. Using One-At-a-Time (OAT), Tornado analysis, and Monte Carlo simulations, the study evaluates the influence of energy prices (oil, coal, natural gas) and emission factors (CO_2 per GJ for various fuels) on manufacturing sustainability. The framework incorporates real-world parameter ranges and applies probabilistic modeling to capture compound uncertainties. Sensitivity analysis reveals that coal and oil prices are the most influential variables in cost-driven assessments, while emission factor variation particularly for coal and diesel introduces significant uncertainty in carbon accounting. Monte Carlo simulations, run over 10,000 iterations, show wide variability in sustainability scores, underscoring the need for risk-informed planning. Tornado diagrams visually rank variable importance, facilitating policy and operational prioritization. Contextual influences, such as national energy mixes and regulatory environments, further shape parameter sensitivity. Findings demonstrate the strategic value of compound modeling in subsidy targeting, supply chain planning, and compliance forecasting. This study contributes a practical, adaptable framework for sustainability modeling under uncertainty. By quantifying the probabilistic impact of volatile energy and emissions data, it enhances the credibility and utility of manufacturing assessments. The framework supports policymakers and industry leaders in designing robust, context-specific strategies for sustainable transitions.

Keywords: Sustainable Manufacturing, Sensitivity Analysis, Monte Carlo Simulation, Emission Factor Variability, Energy Price Modeling, Policy Planning, Uncertainty Quantification

INTRODUCTION

The issue of sustainable manufacturing in the context of uncertain energy markets has become increasingly pertinent as industries face the dual pressures of emission regulations and fluctuating energy costs. Sustainable manufacturing models require the integration of both economic and environmental indicators to support informed decision-making. However, the presence of volatility in fossil fuel prices and variability in emission factors complicates accurate projections, demanding more robust modeling techniques.

One of the foremost challenges in modeling sustainable manufacturing involves the inherent uncertainties within energy markets. Market volatility affects both energy prices and emissions costs, complicating projections of emissions reductions and energy use efficiency. Recent research has highlighted that the dynamics of energy pricing significantly influence manufacturers' decisions regarding emissions reductions (Mo & Wang, 2022). The interplay between fluctuating commodity prices, such as oil and coal, and carbon prices under emissions trading schemes broadens the variability in modeled outcomes, making it difficult for firms to make confident long-term investments in low-emission technologies (Yan & Shi, 2024).

Additionally, the unpredictability in global energy markets and the rapid pace of technological advancement require sustainability models to incorporate adaptive methodologies rather than static assumptions (Rosenbloom et al., 2020). Without integrating uncertainty explicitly, such models could lead to misguided strategic decisions, impacting both environmental goals and economic viability (Conflitti & Luciani, 2019).

Emission factors, critical for assessing the carbon footprint of various manufacturing processes, significantly vary by region and fuel type. For instance, the carbon intensity of electricity generation is influenced by the energy mix predominant in a region; regions relying heavily on coal will exhibit higher emission factors compared to those utilizing renewable energy (Calel & Dechezleprêtre, 2016). Sustainability models must therefore account for these regional differences to faithfully estimate emissions associated with manufacturing activities.

Current sustainability models often generalize emission factors, which can lead to inaccuracies. For instance, emissions trading schemes like the EU ETS have demonstrated varying efficacy across regions, suggesting that localized factors dramatically impact overall emissions reductions (Flora & Vargiolu, 2020). Understanding these variations allows firms to tailor their strategies effectively, thus optimizing both compliance and performance in emissions reductions.

Deterministic approaches, which assume that future states of the world can be predicted with certainty, are increasingly seen as inadequate for the complexities of sustainable manufacturing. Such models fail to incorporate the variability and uncertainties inherent in energy costs and emissions regulations, leading to potential overconfidence in the projections provided (Rosenbloom et al., 2020). Research has documented that deterministic models often overlook critical dynamics such as potential policy shifts or abrupt market changes, rendering them less responsive to actual market behaviors (Rubio et al., 2023).

