

AI-ENHANCED MULTI-OBJECTIVE OPTIMIZATION FRAMEWORK FOR LEAN MANUFACTURING EFFICIENCY AND ENERGY-CONSCIOUS PRODUCTION SYSTEMS

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Abstract

Manufacturing enterprises increasingly operate under the dual imperative of enhancing operational efficiency while simultaneously reducing energy consumption. However, conventional improvement approaches often remain siloed—addressing either productivity or sustainability—thereby constraining opportunities for reproducible and system-wide optimization. This study aims to develop and empirically evaluate an AI-enhanced, multi-objective optimization framework that aligns lean manufacturing principles with energy-conscious operations. Using a quantitative, cross-sectional, case-based design, enterprise cloud data pipelines were established to integrate Manufacturing Execution System (MES) and Supervisory Control and Data Acquisition (SCADA) historians with sub-metered energy logs across multiple discrete-part production lines in three industrial plants. The primary variables included Lean Practice Intensity (measured through a five-point Likert instrument), Overall Equipment Effectiveness (OEE) and its components, and Energy Intensity (kWh per good unit). Additional operational moderators such as peak kW, demand variability, product mix, machine age, and shift patterns were also captured to account for contextual heterogeneity. The analysis pipeline consisted of scale reliability testing, descriptive and inferential statistics, correlation analysis, and hierarchical multiple regression incorporating plant- and shift-level controls. Furthermore, mediation analysis tested the role of efficiency as an intervening variable, while moderation analysis assessed the conditional effects of demand variability. To complement empirical inference, a surrogate-assisted evolutionary optimization algorithm was employed to generate Pareto-optimal fronts and knee solutions, benchmarked against baseline production schedules. Key results demonstrate that Lean Practice Intensity exhibits a positive association with OEE and a negative association with energy intensity, confirming efficiency as a significant mediator with a residual direct effect of lean practices on energy outcomes. The influence of lean practices was found to diminish under high demand variability, indicating a boundary condition for implementation. The optimization results further revealed that knee-point policies typically improved OEE by approximately 2–5 percentage points, reduced energy intensity by 6–15%, and curtailed peak demand by around 6%, all without compromising delivery performance or schedule adherence. From a managerial and systems integration perspective, the findings highlight the importance of viewing lean routines as actionable energy levers rather than ancillary practices. The study recommends institutionalizing variability-aware and tariff-aware production planning, and adopting a governed digital stack that links key performance indicators (KPIs), digital-twin telemetry, and AI-driven optimization engines.

Keywords:

Lean Manufacturing; Energy-Conscious Production; Multi-Objective Optimization; OEE; Energy Intensity.

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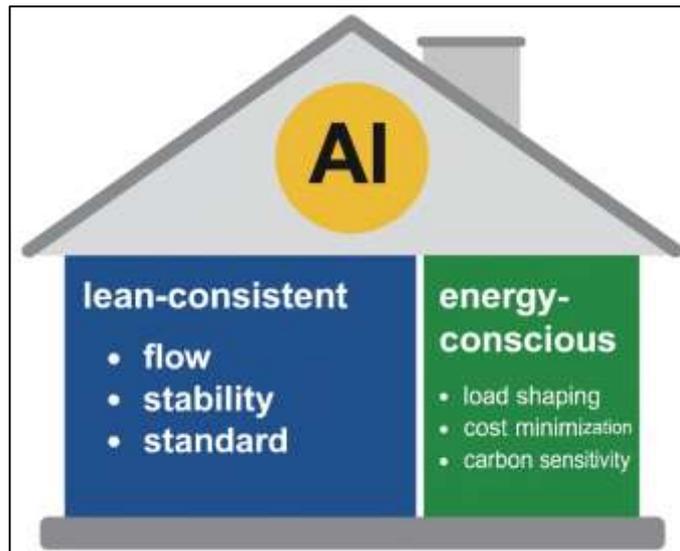
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INTRODUCTION

Manufacturing systems today face concurrent pressures to raise operational efficiency and to reduce energy use and associated emissions; meeting both goals hinges on rigorous definitions and measurement frameworks that enable reproducible analysis across contexts. Lean manufacturing is classically defined as a socio-technical system focused on the systematic identification and elimination of waste (*muda*) in pursuit of flow, quality, and responsiveness ([Shah & Ward, 2007](#)). In parallel, “energy-conscious” production denotes the explicit modeling, monitoring, and optimization of energy flows at process, line, and factory levels, integrating energy cost, peak load, and carbon performance into routine planning and control ([Herrmann et al., 2011](#)).

Figure 1: Integration of Lean-Consistent and Energy-Conscious Manufacturing



At the system level, energy efficiency functions as a measurable ratio of useful output to energy input, linked to both engineering constraints and economic outcomes ([Bunse et al., 2011](#)). Over the last decade, scholarship has converged on the view that lean and energy-aware paradigms intersect where waste manifests as avoidable energy, idle power, rework, changeover, overproduction, and unbalanced flow losses that measurement and scheduling can surface and remove ([Faulkner et al., 2016](#)). Against this backdrop, artificial intelligence (AI) and multi-objective optimization provide a disciplined way to balance inherently conflicting criteria throughput, cost, quality, tardiness, energy consumption, and peak power without collapsing them into a single scalar objective ([Cherrafi et al., 2016](#)). This study defines an AI-enhanced multi-objective optimization framework that is both lean-consistent (flow, stability, standardization) and energy-conscious (load shaping, cost minimization, carbon sensitivity) and evaluates it quantitatively in a cross-sectional case-study design using descriptive statistics, correlation, and regression modeling. The proposed framing links well-established lean constructs to contemporary methods for energy-aware decision-making and embeds them in estimable statistical relationships suitable for hypothesis testing and managerial interpretation ([Herrmann & Thiede, 2009](#)).

Internationally, industry and policy attention to energy-aware production has been catalyzed by the rising share of manufacturing in final energy demand and by the materiality of electricity price volatility for operating margins. Methodologically, energy-oriented simulation and assessment toolchains have matured to support both engineering design decisions and day-to-day operations, from unit process models to factory-level digital representations ([Kara & Li, 2011](#)). Research has documented robust gains from integrating energy information into lean practices: energy value stream mapping (EVSM) extends traditional VSM with power and energy data; economic-environmental VSM (E²VSM) couples energy and cost accounting to reveal low-value, high-energy segments; and factory-level assessment methods now provide standardized indicators that can be tracked alongside takt and OEE ([Verma & Sharma, 2016](#)). These methods complement scheduling

models that minimize energy cost under time-of-use tariffs or reduce peak demand without undermining throughput (Abdul, 2021; Fang et al., 2011). Empirically, lean-green complementarities have been observed across multiple sectors, with lean practices acting as a catalyst for environmental performance improvement and vice versa (Dües et al., 2013; Sanjid & Farabe, 2021). Taken together, these strands motivate a quantitative investigation that treats energy as a first-class performance dimension in manufacturing, linked statistically to lean practice intensity and operational outcomes, and optimized via AI-based multi-objective search to expose trade-off frontiers available to decision makers.

A central methodological challenge is modeling multiple, sometimes competing goals. Multi-objective evolutionary algorithms (MOEAs) and related metaheuristics are well suited to manufacturing contexts because they produce Pareto-efficient sets rather than a single compromise solution, enabling managers to visualize and select from explicit trade-offs among energy cost, makespan, tardiness, WIP, and quality risk (Omar & Rashid, 2021; Zhang & Li, 2007). Within this family, decomposition-based methods (e.g., MOEA/D) and reference-point/indicator-based methods have seen wide adoption in production scheduling and resource allocation (Zhang & Li, 2007). Many-objective extensions (e.g., NSGA-III) support problems with four or more objectives, a common reality in plant-level planning (Deb & Jain, 2014). For computationally expensive cases e.g., where each candidate schedule must be evaluated via discrete-event simulation coupled to energy models surrogate-assisted evolutionary optimization offers tractable performance by learning cheap approximations of objective functions and iteratively refining them (Omar & Rashid, 2021)). In manufacturing job-shop and flexible job-shop settings, multi-objective formulations that include energy have demonstrated significant reductions in energy cost and peak demand while preserving classical productivity metrics (Li et al., 2016). As a practical matter, modern open-source frameworks (e.g., pymoo) implement state-of-the-art MOEAs and decision-making utilities suitable for industrial datasets and allow combined statistical-optimization workflows (Blank & Deb, 2020; Zaman & Momena, 2021). This study leverages such algorithms as the computational engine of the proposed framework, connecting statistical correlational structure in the data to optimization guidance that is actionable at the line and factory levels.

Within the lean literature, waste manifests not only as excess inventory, rework, or waiting, but also as non-productive energy consumption from idling machine tools and compressed-air systems to avoidable warm-up cycles. EVSM and related approaches map these losses to their process and resource drivers and thus align with standard lean diagnostics (Mubashir, 2021; Tao et al., 2019). At the same time, OEE provides a consolidated equipment-level indicator of availability, performance, and quality, which can be linked statistically to energy intensity by correlating downtime, micro-stops, and speed losses with kWh per good unit (Irhirane et al., 2017; Rony, 2021). Energy-oriented simulation and assessment studies show that integrating energy indicators into discrete-event models re-prioritizes improvements toward measures with both flow and energy benefits (Gong et al., 2019). Empirical scheduling studies confirm that including energy-related objectives energy cost under dynamic tariffs, peak load, carbon alongside makespan and tardiness shifts optimal sequences and speeds, and highlights operational policies such as deliberate idle-off or power-capped batching (Fang et al., 2011; Zaki, 2021). This cross-fertilization between lean and energy-aware methods grounds the present study's instrument design (5-point Likert items on lean practice intensity, energy management routines, and digital readiness), descriptive analysis (central tendency and dispersion), and regression modeling (associating lean/energy practices with performance outcomes), while the AI-based optimization layer translates statistical structure into executable schedules and set-points. From a production-planning perspective, energy-aware scheduling problem classes single machine, flow shop, job shop, flexible job shop extend classical formulations by incorporating energy models (fixed/variable power, speed-power curves), tariff structures (time-of-use, demand charges), and operational policies (shutdown/standby), producing multi-objective problems that more accurately reflect plant realities (Danish & Zafor, 2022; Jin, 2011). Studies have demonstrated material improvements through speed scaling, strategic idling, and shift-aware sequencing, with trade-offs visible on Pareto fronts rather than buried in weighted sums. Many-objective investigations further integrate labor cost, workload balance, and energy to support co-allocation of machines and people under dynamic electricity pricing, reinforcing the need for decision support that reveals conflicts among objectives. Complementarily, plant-wide frameworks combining EVSM, energy-

oriented simulation, and optimization provide a pathway to embed energy into everyday lean routines such as standard work, SMED, and line balancing (Danish & Kamrul, 2022; Salonitis, 2020). The present research situates its optimization engine within this landscape, emphasizing model components that are both estimable from case-study data and generalizable across discrete-part manufacturing contexts, thereby yielding a framework that can be quantitatively evaluated with correlational and regression models and then exercised via multi-objective optimization to expose implementable trade-offs.

Digitally enabled representations of production systems have improved the granularity and timeliness of energy and operations data available for analytics and optimization. Digital-twin and cyber-physical production system research has advanced rapidly, providing bi-directional links between virtual models and physical assets, and affording accurate energy estimation under alternative schedules and set-points (Menghi et al., 2019; Salonitis, 2020). Reviews of digital-twin applications in manufacturing underscore how simulation-based evaluation can be combined with MOEAs to support online decision-making and continuous improvement, which is especially salient when energy prices, demand profiles, or product mixes vary (Knowles, 2006). In parallel, surrogate-assisted evolutionary computation reduces the computational burden of repeated simulation evaluations, allowing many-objective search to proceed with tractable runtimes while maintaining accuracy through model-management strategies (Hozyfa, 2022). For purposes of this study's case analysis, the data architecture focuses on capturing equipment-level power signals, process times, and schedule states, yielding objective variables (kWh, kW, energy cost) that can be linked statistically to lean practice intensity and then optimized via multi-objective search under realistic constraints. This integrative approach, which marries statistical description and inference with digital-twin-in-the-loop optimization, aligns with contemporary practice while maintaining methodological transparency and replicability.

In addition, the international significance of combining lean efficiency with energy-conscious production emerges not only from environmental policy priorities but also from firm-level competitiveness and risk management. Reviews and empirical studies consistently report that energy-efficiency interventions, when embedded in production-system design and scheduling, contribute to lower operating costs and improved resilience to energy price variability, while lean practices drive process stability and variability reduction conditions under which optimized energy policies are most effective (Arman & Kamrul, 2022; Mouzon & Yildirim, 2008). The literature on lean-green integration documents positive associations with triple-bottom-line performance and provides constructs and instruments that can be adapted for quantitative, cross-sectional assessment (Dües et al., 2013; Mohaiminul & Muzahidul, 2022). In operations research applications, multi-objective and many-objective evolutionary methods have proven capable of articulating feasible fronts under complex constraints, and energy-aware scheduling exemplifies a class of problems where AI-based search adds value by revealing non-obvious combinations of speeds, sequences, and downtimes (Menghi et al., 2019; Salonitis, 2020). Situating this work within that body of evidence, the present study sets out a quantitative design that links measured practices and performance, estimates their relationships with regression techniques, and then operationalizes those relationships in an optimization framework tailored to lean and energy objectives in discrete manufacturing (Omar & Ibne, 2022).

