Optimization of Production Control Based on Green Metrics to Reduce Production Emissions and Waste: A Multi-Objective Approach in the Wood-Processing Manufacturing Industry

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ABSTRACT

The manufacturing industry is a dominant contributor to global greenhouse gas emissions and industrial solid waste, necessitating a paradigm shift from output-centric to sustainability-integrated production management. This study develops and validates a multi-objective production control optimization model that embeds green metrics as core performance dimensions within the production decision-making framework of a wood-processing company in Kalimantan, Indonesia. The model integrates three simultaneous objective functions—minimizing CO_2-equivalent emissions, minimizing solid waste generation, and maximizing production output—subject to 18 operational, environmental, and regulatory constraints and governed by 28 decision variables. Green metrics dimensions were prioritized through the Analytical Hierarchy Process (AHP), yielding weights of 0.342 (greenhouse gas emissions), 0.261 (solid waste management), 0.198 (energy efficiency), 0.124 (water consumption), and 0.075 (material toxicity), with a Consistency Ratio of 0.043, confirming reliable expert judgment. Environmental waste streams were identified using the Green Value Stream Mapping (G-VSM) method, revealing four previously undetected waste categories including volatile organic compound (VOC) emissions and unrecovered wood-dust biomass. Model validation against three months of historical production data demonstrated a prediction accuracy of 94.7%, with parametric stability maintained at ±15% variation. Following six months of staged implementation (January–June 2024), CO_2eq emissions declined by 28.6% (from 4,782 to 3,412.8 ton/yr), solid waste decreased by 34.2% (from 1,467.4 to 965.8 ton/yr), and energy consumption fell by 22.4% (from 7,518.3 to 5,831.0 MWh/yr)—all exceeding predetermined targets. Simultaneously, production output increased by 18.3% and operating costs decreased by 15.7%. Emission intensity was reduced from 76.6 to 46.2 kg CO_2eq/m³, placing the company below the Southeast Asian industry benchmark of 58.3 kg CO_2eq/m³ (UNIDO, 2023). Financial analysis indicates a payback period of 7.4 months and a Net Present Value of IDR 18.9 billion over five years. These findings affirm that green metrics-integrated production control delivers simultaneous environmental and economic performance improvements, offering a replicable framework for sustainable manufacturing transformation.

Keywords : Carbon Emissions Reduction; Green Metrics; Green Value Stream Mapping; Multi-Objective Programming; Production Control Optimization; Sustainable Manufacturing; Wood-Processing Industry.

INTRODUCTION

The manufacturing sector constitutes one of the primary sources of anthropogenic greenhouse gas (GHG) emissions and industrial solid waste globally. According to the Intergovernmental Panel on Climate Change (IPCC, 2022), manufacturing activities account for approximately 23% of global CO_2 emissions, with material transformation processes, thermal energy generation, and waste handling representing the most significant emission pathways. In emerging economies such as Indonesia—where the manufacturing sector contributed 19.3% of GDP in 2023 (BPS, 2023)—industrial growth has historically been pursued with insufficient consideration of environmental externalities, resulting in progressively degrading ecosystem quality and increasing regulatory and reputational risk for manufacturing enterprises.

Production control, defined as the systematic coordination of manufacturing inputs, processes, and outputs to achieve planned targets within specified constraints, has traditionally been optimized against singular economic objectives such as throughput maximization and unit cost minimization. This narrow

optimization focus has frequently resulted in resource-inefficient operating points characterized by excessive energy consumption, sub-optimal material utilization, and unquantified emission burdens. The emergence of green manufacturing as a strategic paradigm challenges this convention by asserting that environmental performance indicators must be embedded within—rather than appended to—the production management system (Chandrahadinata & Fadilah, 2025; Rajak et al., 2022).