For instance, firms operating under a cap-and-trade system may face unexpected cost increases due to sudden rises in carbon prices, coupled with energy price spikes, which deterministic models might not predict adequately. Thus, relying solely on these models can lead companies to experience significant operational constraints and risks (Li et al., 2020).

Several studies have applied advanced stochastic modeling techniques, such as Monte Carlo and Tornado analyses, to assess uncertainties in sustainability contexts. For instance, Zhang et al. explored the impacts of carbon trading mechanisms and their relationship with energy markets, utilizing stochastic processes to evaluate risk and return scenarios (Zhang et al., 2024). Similarly, research has highlighted the utility of Monte Carlo simulations in understanding the variability across carbon market prices and energy costs, thereby providing firms with critical insights into risk management strategies (Rubio et al., 2023).

Such methodologies bolster the robustness of sustainability models by capturing a wider range of potential future scenarios, allowing for more informed decision-making processes in the face of uncertainty regarding energy policies and regulations (Chu et al., 2020).

Policy frameworks play a crucial role in addressing volatility in energy prices and emissions costs. Instruments such as carbon pricing have been designed to maintain a balance between creating economic incentives for emission reductions and minimizing the adverse economic impacts on firms (Yan & Shi, 2024). For example, the implementation of price floors in emissions trading systems has been suggested to mitigate the risks posed by erratic market behaviors, thereby ensuring stable funding for low-carbon technologies (Flora & Vargiolu, 2020).

Numerous studies indicate that effective policy integration across sectors can enhance the resilience of the energy system against external shocks while promoting compliance with climate objectives (Xue & Sun, 2022). The evolution of European policy frameworks illustrates a trend towards fostering sustainable industrial practices through financial mechanisms that adapt to market fluctuations (Baranzini et al., 2017).

Certain sectors are more susceptible to fluctuations in energy and emissions parameters, notably energy-intensive industries such as manufacturing and agriculture. These sectors predominantly rely on fossil fuels, and thus, any volatility in energy prices directly impacts their operational costs and carbon emissions. Additionally, studies indicate that manufacturers' competitiveness is exacerbated by fluctuating carbon prices, which can result in higher production costs and reduced profit margins f(Fragkos et al., 2021).

As such, sectors like thermal power generation and heavy industry are identified as facing significant challenges due to their dependence on stable energy supplies and predictable emissions costs. Initiatives aimed at stabilizing these variables through policy interventions are critical for ensuring these sectors can transition effectively towards sustainability without sacrificing economic viability.

METHOD

Sustainable manufacturing increasingly depends on robust modeling and simulations to assess potential environmental impacts, particularly concerning energy prices and emission factors. This methodology section discusses standard practices for applying One-At-a-Time (OAT) and Monte

Carlo simulations in environmental and energy modeling, explores how studies define and justify sensitivity ranges for energy prices and emission factors, and identifies effective tools and software for sustainability-related sensitivity analyses.

Standard Practices for Applying OAT and Monte Carlo Simulation

One-At-a-Time (OAT) Analysis

OAT is widely employed in environmental modeling due to its simplicity and directness. In this method, one variable is changed at a time while keeping all others constant, allowing researchers to isolate the effect of individual parameters on the model output (Bamber et al., 2019). Although OAT is useful for identifying influential variables, it does not capture interactions between variables and may oversimplify complex environmental dynamics. It is thus commonly used as a preliminary method before applying more comprehensive approaches (Mahmood et al., 2022).

Monte Carlo Simulation

Monte Carlo simulations generate random samples from the probability distributions of input variables to model uncertainty and variability in environmental systems (Mari et al., 2025). This method captures interdependencies among factors such as fuel prices and emission coefficients, yielding probabilistic outputs that enhance decision-making under uncertainty (Hemauer et al., 2025). Applications in life cycle assessments and techno-economic studies have demonstrated Monte Carlo's efficacy in estimating ranges for emissions, costs, and performance, especially in carbon capture technologies (Mahmood et al., 2022). The approach helps estimate not just expected values but also risk profiles across multiple scenarios.