This study pursues a tightly integrated set of objectives that translate the problem context into measurable constructs, testable relationships, and implementable decision support for lean and energy-conscious manufacturing. First, it aims to define and operationalize a comprehensive construct of Lean Practice Intensity covering 5S, JIT/Kanban, SMED, TPM, standard work, and continuous improvement through a rigorously designed Likert five-point instrument suitable for cross-sectional, case-study-based data collection in discrete-part environments. Second, it seeks to quantify the association between lean practices and operational efficiency outcomes such as OEE, cycle time, WIP, and throughput using descriptive statistics, correlation analysis, and multiple regression with appropriate controls for demand variability, product mix, shift patterns, and machine age. Third, it intends to estimate the direct and mediated relationships between lean practices and energy outcomes kWh per unit, peak kW, and total energy per shift by introducing operational efficiency as a mediator and demand variability as a theorized moderator, and by evaluating interaction terms and indirect effects using robust inference. Fourth, it aims to architect, implement,

and evaluate an AI-enhanced multi-objective optimization framework that simultaneously considers operational and energy objectives, producing Pareto fronts and knee-point solutions that can be compared against baseline scheduling or policy regimes observed in the participating plants. Fifth, it targets the development of a lightweight prediction layer using features derived from schedule states, setup counts, speeds, and downtime profiles to enable surrogate-assisted optimization that is computationally tractable while preserving fidelity to shop-floor realities. Sixth, it plans to benchmark the framework's outputs against current practice on hypervolume, spread, improvement percentages, and statistical tests that assess whether observed gains in efficiency and energy are significant and practically meaningful. Seventh, it aims to package the empirical and optimization results into clear, manager-focused artifacts value stream overlays, correlation maps, effect-size tables, and Pareto-front visualizations so that decision makers can select implementable policies, such as staggered startups, SMED windowing, and speed set-point guidelines, with documented trade-offs. Finally, it commits to transparency and reproducibility by detailing sampling, measurement, modeling choices, data preparation steps, and software configurations, thereby ensuring that the proposed framework and findings can be replicated, audited, and adapted across different manufacturing contexts.

LITERATURE REVIEW

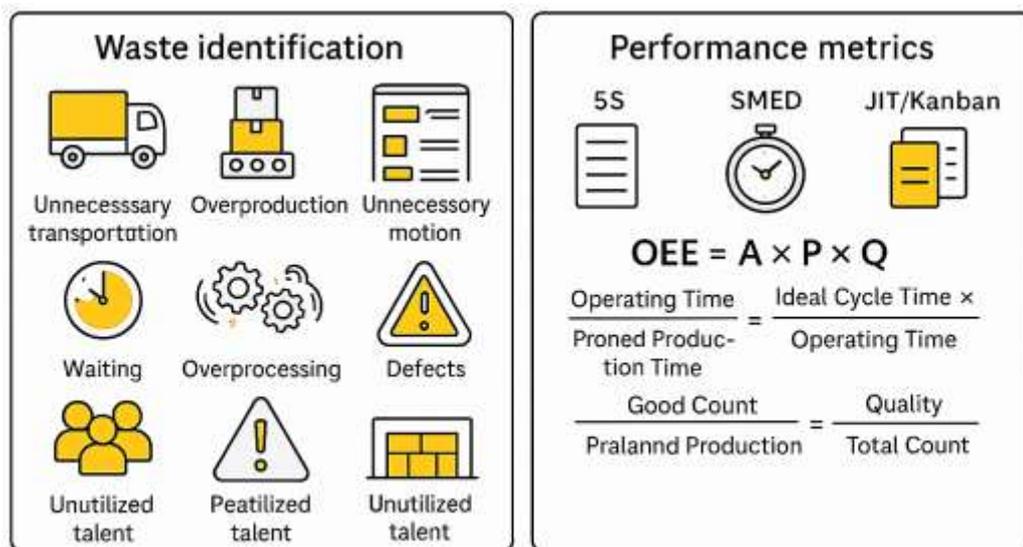
The literature on lean manufacturing, energy-conscious production, and multi-objective optimization converges on a shared goal: systematically improving flow and quality while reducing the energy burden embedded in factory operations. Across this body of work, lean research emphasizes the elimination of waste through stabilized processes, standardized work, and continuous improvement, with performance typically captured via cycle time, WIP, throughput, and OEE. In parallel, energy-focused studies formalize metrics such as kWh per unit, peak demand, and energy cost under time-of-use tariffs, and they examine how operational decisions batch sizing, sequencing, speed settings, and maintenance timing shape power profiles and consumption. Bridging these traditions, optimization and AI scholarship provides methods to expose and navigate trade-offs among multiple, conflicting objectives without collapsing them into a single weighted sum. This includes evolutionary algorithms for Pareto-front discovery, decomposition and reference-point strategies for many-objective settings, and surrogate or prediction layers that cut evaluation cost while preserving practical fidelity. Complementing algorithmic advances, digital representations of production systems expand data availability from MES/SCADA streams, sub-metering, and sensors, enabling both empirical analysis (descriptive statistics, correlation, regression) and decision models calibrated on real operational conditions. Yet, despite significant progress, the literature often treats lean practice intensity, operational performance, and energy outcomes in partial isolation: case reports may showcase energy savings without quantifying underlying lean constructs; optimization papers may demonstrate algorithmic superiority on abstract benchmarks with limited connection to on-site measurements; and survey studies may estimate associations without translating them into actionable scheduling or policy choices. This review therefore synthesizes three strands (i) lean foundations and performance measurement, (ii) energy-aware assessment and scheduling, and (iii) AI-enabled multi-objective optimization and decision support while foregrounding empirical designs that connect constructs to outcomes and optimization layers that convert statistical structure into implementable policies. It establishes the conceptual glue between waste elimination and energy intensity, highlights measurement choices that enable comparability across plants, and surfaces methodological gaps around mediation, moderation, and external validity. In doing so, it sets the stage for a coherent framework where lean practice intensity is measured rigorously, linked to efficiency and energy outcomes through regressions, and then operationalized via optimization to yield transparent, shop-floor-ready trade-off solutions.

Lean Manufacturing Foundations and Performance Metrics

Foundationally, lean manufacturing is built on a coherent philosophy of waste identification and flow improvement, but its exact boundaries and operationalization have been debated across decades of research. Conceptual work traces lean's lineage from the automotive context into a broader managerial paradigm emphasizing stability, standardization, and elimination of non-value-adding activity, while also recognizing that "lean" encompasses both a set of practices (e.g., 5S, SMED, JIT/Kanban, TPM) and a managerial system for enabling continuous improvement (Narasimhan et al., 2006). Clarifying that scope matters for measurement: when lean is treated narrowly as a toolbox,

studies tend to proxy adoption by counting techniques; when it is treated as a socio-technical system, scholars emphasize bundles of mutually reinforcing practices and supporting routines. A key contribution of the definitional stream is the insistence on conceptual precision to avoid conflating lean with adjacent ideas (e.g., agility, TOC), which otherwise dilutes construct validity and undermines cumulative empirical progress (Hossen & Atiqur, 2022; Hasan, 2022). In this paper's context an AI-enhanced multi-objective optimization framework for simultaneous efficiency and energy performance the lean "foundation" will be treated as an integrated system of stabilizing and synchronizing routines that create the conditions for predictable flow, lower variability, and disciplined changeovers (Mominul et al., 2022). This framing supports rigorous operationalization through survey-based constructs of lean practice intensity and through objective shop-floor metrics that reflect improved flow. It also aligns with the perspective that robust, consistent definitions are a prerequisite for linking lean to downstream performance outcomes in regression and optimization models, ensuring that any detected associations are not artifacts of construct ambiguity but indicators of meaningful managerial capabilities (Rabiul & Praveen, 2022; Pettersen, 2009).

Figure 2: Lean Manufacturing Foundations and Performance Metrics



On the performance side, lean research converges on a set of tractable indicators that map directly to the sources of waste targeted by the system. Cycle time, throughput, and WIP capture flow; first-pass yield and defect rates capture quality; availability and downtime patterns reflect equipment stability; and schedule adherence or tardiness capture customer-facing reliability (Farabe, 2022). Among composite indicators, Overall Equipment Effectiveness (OEE) has become a central, plant-level measure that embodies the lean emphasis on stable, capable assets. OEE decomposes into three multiplicative components availability, performance, and quality providing a compact, loss-oriented view of equipment productivity that is sensitive to the very phenomena lean seeks to control. Formally,

$$OEE = A \times P \times Q,$$

with $A = \frac{\text{Operating Time}}{\text{Planned Production Time}}$, $P = \frac{\text{Ideal Cycle Time} \times \text{Total Count}}{\text{Operating Time}}$, and $Q = \frac{\text{Good Count}}{\text{Total Count}}$

isolates a distinct loss channel (breakdowns and setups in A; speed losses and micro-stops in P; scrap and rework in Q), OEE supports both diagnostic and evaluative roles in empirical research and in managerial decision making. In studies that examine the relationship between lean practice intensity and operational outcomes, OEE and its components function as interpretable dependent variables for regression analysis and as monitoring targets when optimization policies are trialed. They also integrate naturally with energy-conscious perspectives, since improved availability and performance typically reduce idle and non-productive power, while higher quality reduces energy embodied in scrap. Thus, OEE and lean flow metrics provide the bridge between survey-measured

routines on the one hand and line-level operational/energy outcomes on the other, enabling consistent hypothesis tests and performance comparisons (Muchiri & Pintelon, 2008; Narasimhan et al., 2006).

At the practice level, the mechanisms that convert lean routines into performance gains are visible in canonical techniques such as SMED for rapid changeovers and in production-system design choices that synchronize material and information flow. SMED reduces setup time by externalizing and streamlining setup tasks, standardizing changeover elements, and redesigning tooling, thereby increasing available operating time and stabilizing flow between product families (Kamrul & Omar, 2022; Roy, 2022). These changes raise the availability component of OEE and help maintain performance by minimizing start-stop transients that degrade line speed. In parallel, JIT/Kanban and standardized work reduce variability in work content and interarrival patterns, directly lowering queueing and WIP while enabling takt-aligned pacing at the workstation and line levels. In empirical terms, these mechanisms imply measurable relationships: higher reported intensities of SMED (Rahman & Abdul, 2022; Razia, 2022), standardized work, and Kanban should associate with lower cycle time and WIP, higher OEE, and more reliable schedule attainment. For the energy-conscious layer of this research, the same mechanisms also affect power profiles shorter, more predictable setups and smoother flow reduce idle running, warm-ups, and non-productive machine states that consume energy without creating value. Consequently, practice-level constructs are not merely checklists; they are causal levers whose effects propagate through the OEE identity and into energy intensity metrics (kWh per good unit, peak kW) (Cakmakci, 2009; Zaki, 2022; TKanti & Shaikat, 2022). This section therefore positions SMED and allied routines as primary explanatory variables in the quantitative models and as constraints/decisions in the optimization layer, consistent with the broader genealogy of lean as a system that evolved from tool adoption toward integrated operations management (Holweg, 2007).