Green metrics, as a structured set of quantitative environmental performance indicators, provide an operational mechanism for integrating ecological accountability into production decision-making. They encompass dimensions such as carbon emission intensity, material utilization efficiency, solid waste generation per production unit, energy consumption per output, water withdrawal intensity, and toxicological footprint of materials (Hardini et al., 2022). When embedded within a multi-objective optimization framework, green metrics enable production planners to simultaneously pursue economic efficiency and environmental stewardship—a condition increasingly demanded by international trade partners, regulatory bodies, and socially conscious consumers.

Despite the theoretical maturity of green manufacturing concepts, empirical evidence from the Indonesian manufacturing sector reveals a significant implementation gap. A study by Kusumawati et al. (2022) found that only 23% of medium-to-large manufacturing enterprises in Kalimantan had implemented a standardized environmental management system, constrained by limited technical capacity for environmental impact measurement and perceived high implementation costs. The wood-processing sector—a strategically important industry in East Kalimantan given the region's forestry resources—remains particularly underserved in terms of green metrics integration, despite generating substantial process emissions and lignocellulosic waste streams.

The novelty of this research lies in the development of a validated, multi-objective production control optimization model that simultaneously minimizes CO_2eq emissions, minimizes solid waste, and maximizes production output within a unified mathematical framework adapted to the operational realities of the Indonesian wood-processing industry. The model incorporates green metrics priorities determined through Analytical Hierarchy Process (AHP) weighting and integrates environmental waste identification via Green Value Stream Mapping (G-VSM). Unlike prior studies that optimize a single environmental objective or treat environmental performance as a post-hoc analysis, this approach embeds environmental constraints directly into the objective function architecture, ensuring that environmental performance is structurally—rather than incidentally—improved through production scheduling decisions.

The primary research objectives are: (1) to develop a multi-objective linear programming (MOLP) model integrating quantified green metrics into the production control framework; (2) to determine the relative priority weights of green metrics dimensions using AHP; (3) to identify and classify environmental waste streams along the production process using G-VSM; (4) to validate the model against actual production conditions and implement it across a six-month operational period; and (5) to evaluate the environmental, operational, and financial outcomes of model implementation and derive generalizable insights for sustainable manufacturing practice.

LITERATURE REVIEW

Green Manufacturing and the Sustainability Imperative in Industry

Green manufacturing is broadly defined as a production paradigm that systematically seeks to minimize the negative environmental impacts of manufacturing activities through the adoption of efficient, resource-conserving, and pollution-preventing processes and product designs (Rajak et al., 2022). As articulated by Prasetyo et al. (2019, as cited in Chandrahadinata & Fadilah, 2025), the core objective of green manufacturing is the creation of goods through production processes that carry the minimum feasible negative environmental footprint—encompassing emissions to air, water, and land; solid waste generation; energy intensity; and toxicological risk to workers, communities, and ecosystems.

The operationalization of green manufacturing at the process level requires the adoption of quantitative environmental performance measurement systems. Without structured measurement, improvement initiatives remain qualitative and non-accountable. Kusumawati et al. (2022) demonstrated through empirical analysis that the principal barriers to environmental management system adoption in Kalimantan's manufacturing

sector are instrumental rather than motivational: enterprises generally recognize the strategic value of environmental performance but lack the technical infrastructure to measure, monitor, and manage it systematically. This finding underscores the critical role of green metrics as an enabling technology for green manufacturing implementation.

At the institutional level, green manufacturing practices are increasingly mandated by international regulatory frameworks, including the European Union's Carbon Border Adjustment Mechanism (CBAM, 2023), which imposes carbon tariffs on imported goods from countries without equivalent carbon pricing, and by voluntary international standards such as ISO 14001 (Environmental Management Systems) and ISO 50001 (Energy Management Systems). Indonesian manufacturing exporters are therefore subject to growing external pressure to demonstrate quantified environmental performance, making the integration of green metrics into production control not merely a sustainability aspiration but a competitive and regulatory imperative.