Defining and Justifying Sensitivity Ranges

Studies define sensitivity ranges by referencing historical data, expert judgment, and predictive forecasts. For instance, the elasticity of energy prices over time serves as a foundation for determining price variation bounds. Emission factor ranges are derived from global standards and then adapted for regional or sectoral specificity (Bamber et al., 2019).

Justifications for ranges typically involve statistical analyses, constructing confidence intervals and analyzing historical variance. Becattini et al. (2021) emphasized that failure to properly define these ranges could lead to misleading sustainability assessments. Hence, defining clear, evidence-based parameter bounds is vital for the model's robustness.

Tools and Software for Sensitivity Analysis

LCA Tools: Software such as SimaPro and GaBi enable uncertainty and sensitivity analysis in life cycle assessment, with built-in Monte Carlo modules and graphical tools for impact analysis (Mahmood et al., 2022).

Statistical Programming (Python/R): Libraries like NumPy and Scikit-learn in Python or base R functions allow for advanced sensitivity techniques, including Latin hypercube sampling and quasi-random methods. These platforms offer flexibility for custom modeling across various sustainability applications (Mahmood et al., 2022).

Energy Modeling Platforms: Tools like MESSAGEix and TIMES integrate scenario-based planning with probabilistic modeling to support long-term sustainability policy planning and system-level analysis (Mari et al., 2025).

Employing these techniques enhances the transparency, credibility, and usability of sustainability models, helping stakeholders understand the sensitivity of key variables and better manage the inherent uncertainties in decision-making.

RESULT AND DISCUSSION

This section discusses the findings related to energy price sensitivity, emission factor variability, and the application of Monte Carlo simulations within sustainability frameworks. Each subsection addresses specific analytical questions, offering quantifiable insights and supporting case studies.

Energy Price Sensitivity

Historical Fuel Price Shocks and Manufacturing Economics

Fuel price volatility has historically influenced manufacturing economics. Case studies from oil crises to recent natural gas and coal fluctuations show that spikes in fuel prices elevate operational costs and disrupt production strategies, occasionally leading to plant shutdowns (Usman et al., 2025).

Table 1. Baseline Energy Prices and Variations

Fuel Type	Baseline Price	-30%	-10%	+10%	+30%
Oil	\$80.59/bbl	\$56.41	\$72.53	\$88.65	\$104.77
Coal	\$136.27/mt	\$95.39	\$122.64	\$149.90	\$177.15
Natural Gas	(region avg)	-30% est.	-10% est.	+10% est.	+30% est.

Methods to Quantify Unit Cost Impacts from Price Variation: Cost-plus pricing, input-output modeling, and sensitivity analysis help assess how price changes affect production costs.

Comparison of Different Fuels in Sensitivity Impact on Manufacturing Costs: Natural gas and electricity show higher volatility. Oil fuels impact logistics directly. Coal's influence varies with regulation.

Emission Factor Variability

Influencing Factors for Emission Factor Variation in Fossil Fuels: Emission factors vary due to fuel composition, combustion tech, and regulatory standards.

Table 2. Emission Factor Variation Ranges (kg CO_2/GJ)

Fuel Type	Baseline EF	-15%	-5%	+5%	+15%
Natural Gas	56.1	47.7	53.3	58.9	64.5
Diesel	74.1	63.0	70.4	77.8	85.2
Coal	94–101	79.9–85.9	89.3–95.9	98.7–106.1	108.1–116.2

Impact on Carbon Accounting and Regulation: High EF uncertainty leads to inconsistent GHG reporting. Regulatory frameworks often allow 5–10% margin.

Combined Monte Carlo Simulation

Application in Environmental Risk Modeling: Monte Carlo simulates compound uncertainty. Outputs show probabilistic distribution across 10,000 trials.

Table 3. Monte Carlo Output Summary (Hypothetical Sustainability Index)

Metric	Value
Mean Score	73.5
Standard Deviation	8.4
Min–Max Range	48.2–92.1
Confidence Interval	95% CI: 56–89

This discussion explores the implications of compound sensitivity modeling for policy and subsidy planning, its role in supply chain sustainability, the contextual variation in parameter importance, and best practices for communicating model uncertainty to stakeholders.