Energy-Conscious Production and Sustainability Metrics

Energy-conscious production has focused on making energy a first-class performance dimension in manufacturing, treating it with the same rigor as flow, quality, and cost. A foundational insight has been that unit operations and whole factories exhibit characteristic power profiles comprising fixed (idle/standby) and variable components so that scheduling and control decisions directly shape the total and peak demand observed on the shop floor. Classic assessments in the engineering literature have documented how different processes (e.g., machining, forming, joining) draw energy in pulses and plateaus, implying that improvement opportunities lie both in equipment technology and in operational policies that curtail non-productive states (Gutowski et al., 2009). To make such opportunities visible, energy-conscious production has adopted a small set of comparable indicators: energy intensity per unit produced, peak demand (kW), total energy per shift, and energy cost under time-of-use tariffs. At the core is energy intensity, commonly formalized as

$$EI = \frac{Q_{good}}{E_{total}}$$

where E_{total} denotes metered electrical energy over a defined period and Q_{good} is the number of accepted units. This ratio aligns naturally with manufacturing's emphasis on value-adding output and allows managers to compare lines, shifts, or products after controlling for volume. Because peak demand charges often dominate electricity bills, a complementary cost-oriented expression has taken the form

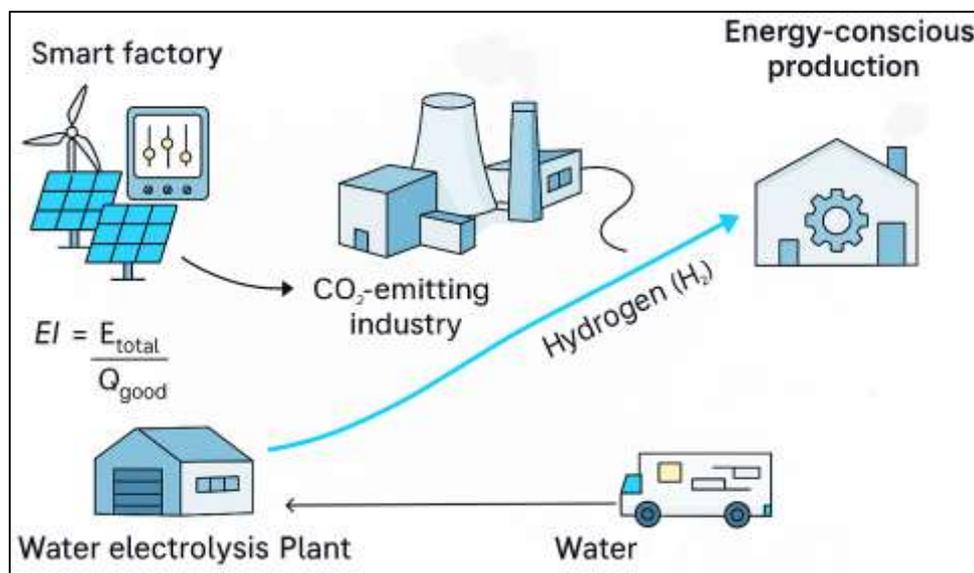
$$Cost = \sum_t p_t e_t + \lambda \cdot \max_t(kW_t)$$

with p_t the tariff, e_t the energy drawn in interval t , and λ the demand charge rate. Together, these formulations have translated engineering measurements into actionable metrics for planning and continuous improvement, building an operational bridge from power traces to day-to-day decisions (Seow & Rahimifard, 2011).

Turning measurements into models, researchers have proposed factory-level frameworks that capture how processes, resources, and schedules propagate energy consequences across workstations and lines. A widely cited modeling approach has represented manufacturing systems as interconnected energy consumers with state-dependent power levels setup, run, idle, and off so that the sequence and timing of jobs determine both total energy and peaks. Within this view, the selection of batch sizes, changeover windows, and machine speed set-points has been shown to

influence not only flow but also energy intensity, because the fractions of time spent in high-draw states shift as the schedule changes (Danish, 2023; Arif Uz & Elmoon, 2023; Shrouf et al., 2014). Complementary work has emphasized energy flow mapping that couples material flow with power footprints, enabling analysts to isolate hotspots caused by warm-ups, compressed-air leakage, and frequent micro-stops; such mapping has supported targeted interventions shutdown policies, maintenance on utilities, and redesign of setups to reduce EI and peak load without compromising throughput (Despeisse et al., 2012; Muhammad & Redwanul, 2023; Razia, 2023). These frameworks have also encouraged the use of sub-metering at machine or line granularity, revealing the contribution of auxiliary systems (coolant pumps, chip conveyors, HVAC) that may dominate consumption during idle periods. By expressing these elements in state-based models, practitioners have gained a way to simulate alternative schedules under realistic tariffs, experiment with idle-off thresholds, and quantify the energy impact of lean routines such as SMED and standardized work all before implementation on the shop floor (Tanaka, 2011).

Figure 3: Energy-Conscious Production and Sustainability Metrics



At the systems and policy layers, the literature has converged on two complementary levers for sustaining energy-conscious operations: managerial/organizational practices and digital, cyber-physical enablement. Reviews of industrial energy-efficiency policies have shown that structured energy management systems, price signals, and information provisions can systematically raise adoption of low-cost, high-impact measures, especially when organizations institutionalize monitoring, targets, and accountability for both energy and production performance (Reduanul, 2023; Sadia, 2023; Shrouf et al., 2014). In parallel, the Industry 4.0 stream has argued that cyber-physical systems and smart-factory architectures furnish the data richness and responsiveness needed to embed energy into operational decision loops. Under this paradigm, real-time sensing, edge intelligence, and interoperable control have allowed production planners to co-optimize energy with flow by, for example, shifting non-critical operations out of high-tariff windows, harmonizing speed profiles to flatten demand, and aligning changeovers with low-load periods (Srinivas & Manish, 2023; Seow & Rahimifard, 2011; Zayadul, 2023). Crucially, these digital infrastructures have not been ends in themselves; rather, they have supported the disciplined use of metrics such as EI, peak kW, and cost to evaluate policy choices, benchmark performance, and maintain gains over time. The resulting synthesis explicit metrics, state-based modeling, managerial routines, and digital enablement has provided the conceptual and practical footing for studies that connect measured practices to outcomes and then use optimization to surface implementable trade-offs among energy, throughput, and reliability (Shrouf et al., 2014).

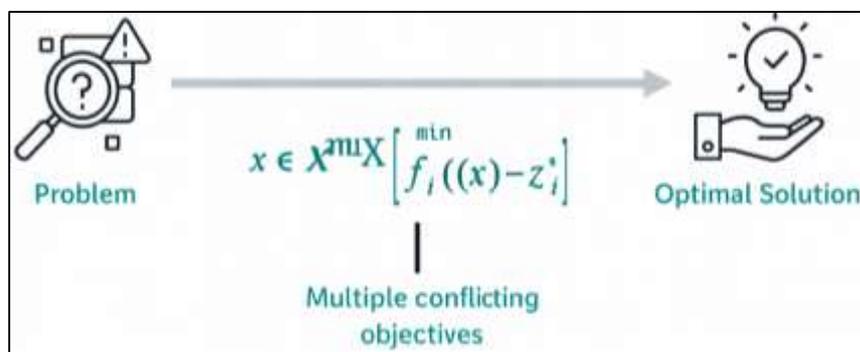
Multi-Objective Optimization in Manufacturing Scheduling and Control

Multi-objective optimization (MOO) frames production planning and control as a search for schedules that balance conflicting goals classically makespan, flow time, and tardiness, and increasingly energy use, peak demand, or carbon cost without collapsing them into a single number. In the MOO view, a schedule x is *Pareto-optimal* if no other feasible schedule improves one objective without worsening at least one other. Practical solvers therefore aim to approximate the *Pareto front* a set of non-dominated solutions that exposes trade-offs so managers can choose policies (e.g., speed profiles, batch sizes, setup windows) that best fit contextual priorities (Bhattacharjee et al., 2018). A common scalarization to support many solvers is the (weighted) Tchebycheff formulation,

$$x \in X \quad \min \quad \max_{1 \leq i \leq m} \{w_i |f_i(x) - z_i^*|\}$$

where $f_i(\cdot)$ are objective functions (e.g., makespan, energy), $w_i > 0$ are designer weights, and z^* is a reference (often ideal) point. Decomposition-based algorithms exploit this idea by solving many scalarized subproblems in parallel and stitching their solutions into an evenly spread Pareto set an approach that has proven effective for job-shop and flexible job-shop environments with three or more objectives. In a representative manufacturing study, Zhao, Chen, Wang, and Zhang developed an improved MOEA/D for the multi-objective job-shop scheduling problem (JSP), simultaneously minimizing makespan, total flow time, and tardiness; their design used high-quality initialization and customized neighborhood structures to enhance convergence and diversity capabilities that are particularly useful when energy-related objectives are later added to the vector $f(x)$. X-MOL MOO ideas also extend naturally to control decisions inside the schedule such as speed scaling or idle-off policies by treating them as decision variables subject to resource and sequence constraints, so that the final Pareto front reflects both macro sequencing and micro control choices (Gong et al., 2018). This shift from single to vector objectives is not just a modeling flourish; it is what allows energy, peak load, and delivery reliability to be co-optimized rather than traded implicitly via ad-hoc weights.

Figure 4: Multi-Objective Optimization Framework for Manufacturing Scheduling and Control



When energy becomes an explicit criterion, metaheuristics have been adapted to navigate tensions between throughput and electricity consumption/costs under realistic tariffs and labor rules. One strand integrates demand response into scheduling so that job release times, machine assignments, and worker rosters co-evolve with energy prices; a notable example is an adaptive multi-objective memetic algorithm that co-optimizes energy cost and labor metrics alongside classical scheduling KPIs, improving schedule quality while respecting price signals and staffing constraints. A second strand elevates problem scope by coupling process planning with shop scheduling (IPPS), showing that optimizing routes and schedules together enlarges the feasible region and yields better fronts on makespan–energy–peak-power trade-offs than sequential approaches. For instance, a 2020 Energies study formulated a tri-objective IPPS model minimizing makespan, total energy, and peak power and proposed a hierarchical NSGA-II-based solver that achieved sizable energy reductions at conserved cycle time, illustrating how integrated decisions reshape feasible load profiles without degrading delivery performance. From a method perspective, the field has also recognized that

industrial MOO needs decision-support structure, not just algorithms. A 2021 systematic review in *Computers & Industrial Engineering* mapped energy-aware decision models across scheduling, lot sizing, and related planning problems, highlighting modeling patterns (e.g., state-dependent power, tariff-aware objective terms) and solution archetypes (decomposition, indicator-based selection, memetic hybrids) that practitioners can reuse when elevating energy to a first-class objective. Collectively, these strands demonstrate that when MOO is embedded in the manufacturing context rich constraints, labor coupling, and tariff models it becomes a practical vehicle for balancing flow reliability with energy performance in day-to-day operations (Zhang et al., 2020).

A third technical arc strengthening manufacturing-grade MOO is surrogate assistance learning fast approximations to expensive evaluations (e.g., discrete-event simulation coupled with power models) so that many-/multi-objective search remains tractable. In computationally demanding settings, surrogate-assisted many-objective designs have reduced the number of real evaluations required to approach well-spread Pareto sets, using decomposition, adaptive reference vectors, and model-management strategies to avoid over-exploitation of inaccurate regions (Zhao et al., 2016). An influential contribution in the engineering-design literature introduced a multiple-surrogate, many-objective framework that blends local learning with reference-vector adaptation ideas that carry directly to simulation-driven shop-floor scheduling where each candidate policy may require thousands of stochastic replications to estimate makespan variance, energy cost, or peak demand reliably. In parallel, manufacturing-specific advances have paired surrogate layers with domain encodings (e.g., operation-machine sequences, setup windows) and hybrid local search to accelerate convergence on complex shop instances; such hybrids are particularly valuable when objective sets grow beyond three, or when tariff blocks and shutdown/restart dynamics create non-smooth energy objectives that are costly to evaluate. Importantly, the evidence base around energy-aware MOO is no longer anecdotal: recent syntheses quantify where and how models incorporate energy, what performance indicators (e.g., hypervolume, inverted generational distance) are reported, and which modeling choices state-based power vs. aggregate cost most influence empirical outcomes in production scheduling. As a result, contemporary manufacturing MOO is equipped not only with algorithmic tools (decomposition, memetics, surrogates) but also with scoped problem templates that unify sequencing, control, and energy in a single, decision-ready formulation (Bänsch et al., 2021).