Life Cycle Assessment as an Environmental Accounting Framework

Life Cycle Assessment (LCA) is the methodological standard for quantifying the environmental burdens associated with a product or process across its entire life cycle, from raw material extraction through processing, use, and end-of-life disposal (ISO 14040:2006; ISO 14044:2006). LCA enables the identification of environmental hotspots—those life cycle stages that contribute disproportionately to total environmental impact—and supports the prioritization of improvement interventions. Putri (2017, as cited in Krisi et al., 2022) characterizes LCA as a systemic impact inventory methodology that generates actionable intelligence for the formulation of environmentally optimized production strategies.

Pedersen and Remmen (2022) demonstrated that the integration of LCA with Life Cycle Costing (LCC) provides decision-makers with a holistic environmental-economic performance picture, enabling cost-effective prioritization of decarbonization investments and identification of synergies between environmental improvement and cost reduction. This combined LCA–LCC approach is particularly relevant to the wood-processing industry, where thermal energy generation (kiln drying) and chemical use (finishing and coating processes) create both significant environmental burdens and addressable cost efficiency opportunities. The present study adopts LCA boundary definitions for emission factor assignment while incorporating LCC logic in the financial evaluation of model implementation outcomes.

Multi-Objective Optimization in Green Production Planning

Multi-objective linear programming (MOLP) provides a formal mathematical framework for the simultaneous optimization of multiple, potentially conflicting objective functions subject to a set of operational and regulatory constraints. In the context of green manufacturing, MOLP enables the formulation of production plans that balance environmental performance objectives—such as emission minimization and waste reduction—against conventional economic objectives such as output maximization and cost minimization (Alfarisi et al., 2023).

Alfarisi et al. (2023) applied MOLP to production planning in a major Indonesian cement manufacturer, developing a model with 12 decision variables and 8 constraint functions. Their results demonstrated CO_2 emission reductions of up to 22% without compromising production output, with the model maintaining solution stability across a parameter sensitivity range of ±15%. This foundational work establishes the viability and robustness of MOLP-based green production planning in the Indonesian industrial context, though the cement sector's relatively standardized process chemistry differs substantively from the multi-stage, material-diverse processes characteristic of wood processing.

The application of MOLP in wood-processing manufacturing introduces additional complexity arising from the variability of timber feedstock properties, the heterogeneity of product specifications, the multiple finishing chemistry systems employed, and the diversity of energy sources used across kiln drying, cutting, and assembly operations. The present study extends the MOLP framework to this more complex operational environment by incorporating a larger decision variable set ($n = 28$) and a more comprehensive constraint structure ($m = 18$), while maintaining the pasrametric stability requirements demonstrated by Alfarisi et al. (2023).

Green Value Stream Mapping for Environmental Waste Identification

Green Value Stream Mapping (G-VSM) extends the conventional lean manufacturing Value Stream Mapping (VSM) methodology by incorporating environmental waste flows—emissions, energy losses, water consumption, and chemical discharges—alongside the conventional waste categories of overproduction, waiting, transport, overprocessing, inventory excess, motion, and defect generation (Brown et al., 2014; Womack & Jones, 2003). G-VSM thus provides a comprehensive visual representation of both value creation and environmental burden across the production process, enabling the concurrent identification of productivity improvement and environmental reduction opportunities.

Hardini et al. (2022) demonstrated the diagnostic power of G-VSM in the Jepara furniture industry, identifying seven categories of environmental waste that had remained invisible to conventional VSM analysis. Their study found that targeted interventions against G-VSM-identified waste streams could achieve carbon emission reductions of 19.4% and annual energy cost savings of 23.1%. The present study applies G-VSM as the primary environmental waste identification tool in the baseline assessment phase, providing the empirical grounding for the subsequent development of the green metrics-integrated MOLP model.

Analytical Hierarchy Process for Multi-Criteria Decision Making

The Analytical Hierarchy Process (AHP), developed by Saaty (1980), is a structured multi-criteria decision-making (MCDM) methodology that enables the determination of relative priority weights among competing decision criteria through a systematic pairwise comparison process. AHP decomposes complex decisions into hierarchical structures and quantifies expert judgment through ratio-scale comparisons, with the reliability of the resulting weight vector assessed through the Consistency Ratio (CR), where $CR < 0.10$ is the accepted threshold for reliable judgment (Saaty, 1980).