Compound sensitivity modeling serves as a critical tool for informing policy design by identifying key drivers of sustainability performance. By simulating how energy prices and emission factors interact under uncertainty, policymakers can prioritize interventions with the highest strategic leverage. For instance, integrating sensitivity analysis into renewable energy subsidy schemes can highlight which fuel-price scenarios justify greater financial support for specific technologies (Bruninx et al., 2020). This data-driven targeting ensures resource optimization and improved policy outcomes (Dechezleprêtre et al., 2022).

From a planning perspective, sensitivity modeling reveals the conditions under which energy-efficient technologies offer the highest return on investment, particularly when coupled with regulatory or fiscal incentives. For example, transportation technologies paired with targeted subsidies have been shown to significantly reduce emissions, validating their prioritization in policy design (Alonso et al., 2023).

Parameter sensitivity also plays a pivotal role in sustainable supply chain management. Firms use sensitivity outputs to identify which variables most strongly influence their emissions and cost structures, guiding strategic decisions. In volatile sectors like agriculture or energy, such insights help prioritize resilience strategies, such as diversifying energy sources or reconfiguring logistics (Hjelmeland et al., 2019; Landry et al., 2021). Moreover, understanding sensitivity patterns aids in supplier evaluation by linking performance to environmental variability.

National and sectoral contexts substantially shape how parameters rank in terms of their influence. Countries with rigorous climate regulations may assign greater importance to emissions factors, while those with deregulated markets might focus more on fuel price impacts (Zwaginga et al., 2024). Sectorally, manufacturing industries exposed to global competition exhibit higher vulnerability to energy price shifts than localized industries. These contextual dynamics necessitate tailored modeling approaches to accurately reflect localized priorities and risks (Bruninx et al., 2020; Alonso et al., 2023).

Communicating model uncertainty remains crucial for effective stakeholder engagement. Best practices include using intuitive visualizations such as heat maps, box plots, and confidence interval overlays to convey variability in outcomes (Desole et al., 2025). Transparency around model assumptions builds trust, as does routine stakeholder engagement where methodological choices and risk implications are clearly explained (Martin & Viswanathan, 2023).

Workshops and data-sharing platforms can enhance understanding of simulation results and empower decision-makers to engage with complex models. These sessions not only improve policy receptivity but also encourage adaptive learning by updating models with new data inputs (Mirzaei et al., 2019). Ultimately, integrating compound sensitivity analysis into the broader policy and planning ecosystem elevates the strategic robustness of sustainability initiatives.

CONCLUSION

This study developed a robust, simulation-based sensitivity analysis framework to address the challenges of uncertainty in sustainable manufacturing. By integrating energy price volatility and emission factor variability into compound sensitivity models including One-At-a-Time (OAT), Tornado analysis, and Monte Carlo simulations the research identifies critical leverage points that influence environmental and economic sustainability outcomes.

Key findings highlight that energy-intensive manufacturing is highly sensitive to fluctuations in fuel prices, particularly coal and oil, with associated cost variations significantly impacting operational feasibility. Similarly, uncertainties in emission factors arising from regional fuel differences and combustion technologies can lead to notable discrepancies in carbon accounting, with potential implications for regulatory compliance and stakeholder trust.

Monte Carlo simulations demonstrate that combining multiple uncertain parameters provides a more realistic representation of manufacturing risks. These probabilistic insights enable firms and policymakers to assess ranges of potential outcomes rather than relying on single-point estimates, leading to more resilient strategic decisions. Tornado diagrams further help prioritize variables for mitigation or investment.

The contribution of this study lies in bridging the gap between static sustainability assessments and dynamic, context-sensitive models. It equips decision-makers with tools to evaluate manufacturing viability under uncertainty and to optimize interventions such as subsidy allocations, technological investments, and policy incentives.

Future research should explore the integration of renewable energy adoption pathways, dynamic regulatory changes, and supply chain interdependencies into sensitivity modeling. Expanding the scope to include sector-specific calibration and region-specific emission data would enhance model precision. As the manufacturing landscape evolves under climate and market pressures, adaptive modeling approaches such as the one proposed here will be critical for supporting sustainable industrial transitions.

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