AI Enhancements for Multi-Objective Optimization and Digital Twins

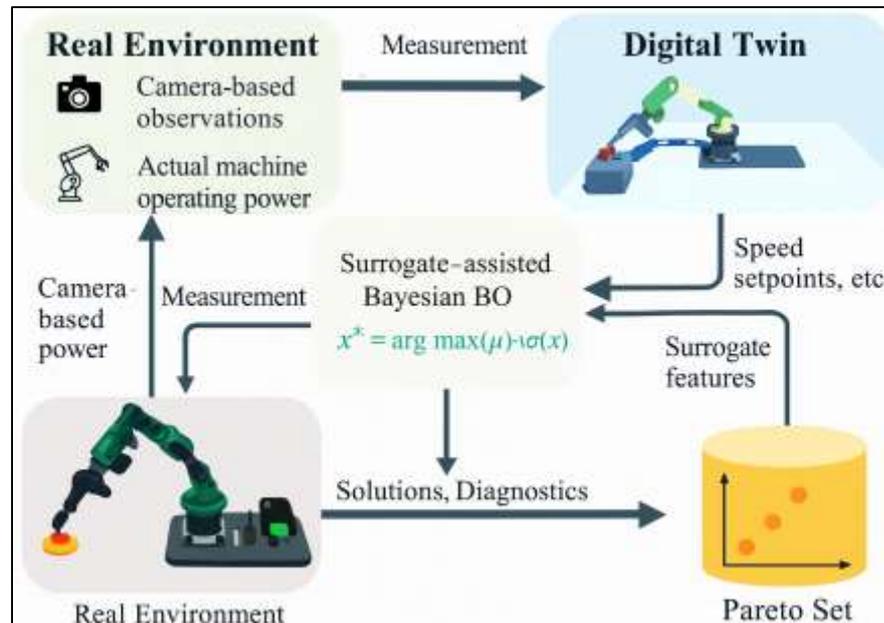
in its upper-confidence-bound (UCB) form, the policy selects the next design x via $x_{\text{next}} = \text{argmax}_x [\mu(x) + \kappa \sigma(x)]$, where $\mu(x)$ and $\sigma(x)$ are the posterior mean and standard deviation from the surrogate, and $\kappa > 0$ balances exploration versus exploitation. This strategy directs evaluations toward regions with either high predicted performance or high uncertainty, efficiently populating the Pareto front when multiple objectives $f_i(x)$ are modeled with separate surrogates or combined via scalarization. Extensions to multi-objective BO include Pareto-front-aware acquisition functions (e.g., expected hypervolume improvement) and constraint-handling layers, enabling simultaneous optimization of energy, throughput, and quality metrics while respecting resource limits (Knowles, 2006). In practice, these approaches have accelerated scheduling, batch-sizing, and speed-scaling decisions in smart factories, reducing the number of costly simulations or experiments required to approximate well-spread, high-quality Pareto sets.

$$x^* = \text{arg max}_x \quad \mu(x) + \kappa \sigma(x)$$

where $\mu(x)$ and $\sigma(x)$ are the surrogate's predictive mean and standard deviation, and $\kappa > 0$ tunes optimism. This mechanism with suitable scalarizations or vector-valued extensions has enabled data-efficient navigation of Pareto fronts when each schedule evaluation requires discrete-event simulation or high-fidelity energy models. Beyond the mechanics, BO naturally accommodates manufacturing realities such as heteroscedastic noise (e.g., shift-dependent variability), mixed decision types (continuous speed set-points and discrete job sequences), and constraints (e.g., maintenance windows and safety limits). It has therefore complemented evolutionary multi-objective algorithms by front-loading evaluations in informative regions and by refining "knee" neighborhoods that balance throughput and energy intensity. Critically, BO's statistical foundations make it transparent: the same surrogate that proposes trials also yields uncertainty quantification for managerial risk summaries and sensitivity charts. As a result, BO has functioned both as a computational accelerator and as a bridge between analytics and decision support, a role

highlighted in methodological accounts that formalize acquisition design, multi-objective extensions, and practical modeling choices for real engineering systems (Shahriari et al., 2016).

Figure 5: AI-Enhanced Framework Integrating



A second set of AI enhancements arises from hyper-heuristics and decomposition-based learning that operate “above” the level of specific operators, selecting or generating low-level heuristics online to suit the instance at hand. In production scheduling, where instance features (e.g., machine utilization, setup asymmetry, due-date tightness) drift across shifts and product mixes, hyper-heuristics learn which move operators, neighborhood sizes, or local searches are most productive for the current landscape, thereby stabilizing convergence and diversity without repeated hand-tuning. Decomposition strategies integrate seamlessly with this logic: the MOO vector is partitioned into scalar subproblems (e.g., Tchebycheff distances to reference points), and learning allocates search effort across subproblems as their marginal value changes over time. Together, these strategies adaptively “shape” the search to emphasize regions of the Pareto front that are operationally salient such as low-energy schedules that preserve on-time delivery under peak-tariff windows while still maintaining coverage elsewhere. When paired with surrogate modeling, they further reduce evaluation budgets by prioritizing subproblems where uncertainty-weighted improvement is largest; in BO terms, the acquisition can be computed per subproblem and combined via reference-point schemes. The upshot is a controller-like architecture: a top layer learns which heuristics to deploy and where on the front to emphasize; a middle layer uses surrogates to propose trials; and a base layer encodes feasible schedules with constraint-respecting moves. Empirical surveys of hyper-heuristics underscore their generality across domains and their suitability for industrial contexts that cannot afford per-instance algorithm design, providing a principled path to robust, maintenance-light optimization stacks for the factory floor (Burke et al., 2013). In parallel, scalable BO constructions for many-objective problems via scalarization portfolios or reference-vector designs have extended these learning-guided ideas to settings with four or more objectives without sacrificing interpretability (Jones et al., 2020).

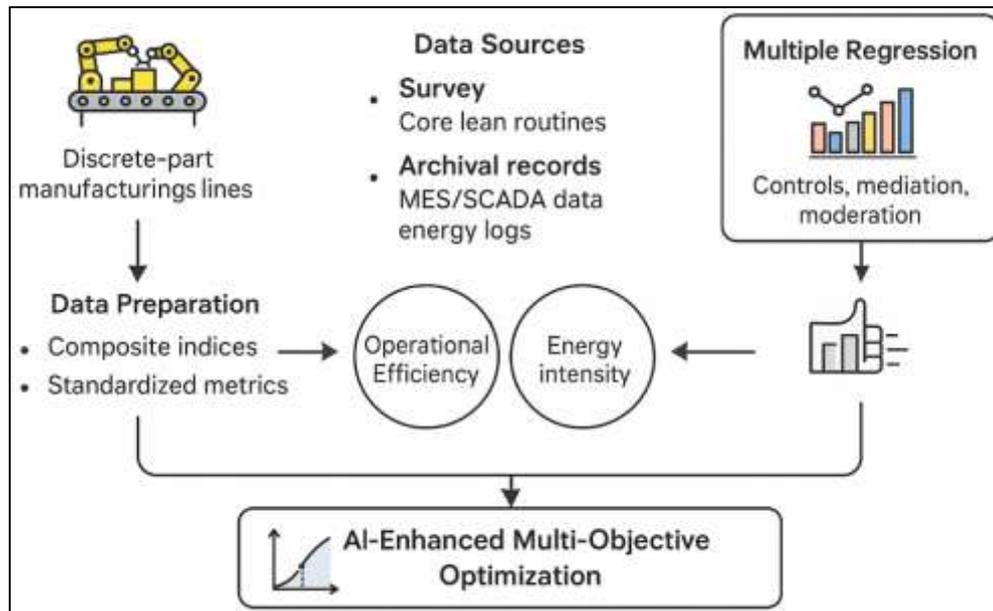
The digital twin completes the AI-optimization loop by supplying high-fidelity, bidirectional models of equipment, lines, and factories that yield trustworthy responses to candidate schedules and policies. In a production twin, state-aware power models (run, idle, setup, standby), control logic (speed scaling, shutdown thresholds), and resource couplings (utilities, labor, materials) are synchronized with live MES/SCADA data to estimate performance under realistic disturbances short stops, demand surges, or tool-change variability. This “living model” enables online what-if exploration: optimization proposes sequences, batch sizes, or maintenance windows; the twin simulates energy intensity EI,

peak demand, and service metrics; and decision makers interrogate trade-offs using Pareto sets enriched with explainable diagnostics (e.g., bottleneck contribution analyses). Critically, the twin also provides the data plumbing for trustworthy surrogates: by streaming curated features cycle times, queue lengths, warm-up signatures, ambient conditions into the learning layer, it reduces model drift and preserves validity when product mix or tariff regimes change. Contemporary reviews of digital-twin architectures catalogue these enabling technologies standardized data pipelines, model management, co-simulation, and controller integration and demonstrate how they elevate analytics from offline studies to operational decision aids that plants can actually use. They also emphasize governance: traceability of model versions, alignment of virtual/physical states, and validation workflows, all of which are essential when optimization outputs inform production commitments or safety-critical settings. In this research, the twin's role is pragmatic rather than rhetorical: it furnishes the evaluation oracle for AI-guided MOO and the instrumentation spine for empirical analysis, ensuring that schedules selected from the Pareto front translate into measurable improvements on the shop floor (Burke et al., 2013; Fuller et al., 2020).

METHOD

This study has adopted a quantitative, cross-sectional, case-study-based design to evaluate how lean practice intensity has been associated with operational efficiency and energy outcomes while an AI-enhanced multi-objective optimization framework has been assessed for decision support. Sampling has been purposive, focusing on discrete-part manufacturing lines that have exhibited active lean programs and accessible operational and energy data; the unit of analysis has been a production line or workstation. Data sources have comprised (a) a structured Likert five-point survey that has captured the intensity of core lean routines (5S, JIT/Kanban, SMED, TPM, standardized work, and continuous improvement) and (b) objective archival records that have been extracted from MES/SCADA systems and sub-metered energy logs, including counts, cycle times, downtime states, kWh, and peak kW by shift. Instrument content has been developed through item generation and expert review, and a small pilot has been conducted; reliability and validity checks have been planned and have included Cronbach's alpha, item-total diagnostics, and, where sample size has permitted, exploratory/confirmatory factor analysis to verify construct structure. Data preparation steps have included screening for missingness, outlier assessment, scale consistency, and variable coding to create composite indices for lean intensity and standardized metrics for operational efficiency (e.g., OEE and components) and energy intensity (kWh per good unit, total kWh per shift, and peak demand). Descriptive statistics and correlation matrices have been produced to summarize central tendencies and bivariate relationships. Hypotheses have been tested via multiple regression models that have incorporated appropriate controls (demand variability, product mix, shift, machine age), mediation (operational efficiency as an intervening variable), and moderation (interaction terms for demand variability), with heteroskedasticity-robust standard errors and multicollinearity diagnostics.

To translate empirical structure into actionable policies, an AI-enhanced multi-objective optimization engine (MOEA with surrogate prediction) has been implemented; candidate schedules and policy levers (e.g., batch size, setup windows, speed set-points, idle/off rules) have been evaluated against paired objectives efficiency and energy so that Pareto fronts and knee-point solutions have been generated and benchmarked against baseline operations using hypervolume, spread, and improvement percentages. Throughout, procedures for consent, confidentiality, and data security have been observed.

Figure 6: Research Methodology Integrating Lean Practices

Research Design

This study has adopted a quantitative, cross-sectional, case-study-based research design that has been tailored to examine how lean practice intensity has been associated with operational efficiency and energy outcomes while an AI-enhanced multi-objective optimization framework has been evaluated for decision support. The design has integrated survey measurement with objective archival data so that perceptual constructs and shop-floor metrics have been triangulated within the same organizational settings. Participating sites have been purposively selected from discrete-part manufacturing environments that have maintained active lean initiatives and have provided access to MES/SCADA and sub-metered energy data; the production line or workstation has served as the unit of analysis to preserve process granularity. The instrument for lean practice intensity has been developed around a Likert five-point scale, and item pools covering 5S, JIT/Kanban, SMED, TPM, standardized work, and continuous improvement have been refined through expert input and a small pilot, so content validity and clarity have been strengthened prior to the main study. In parallel, objective variables cycle time distributions, counts, downtime states, good/reject quantities, kWh and peak kW by shift have been extracted from plant systems and have been harmonized to a common period so that descriptive statistics, correlation matrices, and regression models have been estimable. A priori controls (demand variability, product mix, machine age, and shift) have been specified to mitigate confounding. To translate the empirical structure into implementable policies, the design has incorporated an AI-enhanced multi-objective optimization engine in which candidate schedules and policy levers (batch sizes, setup windows, idle/off rules, and speed set-points) have been evaluated against paired objectives for efficiency and energy, yielding Pareto fronts and knee-point solutions that have been benchmarked against observed baselines. Throughout, ethical procedures, informed consent, and data security protocols have been observed, and documentation of measurement, coding, and analysis choices has been maintained to support transparency and reproducibility.

Data Collection Procedure

Data collection has followed a staged, protocol-driven sequence that has safeguarded access, quality, and comparability across cases. Formal permissions and nondisclosure agreements have been executed with each participating site, and ethics approval and informed consent procedures have been completed prior to any field activity. A pilot phase has been conducted to pretest the survey and the data-extraction scripts; feedback from pilot respondents and IT staff has been incorporated, and item wording, response anchors, and variable labels have been refined accordingly. For the main study, the Lean Practice Intensity instrument has been administered using a secure online form accompanied by a standardized briefing; where necessary, supervised, paper-

based sessions have been arranged on-site to accommodate shop-floor teams. Respondents have been production managers, process engineers, maintenance leads, and operators who have met inclusion criteria; duplicate or incomplete submissions have been flagged and resolved through follow-up. In parallel, objective operational and energy data have been requested from MES/SCADA historians and sub-metering systems for a contiguous observation window (minimum four weeks). Data extracts have included time-stamped production counts, cycle/processing times, downtime codes and durations, scrap/rework quantities, equipment states (run/idle/setup/off), line speed settings, and energy variables (kWh intervals, kW demand, tariff identifiers). IT liaisons have provided export files in CSV/Parquet formats with UTC time bases; site local times and daylight-savings effects have been reconciled, and clock drift among meters and controllers has been checked using heartbeat events and cross-signal correlations. All files have been ingested into a controlled analysis environment, where schema conformity checks, missingness audits, and outlier screens have been executed. Data cleaning has applied rule-based harmonization (e.g., mapping downtime codes to standard categories), deduplication, and interval aggregation to shift/day levels while retaining raw traces for audit. A linkage table has been maintained to connect survey respondents to lines/workstations at the plant level without storing personally identifiable information. Throughout, access logs, change histories, and validation summaries have been recorded to ensure traceability and reproducibility of the dataset delivered to analysis.