In the context of green metrics prioritization, AHP enables the translation of expert knowledge—from production engineers, environmental managers, regulatory specialists, and sustainability officers—into quantified weight assignments that reflect the relative environmental significance and management controllability of each green metrics dimension. This weighting informs the objective function coefficients of the MOLP model, ensuring that the optimization prioritizes environmental improvement in dimensions of greatest strategic and ecological importance. The present study employs AHP as the primary weighting methodology, with consistency validation confirming the reliability of the expert panel judgments used.

RESEARCH METHOD

Research Design and Framework

This study adopts a mixed-methods, applied research design that integrates quantitative modeling with empirical measurement and structured expert elicitation. The research is structured in five sequential phases: (1) baseline environmental and production performance assessment; (2) environmental waste identification and mapping via G-VSM; (3) green metrics dimension weighting via AHP; (4) multi-objective optimization model development and validation; and (5) model implementation and post-implementation performance evaluation.

The research was conducted at a medium-scale wood-processing manufacturing company located in Samarinda, East Kalimantan, Indonesia, with an annual production capacity of approximately 62,400 m^3 of processed wood products. The company operates five primary production processes: wood drying (kiln operations), sawing and cutting, finishing and coating, assembly and gluing, and utilities and support systems. The baseline measurement period covered January to December 2023, while the implementation phase spanned January to June 2024.

Baseline Measurement Protocol

Baseline measurements of CO_2-equivalent emissions, solid waste generation, and energy consumption were conducted using instruments calibrated in accordance with Indonesian National Standard (SNI) requirements. Emission measurements employed indirect calculation methods based on energy consumption data and fuel-specific emission factors derived from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (Tier 2 approach), supplemented by direct VOC emission measurements from finishing and

coating operations using portable photoionization detector (PID) instrumentation. Solid waste was quantified through systematic mass balance analysis at each production stage, with waste streams categorized by type (lignocellulosic residues, chemical waste, wastewater sludge, and mixed waste) and disposition pathway (recovery, recycling, landfill, and controlled combustion).

Green Value Stream Mapping Application

G-VSM was applied following the methodology of Hartini and Ciptomulyono (2015), adapted to the wood-processing context. Current-state value stream maps were constructed for each of the five production processes, documenting material flows, information flows, process parameters, and environmental waste flows. Environmental waste flows included direct process emissions (CO_2, NO_x, VOC), energy losses (kiln heat losses, motor inefficiencies), solid waste generation rates, and wastewater discharge volumes. Future-state maps were developed to identify elimination and reduction opportunities for each identified environmental waste stream, forming the basis for the constraint structure of the MOLP model.

AHP-Based Green Metrics Weighting

An expert panel comprising seven specialists—two production engineers, two environmental management specialists, one regulatory compliance officer, one sustainability consultant, and one academic expert in industrial ecology—conducted pairwise comparisons of five green metrics dimensions: greenhouse gas (GHG) emissions, solid waste management (SWM), energy efficiency (EE), water consumption (WC), and material toxicity (MT). Comparisons were performed using Saaty's 1–9 fundamental scale, with individual comparison matrices aggregated using the geometric mean method (Saaty, 1980). The pairwise comparison matrix is presented in Table 1.

Table 1. AHP Pairwise Comparison Matrix for Green Metrics Dimensions

Dimension	GHG	SWM	EE	WC	MT
GHG	1	2	3	4	5
SWM	1/2	1	2	3	4
EE	1/3	1/2	1	2	3
WC	1/4	1/3	1/2	1	2
MT	1/5	1/4	1/3	1/2	1

Note: GHG = Greenhouse Gas Emissions; SWM = Solid Waste Management; EE = Energy Efficiency; WC = Water Consumption; MT = Material Toxicity

The Principal Eigenvector method was applied to derive normalized priority weights from the aggregated comparison matrix. Consistency checking was performed by calculating the Maximum Eigenvalue (λ_max), Consistency Index ($CI = (\lambda_max - n) / (n - 1)$), and Consistency Ratio ($CR = CI / RI$), where $RI = 1.12$ for $n = 5$ (Saaty, 1980).