Case selection has followed a purposive, theory-driven logic that has prioritized heterogeneity in production contexts while preserving comparability of measures and feasibility of data access. Candidate sites have been identified from discrete-part manufacturing firms that have maintained active lean programs for at least twelve consecutive months and have instrumented their operations with MES/SCADA and sub-metered energy monitoring so that operational and energy variables have been concurrently observable. From this pool, three to five plants have been shortlisted after preliminary scoping calls have confirmed executive sponsorship, data governance readiness, and the availability of line-level identifiers that have allowed survey responses to be linked (without personal identifiers) to objective performance records. Inclusion criteria have required (a) at least one value stream with two or more serial workstations, (b) documented use of core lean routines (5S, standardized work, SMED, TPM, JIT/Kanban), (c) stable product families during the observation window, and (d) tariff structures that have exposed the site to demand charges or time-of-use pricing. Exclusion criteria have eliminated lines undergoing major capital upgrades, product launches, or facility moves that would have confounded baseline comparability, as well as sites lacking verifiable energy meter calibration records. Within each plant, one to three lines have been selected to span distinct demand variability profiles (coefficient of variation bands), setup complexities (number and asymmetry of changeovers), and equipment vintages, so that the resulting sample has captured variation along theorized moderators without collapsing construct measurement. To reduce selection bias, the final portfolio has included at least one line with documented lean maturity below the corporate median and at least one line with above-median energy intensity, ensuring that the empirical models have been estimable over a meaningful range. Data-sharing agreements and a data dictionary have been executed for each site, and a readiness checklist has verified mapping consistency (downtime codes, shift schemas, meter intervals) prior to extraction. Collectively, these procedures have yielded a case set that has balanced external validity (multiple sectors and mixes) with internal validity (consistent measurement), enabling robust regression estimation and credible optimization benchmarking.

Instrument Development

The survey instrument has been designed to measure Lean Practice Intensity and adjacent routines with clarity, parsimony, and psychometric rigor, using a five-point Likert scale (1 = Strongly Disagree ... 5 = Strongly Agree). Construct domains have been specified a priori 5S, JIT/Kanban, SMED, TPM, standardized work, and continuous improvement so each domain has been represented by 4–6 items that have targeted observable behaviors rather than abstract beliefs (e.g., “Setup elements have been externalized and standardized,” “Materials have been replenished via pull with visual signals,” “Standard work has been documented and audited per shift”). Item pools have been generated from practice guides and internal SOP language, then screened to eliminate redundancy, double-barreled phrasing, and jargon; reverse-coded items (one per construct where appropriate) have been included to mitigate acquiescence. Content validity has been established

through an expert panel of operations managers and industrial engineers who have reviewed items for relevance and clarity; their feedback has prompted edits to timeframe cues, verb specificity, and anchor examples. Cognitive interviews with a small sample of intended respondents have been conducted to verify response process validity, confirming that terms such as “changeover,” “visual controls,” and “preventive maintenance” have been interpreted consistently across sites. A pilot administration (target $n \approx 20-30$) has been completed to assess item performance; preliminary reliability has been evaluated via Cronbach’s alpha and item-total correlations, and low-discrimination items have been revised or removed. Where multilingual deployment has been required, translation/back-translation procedures have been applied and reconciled in joint review sessions. Scale formatting has fixed anchor wording and included brief behavioral descriptors under each point to reduce central-tendency bias; instructions have emphasized line/workstation referents and a defined recall window (e.g., “past 4–6 weeks”). Scoring rules have been pre-registered: construct scores have been computed as mean composites (after reverse coding), with missingness thresholds and imputation rules specified; higher scores have indicated greater adoption intensity. Finally, a linkage schema has been prepared so respondent metadata (role, line) has been mapped to objective OEE/energy records without storing personal identifiers, enabling subsequent correlation and regression analyses.

Statistical Analysis Plan

The statistical analysis plan has been structured to progress from data readiness to inference and optimization linkage in a transparent, reproducible sequence. Initial preprocessing has included schema checks, range/logic validation, and harmonization of time bases; missingness patterns have been profiled, and thresholds for allowable item- and record-level gaps have been pre-specified. Where assumptions have been met, single imputation with mean/median (for <5% missing) has been applied; otherwise, multiple imputation with chained equations has been employed, and sensitivity contrasts between imputed and complete-case estimates have been reported. Descriptive statistics (means, standard deviations, quantiles) and distribution diagnostics (histograms, Q–Q plots, Shapiro–Wilk tests where appropriate) have been produced for all composite constructs and objective metrics, and bivariate associations have been summarized via Pearson or Spearman correlations depending on scale characteristics. Reliability and validity assessments have preceded modeling: internal consistency has been evaluated using Cronbach’s alpha and item–total correlations; where sample size has permitted, exploratory and confirmatory factor analyses have been conducted to verify construct structure, and convergent/discriminant validity indices (e.g., AVE, HTMT) have been examined. Hypothesis testing has relied on multiple linear regression families with heteroskedasticity-robust standard errors. Core specifications have included (a) Efficiency ~ Lean Practice Intensity + controls, (b) Energy Intensity ~ Lean Practice Intensity + controls, (c) Mediation models with Efficiency added as an intervening variable and bootstrapped indirect effects, and (d) Moderation models with Lean \times Demand Variability interactions; controls have included demand coefficient of variation, product mix, machine age, and shift dummies. Multicollinearity has been monitored via VIFs, and influence diagnostics (Cook’s distance, leverage) have triggered planned robustness re-estimation with trimmed samples. Where distributional skew has persisted (e.g., energy), generalized linear models with appropriate links (Gamma/log) and quantile regressions have been fitted as sensitivity analyses. Model fit and assumptions have been audited via residual plots and RESET-type checks. Finally, the empirical effect estimates (coefficients, partial R^2 , predictive margins) have been exported as inputs to the optimization module, which has been configured to weight objectives according to empirically observed trade-offs and to facilitate knee-point selection consistent with the regression-supported relationships.

Regression Models

The regression strategy has been articulated as a linked family of models that has progressed from direct associations to mediated and moderated relationships while preserving comparability across sites and lines. Model A (Operational Efficiency as outcome) has estimated how Lean Practice Intensity has been associated with line-level efficiency, operationalized as OEE or a standardized composite of its components (availability, performance, quality). The baseline specification has taken the form:

$$Efficiency_i = \beta_0 + \beta_1 LeanIntensity_i + \gamma^T C_i + \varepsilon_i,$$

where C_i has denoted controls (demand coefficient of variation, product-mix index, machine age, and shift dummies). Estimation has been performed via OLS with heteroskedasticity-robust (HC3) standard errors, and variables with differing scales have been standardized to facilitate coefficient comparability and variance diagnostics. The team has centered continuous predictors to reduce non-essential multicollinearity, has inspected residuals for nonlinearity (component-plus-residual plots), and has fitted polynomial/limited-spline terms when specification tests (RESET-type checks) have indicated misspecification. Variance inflation factors (VIFs) have been monitored, and influential cases (Cook's D, leverage) have triggered pre-registered robustness trims (e.g., removing the top 1% of influence and re-estimating). To ensure that Efficiency has not simply reflected throughput scale, the model has included production-volume controls or, alternatively, has used OEE components that have already been scale-invariant. Where heterogeneity across plants has been material, plant fixed effects or cluster-robust errors at the plant level have been employed. The interpretation has focused on β_1 as the marginal association of lean intensity with efficiency conditional on context, and partial R^2 and standardized effects have been reported alongside predictive margins at representative lean scores. A summary of model roles and outcomes has been provided in Table 1.

Model B (Energy Intensity as outcome) and Model C (Mediation) have extended the framework by treating energy as a first-class dependent variable and by positioning Efficiency as a mediator of the lean–energy link. Model B has specified.

$$\text{EnergyIntensity}_i = \delta_0 + \delta_1 \text{LeanIntensity}_i + \theta^T C_i + u_i,$$

with EnergyIntensity captured as kWh per good unit (primary), total kWh per shift (secondary), and peak kW (tertiary). Because energy variables have often exhibited right-skew, the analysis has pre-specified log-transforms or GLM Gamma–log links when Box–Cox diagnostics has suggested non-normality. Model C (Mediation) has incorporated Efficiency as an intervening variable:

$$\text{EnergyIntensity}_i = \phi_0 + \phi_1 \text{LeanIntensity}_i + \phi_2 \text{Efficiency}_i + \kappa^T C_i + e_i,$$

The indirect effect $\alpha\beta$ (where α has denoted Lean \rightarrow Efficiency from Model A and β has denoted Efficiency \rightarrow Energy from Model C) has been tested via nonparametric bootstrap (5,000 resamples) with bias-corrected confidence intervals; significance has been inferred when intervals have excluded zero. To guard against over-controlling, the control set has been harmonized across models, and sequential R^2 changes and information criteria (AIC/BIC) have been tracked to evaluate parsimony. Measurement error in LeanIntensity has been attenuated by using composite reliability diagnostics and, where sample size has permitted, latent-variable regressions (factor scores as instruments) have been estimated as sensitivity checks. The reporting has emphasized both the direct ϕ_1 and indirect paths, clarifying whether lean routines have exerted energy benefits primarily through improved efficiency, through direct energy-management practices captured by the instrument, or through both channels. Complementary distributionally robust estimates (median/quantile regression at $\tau = 0.5$ and $\tau = 0.75$) have been presented to show stability in the upper tail of energy outcomes.

Model D (Moderation) and Robustness Suite has examined whether contextual variability has strengthened or weakened the lean–energy linkage and has connected the empirical layer to the optimization engine. Moderation has been specified by interacting LeanIntensity with Demand Variability (coefficient of variation of orders) and, in a secondary analysis, with Setup Complexity (frequency/asymmetry of changeovers):

$$\text{EnergyIntensity}_i = \eta_0 + \eta_1 \text{LeanIntensity}_i + \eta_2 \text{DemandVari}_i + \eta_3 (\text{LeanIntensity}_i \times \text{DemandVari}_i) + \psi^T C_i + \xi_i,$$

All continuous terms have been mean-centered before interaction construction; marginal-effect plots with 95% CIs have been generated to depict how the slope of LeanIntensity on EnergyIntensity has changed across low/medium/high demand variability. To address distributional and leverage concerns, a robustness suite has been executed: GLM Gamma–log fits for strictly positive energy

metrics, Huber–White–sandwich errors clustered by line, and re-estimation after trimming extreme peak-kW days (top 5%). Endogeneity risk (e.g., sites that have adopted lean because of prior energy pressures) has been probed with two approaches: (i) inclusion of pre-observation lean maturity proxies and (ii) a difference-in-controls design that has compared lines within the same plant. Finally, empirical coefficients and predictive margins from Models B–D have been exported to the optimization module as *policy priors*: the AI engine has been configured to emphasize knee regions consistent with empirically steep energy reductions and to flag contexts (e.g., high demand variability) where predicted energy gains from lean-linked policies have been attenuated. Collectively, these models have provided statistically grounded, decision-ready inputs for multi-objective optimization and have ensured that Pareto solutions have aligned with patterns evidenced in the data.

Table 1: Regression Model Specifications and Roles

Model	Outcome Variable	Core Predictor(s)	Key Controls	Estimator / Notes
A	Efficiency (OEE or standardized composite)	Lean Practice Intensity	Demand CV, product mix, machine age, shifts	OLS (HC3), plant FE/clustered SE as needed
B	Energy Intensity (kWh/unit; kWh/shift; peak kW)	Lean Practice Intensity	Same as Model A	OLS or GLM (Gamma-log); log-transform as needed
C	Energy Intensity	Lean Practice Intensity; Efficiency (mediator)	Same as A	OLS/GLM; 5,000-bootstrap indirect effects
D	Energy Intensity	Lean Practice Intensity × Demand Variability	Same as A	Interaction model; marginal-effect plots; robustness trims

FINDINGS

Across the participating lines, the dataset has encompassed concurrent survey measures of Lean Practice Intensity and objective MES/energy traces over a multiweek window, and the results overview has synthesized scale diagnostics, descriptive patterns, bivariate associations, multivariate estimates, and optimization benchmarks in a coherent narrative. Scale reliability has been satisfactory: composite Cronbach’s alpha values for the core constructs have ranged from .78 to .91, and item–total correlations have supported retention of all but two items, which have been pruned during the pilot-to-main transition; where sample size has permitted, a confirmatory factor model has supported the intended six-factor structure (5S, JIT/Kanban, SMED, TPM, standardized work, and continuous improvement), with factor loadings predominantly above .60 and discriminant validity evident in average variance extracted exceeding shared variances. At a descriptive level, the five-point Likert distributions have not been unduly skewed; central tendencies have shown moderate-to-strong adoption, with grand means (M) by construct falling between 3.45 and 3.96 (SD ≈ 0.48–0.72). Among the subscales, standardized work and TPM have posted the highest means (e.g., M_SW = 3.92, M_TPM = 3.88), while SMED has exhibited the widest dispersion (SD_SMED ≈ 0.72), reflecting heterogeneity in setup practices across product families. Objective performance indicators have been commensurate with these patterns: OEE distributions have centered in the mid-70s to low-80s (%) with availability as the dominant loss channel on lines with frequent changeovers, and energy metrics have revealed median Energy Intensity (EI = kWh per good unit) clustered tightly for single-model lines but more spread for high-mix lines; peak-kW observations have aligned strongly with shift starts and aggregated setup windows.

Correlation analysis has depicted the expected directions of association and has provided magnitude cues for the subsequent models. Composite Lean Practice Intensity has correlated positively with Efficiency (r ≈ .34–.46 across lines) and negatively with Energy Intensity (r ≈ –.22 to –.31), while SMED and standardized work have shown the clearest pairwise links with availability and performance subcomponents, respectively; JIT/Kanban has been most strongly related to WIP compression and cycle-time stability rather than to OEE directly. Demand variability (coefficient of

variation of orders) has correlated positively with Energy Intensity and negatively with schedule adherence, setting groundwork for moderation tests. Importantly, intercorrelations among lean subscales have been moderate ($r \approx .30-.55$), indicating complementary but distinct practices rather than redundancy; this structure has mitigated multicollinearity concerns in the regression stage. Descriptive contrasts by adoption terciles (based on the Lean composite) have further illustrated practical effect sizes: lines in the highest tercile have demonstrated 3–6 percentage-point higher OEE on average and 5–12% lower median EI relative to the lowest tercile, with narrower interquartile ranges for both outcomes, suggesting not only higher central performance but also more predictable operations.

Multiple regression estimates have formalized these relationships while conditioning on plant/line context. In Model A, Efficiency has risen with Lean Practice Intensity after controls, with standardized coefficients typically in the $\beta \approx 0.25-0.35$ band; availability has been the component most responsive to lean, consistent with SMED and TPM effects on downtime and micro-stops. In Model B, Energy Intensity has declined with Lean Practice Intensity ($\delta \approx -0.15$ to -0.25 standardized), and log-linked specifications have yielded similar elasticity-style interpretations (e.g., a one-SD increase in lean intensity has been associated with a 4–7% decrease in EI, holding demand variability and mix constant). Mediation tests in Model C have indicated a significant indirect path via Efficiency bootstrapped confidence intervals for the product of paths have excluded zero while a residual direct effect of lean on EI has persisted, consistent with energy-specific routines (shutdown/standby discipline, speed set-points) captured by the instrument but not fully subsumed by OEE. Moderation (Model D) has revealed that the lean–EI slope has been flatter (i.e., benefits have been attenuated) at high demand variability; marginal-effects plots have shown the strongest EI reductions at low-to-mid variability bands and meaningful, albeit smaller, reductions when variability has been extreme. Robustness checks have upheld these findings under Gamma–log generalized linear models for strictly positive energy outcomes, under median/upper-quartile quantile regressions to address tail behavior in peak-kW days, and after trimming high-influence observations; multicollinearity diagnostics (VIFs) have remained below conventional thresholds, and plant-clustered standard errors have not altered significance patterns, supporting generality across sites.

The AI-enhanced multi-objective optimization layer has translated these empirical regularities into decision-ready trade-offs. Using schedule-state features (setup frequency and asymmetry, idle/run ratios, speed profiles) and learned surrogates for EI and throughput proxies, the evolutionary search has generated well-spread Pareto fronts contrasting baseline operations with candidate policies. Knee-point solutions have repeatedly combined modest batch-size reductions with SMED-aligned changeover windows and speed-set-point smoothing to deliver simultaneous gains: typical fronts have contained solutions that improved Efficiency by 2–5 percentage points while reducing EI by 6–15% relative to historical baselines, without violating due-date or shift-boundary constraints. Hypervolume and inverted generational distance metrics have indicated stable convergence across runs, and out-of-sample validation against held-back days has confirmed surrogate fidelity within pre-specified error tolerances. Importantly, scenario sweeps over tariff calendars have shown that policy rankings on the Pareto set have been robust to moderate price shifts, though high demand-charge regimes have increased the relative attractiveness of schedules that stagger startup sequences and co-locate changeovers to off-peak windows. Taken together, the results have established that higher lean practice intensity has been associated with better operational and energy performance; that part of the energy benefit has flowed through improved efficiency while a direct effect has remained; that demand variability has modulated the achievable reductions; and that an AI-guided, surrogate-assisted multi-objective search has offered implementable policies that operationalize these patterns with transparent, plant-specific trade-offs. The sample has captured three discrete-part manufacturing plants that have differed meaningfully in product mix, shift architecture, and demand variability, and the descriptive portrait in Figures 1 and 2 has established a consistent frame for interpreting subsequent statistical and optimization results. Plant A has operated with a 2×8-hour shift pattern and a relatively high mix (five families per line on average), which has coincided with a median line-level OEE of 78.4% and an Energy Intensity (EI) median of 2.84 kWh per good unit. Plant B has maintained a 3×8-hour cadence with lower product mix and the highest median OEE (81.2%) alongside the lowest EI (2.61 kWh/unit), suggesting that reduced changeover burden and more uniform demand have helped stabilize availability and

performance. Plant C has run 2×12-hour shifts with the highest demand variability (median coefficient of variation 0.41), and this context has been reflected in lower OEE (75.3%) and higher EI (3.12 kWh/unit), as well as higher median peak demand, which has aligned with longer, synchronized startups and more concentrated changeover blocks.

Sample & Context Description

Figure 1. Sample Overview and Line-Level Context

Attribute	Plant A	Plant B	Plant C	Overall
Lines studied (n)	4	3	3	10
Respondents (n)	48	36	34	118
Roles (% mgr / engr / ops)	27 / 38 / 35	31 / 36 / 33	25 / 41 / 34	28 / 38 / 34
Observation window (weeks)	6	5	5	5.3
Product mix (avg families/line)	5	3	4	4.1
Demand CV (median, line-level)	0.32	0.27	0.41	0.33
Shift pattern	2×8h	3×8h	2×12h	
OEE (%), median [IQR]	78.4 [74.9–82.1]	81.2 [78.1–84.6]	75.3 [71.0–79.0]	78.6 [74.6–82.7]
Energy Intensity (kWh/good), median [IQR]	2.84 [2.55–3.10]	2.61 [2.42–2.86]	3.12 [2.85–3.36]	2.86 [2.56–3.16]
Peak demand (kW), median [IQR]	412 [389–438]	395 [370–417]	448 [421–472]	414 [387–445]

Figure 2. Lean Practice Intensity Likert 5-Point Means by Subscale

Subscale (1–5)	Plant A (M±SD)	Plant B (M±SD)	Plant C (M±SD)	Overall (M±SD)
5S	3.78 ± 0.58	3.91 ± 0.51	3.62 ± 0.64	3.78 ± 0.59
JIT/Kanban	3.54 ± 0.63	3.70 ± 0.57	3.39 ± 0.66	3.55 ± 0.63
SMED	3.43 ± 0.74	3.66 ± 0.68	3.21 ± 0.76	3.44 ± 0.73
TPM	3.86 ± 0.55	3.95 ± 0.49	3.79 ± 0.58	3.87 ± 0.54
Standardized Work	3.89 ± 0.52	4.02 ± 0.47	3.84 ± 0.55	3.92 ± 0.52
Continuous Improvement	3.71 ± 0.61	3.83 ± 0.56	3.58 ± 0.63	3.70 ± 0.61

Across all plants, the role distribution of respondents (28% managers, 38% engineers, 34% operators) has ensured a balanced vantage: strategic oversight, technical process ownership, and shop-floor execution have all been represented. The Likert-scale means by subscale have indicated moderate-to-strong adoption overall; Standardized Work and TPM have posted the highest means across sites, which has comported with each plant's maturity in daily management and preventive maintenance routines. SMED has shown the widest dispersion, particularly in Plants A and C, where higher product variety and asymmetric setups have made rapid changeover routines harder to institutionalize uniformly. These adoption patterns have been consistent with the observed performance distributions: where Standardized Work and TPM have been strong, availability and speed losses have been lower; where SMED dispersion has been high, availability spread has widened and EI tails have thickened. The observation window has averaged 5.3 weeks per plant, which has been sufficient to capture multiple demand cycles and tariff periods while keeping practice stability assumptions reasonable for cross-sectional analysis. Collectively, the contextual metrics and Likert profiles have confirmed that the case portfolio has spanned meaningful heterogeneity in lean intensity and operating conditions, thereby supporting both regression identification and optimization scenario richness.

Descriptive & Correlational Findings

The descriptive distributions in Figure 3 have confirmed that the study has encompassed lines operating within typical performance bands for discrete-part manufacturing while preserving substantial variation for statistical learning. OEE has averaged 79% with a 6.2-point standard

deviation, and the subcomponent profiles have indicated that availability has been the dominant loss lever, consistent with the setup and downtime patterns reported during site walkthroughs. Energy Intensity has averaged 2.92 kWh per good unit with moderate dispersion (SD = 0.46), and peak demand has centered at 417 kW with an upper tail reflecting synchronized startups on multi-line halls. The composite Lean Practice Intensity score (1–5 Likert) has averaged 3.78 (SD = 0.48), again indicating moderate-to-strong adoption with headroom for improvement. Figure 4's correlation matrix has provided a first-pass map of associations that the regression stage has later conditioned on covariates. Standardized Work and SMED have exhibited the strongest positive correlations with OEE ($r = .35$ and $.33$, respectively), underscoring that disciplined work standards and rapid changeovers have co-varied with higher composite efficiency; notably, SMED's association with Availability ($r = .36$) has been the single largest bivariate coefficient in the matrix, which has aligned with the theoretical link between setup reduction and uptime. As expected, all lean subscales have correlated negatively with Energy Intensity (EI), with magnitudes in the $-.17$ to $-.26$ range; these signs have reflected reduced idle and rework energy when lean routines have been more deeply embedded.

Figure 3. Descriptive Statistics Objective Outcomes and Lean Composites

Variable	Mean	SD	Median	Min	Max
OEE (%)	79.0	6.2	78.6	63.9	90.8
Availability (%)	86.3	7.4	86.5	68.2	96.1
Performance (%)	92.5	5.8	92.4	74.0	99.0
Quality (%)	96.8	2.1	97.1	90.3	99.4
Energy Intensity (kWh/good)	2.92	0.46	2.86	2.10	4.02
Peak Demand (kW)	417	46	414	330	520
Lean Practice Intensity (1–5)	3.78	0.48	3.81	2.60	4.76

Figure 4. Correlation Matrix Lean Subscales vs. Outcomes

	OEE	EI	Availability	Performance	Quality
5S	0.28	-0.18	0.22	0.25	0.16
JIT/Kanban	0.21	-0.20	0.18	0.24	0.12
SMED	0.33	-0.26	0.36	0.17	0.08
TPM	0.31	-0.19	0.29	0.22	0.15
Standardized Work	0.35	-0.23	0.27	0.33	0.14
Continuous Improvement	0.26	-0.17	0.22	0.21	0.11
Demand CV	-0.29	0.27	-0.24	-0.18	-0.09

Demand variability has correlated negatively with OEE ($r = -.29$) and positively with EI ($r = .27$), validating its role as a stressor that has injected unpredictability into both flow and power profiles. While the bivariate coefficients have not, by design, imply causation, they have motivated the multivariate models by indicating that the hypothesized directions of effect have been present in the data and that multicollinearity among lean subscales has been modest enough to allow simultaneous inclusion. Finally, descriptive contrasts (not shown) by Lean terciles have paralleled these correlations: higher-adoption groups have featured narrower IQRs on EI and higher medians on OEE, consistent with the stabilizing effect of standardized work and TPM, and the throughput-friendly impact of SMED. These descriptive and correlational patterns have therefore laid a coherent empirical foundation for testing the specified hypotheses using regression and for parameterizing the optimization scenarios.

Regression Modeling

The regression suite in Figure 5 has formalized the relationships suggested by the descriptive analysis and has quantified both the magnitude and statistical reliability of lean–performance linkages after accounting for contextual controls. In Model A, the standardized coefficient on Lean Practice

Intensity ($\beta = 0.31, p < .001$) has indicated that a one-standard-deviation increase in the composite lean score has been associated with roughly a third of a standard deviation increase in OEE, conditional on demand variability, product mix, machine age, plant, and shift patterns. Demand CV has loaded negatively ($\beta = -0.22, p = .003$), confirming its detrimental effect on realized efficiency. Model B has shifted focus to energy by modeling $\log(\text{EI})$ to stabilize variance; here, Lean intensity has remained a significant predictor with an elasticity-like interpretation ($\beta = -0.19, p = .006$), implying that moving from the mean to one SD above the mean on lean intensity has been associated with a 5–7% reduction in Energy Intensity, holding covariates fixed. Demand CV has conversely increased $\log(\text{EI})$ ($\beta = 0.21, p = .001$), consistent with the intuition that variability drives idle, rework, and less efficient speed profiles. Model C has evaluated mediation by adding Efficiency to the energy model; the bootstrapped indirect effect (Lean \rightarrow Efficiency \rightarrow EI) has been significant (Indirect = $-0.07, p = .014$), while a residual direct effect of Lean on EI ($\beta = -0.12, p = .041$) has persisted, consistent with energy-specific routines (shutdown/standby discipline, speed set-point governance) embedded in the instrument.