Multi-Objective Linear Programming Model Formulation

1. Decision Variables

The model comprises 28 decision variables representing production volumes across product types ($p = 1, 2, ..., P$) and production routes ($j = 1, 2, ..., J$), utility consumption levels for $k = 1, 2, ..., K$ utility systems, defect rates by process (D_i), and waste recovery quantities by stream (R_m). Formally:

X_pj = Production volume of product type p on route j [m^3/period]
Y_k = Consumption level of utility system k [MWh/period or m^3/period]
D_i = Defect rate at process stage i [%]
R_m = Recovered waste quantity for stream m [ton/period]

2. Objective Function 1: Minimization of CO_2-Equivalent Emissions

The first objective function minimizes the total annual greenhouse gas emissions from all production processes and utility systems:

$$\text{Min } Z_1 = \Sigma_i \Sigma_j E_{ij} \cdot X_{ij} + \Sigma_k E_{uk} \cdot Y_k \quad (1)$$

Where:
E_{ij} = CO_2eq emission factor for process i on route j [kg CO_2eq/m^3]
X_{ij} = Production volume for process i on route j [m^3/period]
E_{uk} = CO_2eq emission factor for utility system k [kg CO_2eq/MWh or kg CO_2eq/m^3]
Y_k = Consumption level of utility system k [unit/period]

3. Objective Function 2: Minimization of Solid Waste Generation

The second objective function minimizes total solid waste generation from process losses and production defects:

$$\text{Min } Z_2 = \Sigma_i \Sigma_j W_{eij} \cdot X_{ij} + \Sigma_m W_defect_m \cdot D_m \quad (2)$$

Where:
W_{eij} = Process waste generation rate for process i on route j [ton/m^3]
W_defect_m = Waste mass generated per unit defect in process m [ton/unit]
D_m = Defect production volume at process stage m [m^3/period]

4. Objective Function 3: Maximization of Production Output Value

The third objective function maximizes the total value-weighted production output across all product types and routes:

$$\text{Max } Z_3 = \Sigma_p \Sigma_j Q_p \cdot X_{pj} \quad (3)$$

Where:
Q_p = Output value per unit of product type p [IDR/m^3]
X_{pj} = Production volume of product type p on route j [m^3/period]

5. Unified Weighted Objective Function

The three objective functions are unified into a single weighted composite objective using the AHP-derived green metrics weights, with the emission and waste minimization objectives normalized to positive maximization direction:

$$\text{Max } Z = w_1 \cdot (-Z_1_norm) + w_2 \cdot (-Z_2_norm) + w_3 \cdot Z_3_norm \quad (4)$$

Where:
w_1 = 0.342 (GHG emission weight from AHP)
w_2 = 0.261 (solid waste management weight from AHP)
w_3 = $(1 - w_1 - w_2 - w_4 - w_5)$ adjusted for production output
Z_norm = normalized objective value [0, 1]

6. Constraint Structure

The model is governed by 18 constraint functions organized into five categories: (1) machine capacity constraints per work shift (4 constraints); (2) raw material availability constraints (3 constraints); (3) maximum regulatory emission limits per process (4 constraints); (4) product quality standard constraints (4 constraints); and (5) energy use limits based on management efficiency targets (3 constraints). The general constraint form is:

$$\Sigma_j a_{ij} \cdot X_{ij} \leq b_i \quad \forall i \in \{\text{capacity, material, quality constraints}\} \quad (5)$$
$$\Sigma_j e_{ij} \cdot X_{ij} \leq E_i^{max} \quad \forall i \in \{\text{emission constraints}\} \quad (6)$$
$$\Sigma_k f_k \cdot Y_k \leq E_t^{otalmax} \quad \{\text{total energy constraint}\} \quad (7)$$
$$X_{ij} \geq 0, Y_k \geq 0, D_m \geq 0, R_m \geq 0 \quad \{\text{non-negativity constraints}\} \quad (8)$$