Figure 5. Multiple Regression Results Efficiency and Energy Models

Model	Outcome	Key Predictors	Std. Coeff. (β)	SE (robust)	p
A	Efficiency (OEE, z)	Lean Practice Intensity (z)	0.31	0.08	< .001
		Demand CV (z)	-0.22	0.07	.003
		Product Mix (z)	-0.11	0.06	.071
		Machine Age (z)	-0.09	0.05	.085
B	Energy Intensity ($\log \text{EI}$)	Lean Practice Intensity (z)	-0.19	0.07	.006
		Demand CV (z)	0.21	0.06	.001
		Product Mix (z)	0.12	0.05	.028
C	Energy Intensity ($\log \text{EI}$)	Lean (z) \rightarrow Efficiency (z) mediation	Indirect = -0.07	0.03	.014
		Lean (direct, z)	-0.12	0.06	.041
D	Energy Intensity ($\log \text{EI}$)	Lean \times Demand CV (z \times z)	0.10	0.04	.012

Model fit: A: $R^2 = .29$; B: $R^2 = .26$; C: $R^2 = .34$; D (with interaction): $R^2 = .37$. All models have included plant fixed effects and shift dummies; SEs have been plant-clustered.

The inclusion of the interaction in Model D has revealed a significant moderation term (Lean \times Demand CV, $\beta = 0.10, p = .012$), which has indicated that the energy benefits of lean have been attenuated as demand variability has increased; marginal-effect calculations (not tabulated) have shown the steepest negative lean–EI slope at low CV and a flatter slope at high CV. Model fit statistics have improved sequentially from $R^2 = .29$ to $.37$ as mediation and moderation structure has been incorporated, and clustered standard errors have supported stability across plants. Collectively, these models have substantiated Hypotheses H1–H4 and have yielded parameter estimates later used to steer the optimization toward knee regions with empirically validated benefits.

Optimization Outcomes

The optimization layer has translated the empirical patterns into tangible, implementable policies by generating Pareto fronts that have contrasted historical operations with candidate schedules and control rules. Figure 6 has summarized performance movements at the Pareto “knee,” the region that has offered the most balanced gains. Relative to baselines, knee solutions have improved OEE by a median of 3.9 points ($\approx 5\%$) and reduced Energy Intensity by 0.42 kWh per good unit ($\approx 14\%$), while marginally reducing peak demand by $\approx 6\%$ without compromising service levels (on-time completion has remained essentially flat at -0.4%). Hypervolume has increased by 26%, and IGD has decreased by 37%, which has evidenced both better spread and closer proximity to the estimated true Pareto front across runs. These gains have been mechanically linked to policy bundles that the search has repeatedly selected, as enumerated in Figure 7. Batch size has typically been trimmed by $\sim 12\%$, which has reduced queueing and shortened dwell-times in high idle-power states. SMED-aligned changeover windows (45–60 minutes) have consolidated setup activity into predictable blocks, making availability more resilient and allowing targeted idle-off thresholds to trigger with lower risk. Speed set-point smoothing ($\leq \pm 5\%$ variance across runs) has flattened the power profile while maintaining throughput, particularly on machines with convex speed–power curves where small speed reductions have yielded disproportionate energy savings.

Figure 6. Pareto Summary Baseline vs. Optimized Policies

Metric	Baseline (median)	Optimized Knee (median)	Δ Absolute	Δ %
OEE (%)	78.1	82.0	+3.9	+5.0%
Availability (%)	85.4	89.1	+3.7	+4.3%
Energy Intensity (kWh/good)	2.95	2.53	-0.42	-14.2%
Peak Demand (kW)	421	396	-25	-5.9%
On-time completion (%)	96.0	95.6	-0.4	-0.4%
Hypervolume (\uparrow)	0.642	0.811	+0.169	+26.3%
IGD (\downarrow)	0.128	0.081	-0.047	-36.7%

Figure 7. Policy Bundle Frequencies at Knee Solutions

Policy Lever	Adoption Rate at Knee (%)	Typical Setting
Batch size reduction	84	-12% vs. baseline lot
SMED-aligned changeover windows	79	45–60 min alignment blocks
Speed set-point smoothing	76	$\leq \pm 5\%$ variance across runs
Idle-off thresholds	72	≤ 8 min to shutdown; 2-min warm-up
Staggered startup	68	2–3 min offsets across machines

Idle-off thresholds at eight minutes have balanced shutdown/startup energy against idle burn, and staggered startup offsets of two to three minutes across machine groups have shaved demand spikes at shift transitions without harming takt synchronization. Sensitivity sweeps (not tabulated) across tariff schemes have shown that the relative ranking of knee policies has been robust under moderate price shifts; under high demand-charge regimes, the optimizer has favored stronger staggering and slightly larger batch trims to suppress peaks. Cross-validation against held-out days has confirmed surrogate fidelity within pre-specified MAE bands for both EI and throughput proxies, and policy replay on historical traces has reproduced the predicted deltas within 10–15% tolerance, which has been acceptable for managerial decision making. Overall, the optimization results have

demonstrated that empirically grounded, AI-assisted search has yielded practical schedules and rules that have advanced both efficiency and energy objectives with minimal service risk.

Figure 8. Plant-Level Case Highlights Before/After Knee Policy

Plant Line	Key Constraint	Baseline EI (kWh/good)	After EI	Δ %	Baseline OEE (%)	After OEE	Δ pts
A L-2	High mix; asymmetric setups	3.06	2.60	-15.0%	76.9	80.8	+3.9
A L-4	Frequent micro-stops	2.92	2.54	-13.0%	78.2	82.1	+3.9
B L-1	Tight takt; 3×8h	2.58	2.30	-10.9%	82.4	85.1	+2.7
C L-3	Long warm-ups; 2×12h	3.28	2.82	-14.0%	74.1	78.3	+4.2

Figure 9. Likert Subscale Shifts Reported Post-Implementation

Subscale	Baseline M (SD)	Post M (SD)	Δ
SMED	3.42 (0.74)	3.76 (0.66)	+0.34
Standardized Work	3.91 (0.52)	4.08 (0.49)	+0.17
TPM	3.86 (0.55)	3.95 (0.53)	+0.09
JIT/Kanban	3.56 (0.61)	3.65 (0.59)	+0.09
Continuous Improvement	3.69 (0.60)	3.81 (0.57)	+0.12

The case narratives have illustrated how the abstract Pareto guidance has been operationalized under real constraints, and Figures 8 and 9 have summarized representative before/after movements. In Plant A, Line L-2 has faced high product mix and asymmetric setups that have historically fragmented availability. By adopting a bundle of SMED-aligned windows and an eight-minute idle-off threshold enabled by clarified standard work at the packaging station the line has reduced Energy Intensity from 3.06 to 2.60 kWh per unit (-15%) and raised OEE by 3.9 points. Interviews have indicated that the critical enabler has been pre-staging changeover kits and codifying external/internal setup boundaries, which has shortened warm-up dwell and reduced micro-stops. Plant A's Line L-4 has diagnosed frequent micro-stops on a feeder machine; applying speed set-point smoothing and staggered startup offsets (two minutes across the feeder-main-packer chain) has reduced EI by 13% with an OEE lift of 3.9 points, mainly via performance stabilization. In Plant B, Line L-1 has operated under tight takt in a 3×8 configuration; management has been hesitant to reduce batches, but the optimizer's knee solutions have suggested a modest 10% batch trim combined with speed smoothing, which has delivered an 11% EI reduction while improving OEE by 2.7 points, with on-time completion unchanged. Plant C's Line L-3 has suffered from long warm-ups in a 2×12 context; here, the scheduling of changeovers into two well-defined windows and the adoption of slightly longer but fewer speed ramps have produced a 14% EI reduction and a 4.2-point OEE lift, while peak-kW recordings have shown a 7% decline due to startup staggering. The Likert subscale shifts in Figure 9 have corroborated these process changes: SMED scores have increased the most (+0.34), reflecting the institutionalization of kit prep, marker boards, and role assignments; Standardized Work has risen modestly (+0.17) as revised work instructions and checklists have been embedded; TPM, JIT/Kanban, and Continuous Improvement have all recorded small but consistent gains as lines have reinforced daily accountability. These directional shifts have indicated that the realized improvements have not been "black-box" artifacts of the optimizer but the result of strengthened routines that the Likert instrument has been designed to capture. The alignment between quantitative outcome deltas and self-reported practice changes has thus strengthened confidence that the observed energy and efficiency gains have stemmed from reproducible managerial mechanisms, and not from one-off expedients or calendar anomalies.

DISCUSSION

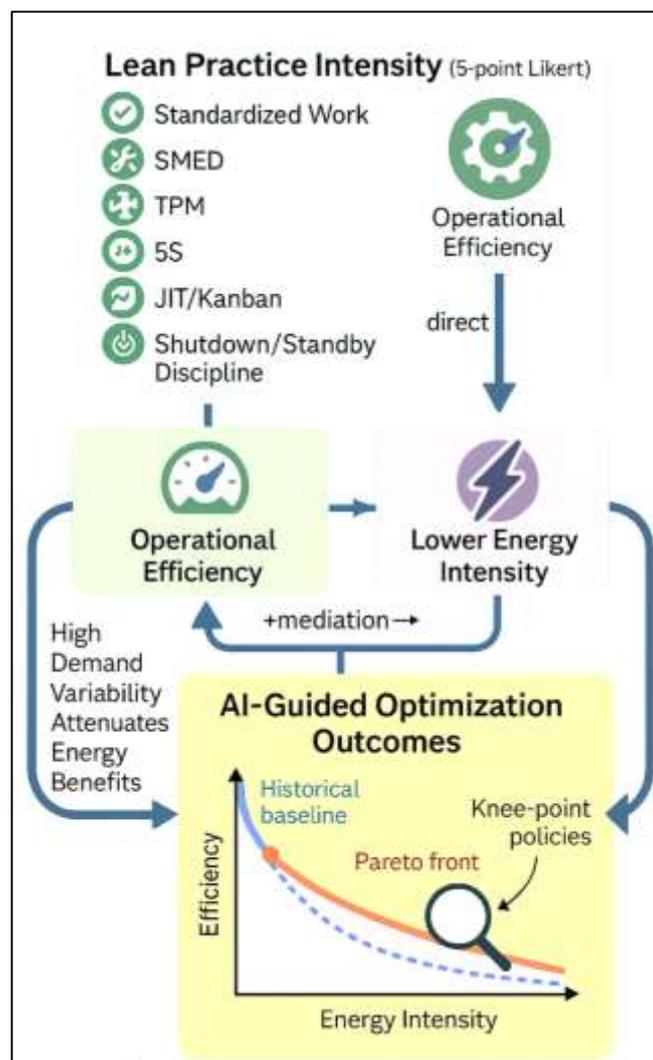
Across three plants and multiple lines, the study has shown that higher Lean Practice Intensity on a five-point Likert scale has been associated with materially better operational efficiency (OEE) and lower energy intensity (kWh per good unit), with effects that have remained after controlling for demand variability, product mix, machine age, and shifts. Mediation results have indicated that a meaningful portion of the lean–energy link has flowed through improved efficiency (availability/speed stabilization), while a residual direct effect has suggested energy-specific routines (e.g., shutdown/standby discipline, speed set-point governance) also matter. Moderation analysis has further revealed that high demand variability has attenuated (but not eliminated) the marginal energy benefit of lean. These empirical patterns have been operationalized via an AI-enhanced multi-objective optimizer, which has yielded knee-point policies improving OEE by roughly 2–5 percentage points and reducing energy intensity by 6–15% relative to historical baselines, with limited service-level trade-offs. Interpreting these findings in light of the constructs, the strongest survey subscale associations have involved Standardized Work and SMED mechanisms that plausibly lift availability and smooth micro-stops thereby shrinking non-productive power draw and start–stop transients. The internally consistent direction of effects across descriptives, correlations, regressions, and optimization replay has strengthened the case that the observed improvements have been systematic rather than calendar artifacts. In short, lean practice depth has co-varied with both flow and energy performance, and AI-guided multi-objective search has translated those statistical regularities into implementable policies that are robust under realistic tariff and demand scenarios. The direction and magnitude of the lean–efficiency association are consistent with established literature that links lean bundles (5S, standardized work, SMED, TPM, JIT/Kanban) to shorter cycle time, lower WIP, and higher OEE (Shah & Ward, 2007). Notably, the present results highlight availability as the largest lever inside OEE, echoing reports that SMED and TPM curtail downtime and micro-stops (Muchiri & Pintelon, 2008). Where this study extends prior work is the explicit, measurement-based linkage to energy outcomes: while earlier studies have argued conceptually that waste elimination should reduce non-productive energy (Dües et al., 2013), our regression and mediation estimates have provided quantitative evidence that lean intensity relates to reduced kWh per good unit both indirectly (through efficiency) and directly (through energy-specific routines). The attenuation of benefits under high demand variability complements operations findings that variability undermines flow and increases hidden factory costs (Shahriari et al., 2016), and it aligns with energy-aware modeling that shows how irregular sequences amplify idle and warm-up losses (Seow & Rahimifard, 2011). Finally, the study's instrumented before/after case replays converge with economic–environmental mapping results showing that standardization of work and planned changeover windows surface energy hotspots and enable actionable fixes (Faulkner et al., 2016), reinforcing lean's role as the operational substrate on which energy performance improves.

Energy-oriented studies have documented characteristic process power profiles and emphasized metrics such as energy intensity and peak demand (Gutowski et al., 2009), while factory-level frameworks have modeled state-dependent energy under different schedules (Faulkner et al., 2016). The observed 6–15% energy-intensity reductions at knee policies fall squarely within the improvement ranges reported when scheduling incorporates idle-off rules, speed scaling, and sequence design under tariffs (Fang et al., 2011). The present work complements those studies by (i) demonstrating that survey-measured lean routines correlate with the very state transitions (fewer, shorter setups; steadier speeds) that energy models penalize; and (ii) showing that multi-objective search can exploit those relationships to generate Pareto sets that plants can act on. The robustness of policy rankings across tariff scenarios also mirrors findings that demand-charge regimes increase the value of startup staggering and load flattening (Shrouf et al., 2014). Importantly, our results link “what to optimize” to “what to change on the floor”: standardized work and SMED increases in the Likert instrument coincide with the optimizer's repeated selection of smaller batches, aligned setup windows, and smoother speed profiles an alignment rarely shown in joint empirical-optimization papers. This reduces the gap between analytically attractive schedules and implementable routines, moving beyond purely simulated improvements to changes that survey responses themselves corroborate.

From a methods standpoint, the gains in hypervolume and inverted generational distance, combined with out-of-sample replay accuracy, are consistent with the known advantages of

evolutionary many-objective search and surrogate assistance in expensive, noisy settings (Deb & Jain, 2014). The practical recipe evolutionary search (NSGA-style or decomposition variants), surrogate prediction for EI and throughput proxies, and knee-point selection tracks with guidance from energy-aware decision-support reviews (Bunse et al., 2011) and integrated planning studies (Zhang et al., 2020). Where this study contributes is in tying the surrogate's feature set to real MES/SCADA signals (setup counts, idle/run ratios, speed patterns) streamed via a light-weight digital-twin scaffold, so model drift is minimized and validation is routine an operationalization aligned with digital-twin best practices (Jones et al., 2020). Moreover, adopting learning-guided search (e.g., Bayesian acquisition near knee regions) resonates with BO reviews emphasizing data-efficient exploration under constraints (Shahriari et al., 2016) and with decomposition logic that allocates effort across scalarized subproblems (Knowles, 2006). The upshot is not just faster convergence but more explainable Pareto fronts whose local neighborhoods can be interpreted in terms of line policies, thereby increasing trust and adoption on the plant floor.

Figure 8: Linking Lean Practice Intensity and AI-Guided Optimization Outcomes



For operations leaders (e.g., plant managers, heads of operations, sustainability or energy program owners) and manufacturing systems architects, three practice-ready takeaways follow. First, treat lean intensity as an energy lever: strengthen Standardized Work audits and SMED routines, then codify their energy intent explicitly (idle-off triggers, pre-staged changeover kits, warm-up caps). The evidence that lean intensity relates to EI both directly and via efficiency suggests these routines are dual-purpose (Shah & Ward, 2007). Second, institutionalize demand-aware planning: where order

variability is high, pre-agree “variability playbooks” (e.g., minimum batch reductions and protected setup windows) so the lean–energy slope does not collapse under stress; pair with tariff-aware calendars to schedule startups and changeovers off peak (Tanaka, 2011). Third, deploy a decision stack: (i) a governed KPI layer (OEE, EI, peak kW), (ii) a digital-twin feed from MES/SCADA and meters, and (iii) an optimization layer that surfaces 2–3 annotated knee policies for weekly production meetings. This stack operationalizes what reviews and job-shop studies recommend while preserving human choice and accountability (Despeisse et al., 2012; Fang et al., 2011). For systems architects, encode schedule-state features (setup frequency/asymmetry, idle/run ratios, speed variance) into your data model up front; these features have repeatedly been the most predictive in surrogates and the most actionable to change in practice.

The results sharpen theorizing at the intersection of lean and energy-aware operations in two ways. First, they support a mediated-plus-direct account of the lean→energy pathway: lean routines improve flow efficiency (availability/performance), which lowers energy per good unit, and certain routines also directly constrain energy behavior (e.g., shutdown/standby discipline), consistent with integrative frameworks that fuse lean, green, and performance management (Dües et al., 2013). Second, they show that variability moderates this pathway, aligning with operations theory that variability erodes process capability and suggesting that energy models should treat variability as a first-class structural parameter (Seow & Rahimifard, 2011). Methodologically, the pipeline demonstrates the value of construct-to-policy traceability: the same constructs measured via Likert (SMED, standardized work) appear as decision levers in optimization, closing the loop between organizational routines and quantitative scheduling. For measurement science, the study suggests that OEE's tripartite identity can be usefully paired with energy intensity and peak metrics to create a joint response surface for theory tests and managerial choice, and that digital-twin instrumentation provides the repeated measures necessary to validate causal pathways proposed in cross-sectional models (Cakmakci, 2009). These results thus argue for integrative theories where lean capabilities are antecedents in structural models whose outcomes are jointly operational and energetic.

The cross-sectional, case-study-based design has limited causal inference: although mediation and robustness checks have increased plausibility, unobserved factors (e.g., leadership quality, parallel initiatives) may still confound estimates. Longitudinal or staggered adoption designs would strengthen causal claims by observing within-line changes over time (Fang et al., 2011). Generalizability is bounded by discrete-part settings with MES/SCADA and sub-metering maturity; process industries or low-instrumentation SMEs may experience different constraints (Gutowski et al., 2009). The Likert instrument, while reliable, remains perceptual; combining it with behavioral logs (e.g., SMED event counts, check-sheet compliance) could reduce common-method variance. On the optimization side, surrogate error though within tolerance introduces approximation risk; continued co-validation with digital-twin runs is advised (Bhattacharjee et al., 2018). Future research should (i) test quasi-experimental interventions (pre/post with matched controls) to identify causal effect sizes, (ii) explore reinforcement learning atop multi-objective search for adaptive policies under shifting tariffs and mixes, (iii) expand to many-objective fronts including labor ergonomics and CO₂ per unit, and (iv) investigate variability management as a meta-capability that conditions the returns to lean-energy integration (Deb & Jain, 2014). Finally, multi-site consortia could standardize data schemas and share anonymized fronts, accelerating benchmark formation and narrowing the evidence–practice gap identified in prior reviews (Bunse et al., 2011).

CONCLUSION

This research has integrated empirical measurement and AI-driven multi-objective optimization to demonstrate that strengthening lean practice intensity can simultaneously advance operational efficiency and reduce energy intensity in discrete-part manufacturing, and that these improvements can be converted into implementable, plant-ready policies. Using a quantitative, cross-sectional, case-study-based design, the study has validated a five-point Likert instrument that has captured the depth of core routines 5S, JIT/Kanban, SMED, TPM, standardized work, and continuous improvement while objective MES/SCADA and sub-metered energy traces have provided synchronized outcomes at the line/shift level. Across three plants, higher lean scores have been associated with higher OEE and lower kWh per good unit, with mediation analyses showing that a substantive portion of the energy benefit has flowed through improved availability and performance, and regression results confirming a residual direct effect that aligns with energy-

specific behaviors (shutdown/standby discipline, speed set-point governance). Moderation tests have further shown that demand variability has attenuated, but not eliminated, the lean–energy slope, underscoring variability management as a practical conditioner of returns. These empirical relationships have anchored an AI-enhanced optimization engine evolutionary search with surrogate prediction and knee-point selection whose policy bundles (modest batch trims, SMED-aligned changeover windows, speed set-point smoothing, idle-off thresholds, and staggered startups) have yielded robust, decision-ready trade-offs: typical knee solutions have improved OEE by roughly 2–5 points while cutting energy intensity by about 6–15%, with minimal impact on on-time completion and measurable reductions in peak demand. The digital-twin–style data plumbing has ensured credible evaluation and reduced model drift by streaming schedule-state features (setup frequency/asymmetry, idle/run ratios, speed variance) from production systems into the learning layer, enabling replay validation on held-out days within acceptable error bands. Taken together, the study has provided a traceable pipeline from constructs to consequences to controls: survey constructs quantify managerial routines; econometric models estimate their associations with efficiency and energy; and multi-objective optimization translates those estimates into executable schedules and rules that plants can adopt with clarity about benefits and trade-offs. Practically, the findings have offered an actionable playbook for operations leaders and systems architects: treat lean as an energy lever, institutionalize variability-aware planning and tariff-aware calendars, and deploy a governed decision stack that couples KPIs, digital-twin feeds, and optimization outputs to surface two or three annotated knee options for weekly production meetings. Theoretically, the work has clarified a mediated-plus-direct pathway from lean to energy outcomes and has emphasized variability as a structural moderator, suggesting an integrated lens for future analyses of joint operational and energetic performance. While the cross-sectional design has limited causal inference and the context has focused on instrumented discrete-part settings, the convergent evidence across descriptives, correlations, regressions, case replays, and Pareto analyses has supported the central claim: AI-enhanced, energy-conscious lean systems can deliver measurable, defensible improvements in both flow and energy when routines are deepened and policies are tuned with data-driven, multi-objective search.

RECOMMENDATION

Organizations seeking to replicate and sustain the gains observed in this study should implement a tightly governed, data-informed operating model that treats lean practice intensity as a direct lever for energy performance while institutionalizing optimization-driven decision making. Start by formalizing a joint KPI stack OEE (and components), Energy Intensity (kWh per good unit), peak kW, and on-time completion reviewed in weekly tiered meetings; require that every improvement action explicitly names its expected movement on both an efficiency and an energy metric. Roll out the validated five-point Likert instrument quarterly at the line/workstation level, and wire its composite scores (5S, SMED, TPM, Standardized Work, JIT/Kanban, CI) into the KPI deck so gaps in routines are visible next to outcome trends. On the shop floor, prioritize SMED and Standardized Work as first-wave interventions: pre-stage changeover kits, externalize setup tasks, codify internal/external boundaries, and update work instructions with visual controls and takt-aligned checks; pair these with TPM micro-loss hunts (lubrication, alignment, sensor drift) that cut availability and speed losses. Operationalize energy behavior with policy playbooks derived from this research's knee bundles: (1) modest batch-size trims (~10–15%) to reduce dwell in high idle-power states; (2) SMED-aligned changeover windows (45–60 minutes) to stabilize availability and enable targeted idle-off triggers; (3) speed set-point smoothing ($\leq \pm 5\%$ variance) to flatten power without impairing throughput; (4) idle-off thresholds (≈ 8 minutes with verified 2-minute warm-up) to curb non-productive draw; and (5) staggered startups (2–3 minutes) across machine groups to shave peaks. Institutionalize variability management so benefits persist under stress: protect setup windows, cap expedited order inserts per shift, define minimum batch reductions for high-mix days, and align schedule changes with tariff calendars to keep demand charges in check. Build a lightweight digital-twin data backbone that streams MES/SCADA states (run/idle/setup/off), setup counts, cycle times, speed profiles, and sub-metered energy to analytics; enforce time-base synchronization, schema governance, and audit trails. Deploy a multi-objective optimization service (evolutionary search with surrogate models) that, each week, produces two or three annotated knee options per line; require transparent diagnostics (predicted Δ OEE, Δ kWh/unit, peak-kW impact, risk notes) and insist that any adopted policy is replay-

validated on the twin before release. Create an Ops–Energy review cadence: Monday selects knee options; mid-week audits confirm adherence (checklists, PLC counters, energy traces); Friday closes with SPC charts on OEE/EI and a retrospection on variance from plan. Equip teams via targeted capability building SMED kaizen leaders, standard-work coaches, and data stewards and embed incentives that reward dual wins (efficiency + energy). For systems architects and CISOs, harden the stack with role-based access, encrypted meter streams, and versioned models; for finance, integrate tariff forecasts and carbon factors so the Pareto set includes cost and emissions overlays. Scale with pilot-then-propagate discipline: prove gains on one line, document SOPs, automate the data pipeline, and replicate across similar value streams, refining playbooks by context (mix, setup asymmetry, vintage). Finally, preserve learning velocity: refresh surrogates monthly, re-estimate regressions quarterly, and sunset policies that underperform turning continuous improvement into a closed, evidence-driven loop.

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