Model Validation Protocol

Model validation was conducted using three months of historical production, energy, and waste data (October–December 2023) not used in model calibration. The model's predicted emission, waste, and output values were compared against actual recorded values using the Mean Absolute Percentage Error (MAPE):

$$MAPE = (1/n) \cdot \Sigma |A_t - F_t| / |A_t| \times 100\% \quad (9)$$

Where:
A_t = Actual observed value in period t
F_t = Model-predicted value in period t
n = Number of validation periods

Sensitivity analysis was performed by systematically varying each model parameter by ±5%, ±10%, and ±15% from its calibrated value to assess solution robustness. A model was considered validated and deployable when MAPE ≤ 10% and parametric stability was maintained throughout the ±15% sensitivity range.

RESULT AND DISCUSSION

Baseline Environmental Performance Profile

The baseline measurement conducted over the full year 2023 established the initial environmental performance condition of the company. Total CO_2-equivalent emissions reached 4,782 tons/year for a production output of 62,400 m³, yielding an emission intensity of 76.6 kg CO_2eq/m³. This figure exceeds the Southeast Asian wood-processing industry average of 58.3 kg CO_2eq/m³ (UNIDO, 2024) by 31.4%, indicating substantial improvement potential relative to regional benchmarks and a wider gap of 98.7% relative to the global best practice standard of 38.5 kg CO_2eq/m³ identified in the same reference.

The distribution of emissions, waste generation, and energy consumption across production processes is presented in Table 2. The wood drying process was the dominant emission source, contributing 39.2% of total CO_2eq emissions, primarily attributed to thermal energy generation from biomass combustion in kiln operations. The sawing and cutting process was the second largest emission contributor (26.0%) and the principal generator of solid waste (894.2 ton/yr, representing 60.9% of total solid waste), with lignocellulosic residues—sawdust, offcuts, and bark—constituting the primary waste stream.

Table 2. Distribution of Emissions, Waste, and Energy Consumption by Production Process (2023 Baseline)

Production Process	CO_2eq Emissions (ton/yr)	Proportion (%)	Waste (ton/yr)	Energy (MWh/yr)
Wood Drying	1,876.3	39.2%	312.4	2,840.6
Sawing & Cutting Process	1,243.7	26.0%	894.2	1,920.3
Finishing & Coating	762.4	15.9%	128.8	1,240.8
Assembly & Gluing	524.8	10.9%	89.4	876.2
Utilities & Support	374.8	7.8%	42.8	640.4
Total	**4,782.0**	**100.0%**	**1,467.4**	**7,518.3**

Source: Compiled from direct measurement data (January–December 2023), calibrated per SNI standards.

The G-VSM analysis identified eleven waste streams distributed across the five production processes. Critically, four of these waste streams—representing 32.4% of total identifiable environmental burden—were not detectable through conventional lean VSM analysis and required the green metrics extension for their identification. These four novel waste streams were: (1) volatile organic compound (VOC) emissions from solvent-based coatings in the finishing process, estimated at 18.4 ton/yr in hydrocarbon equivalent; (2) wood dust and fine particle waste from sawing and cutting operations with viable biomass energy recovery potential; (3) wastewater containing dissolved wood extractives and adhesive residues from kiln condensate drainage; and (4) thermal energy losses from kiln exhaust gases attributable to sub-optimal heat recovery system performance. The discovery of these previously unmeasured waste streams substantiates the G-VSM methodology's superior diagnostic capability relative to conventional VSM in environmental waste identification.

AHP-Based Green Metrics Weighting Results

The AHP analysis produced priority weights for the five green metrics dimensions as presented in Table 3. The aggregated pairwise comparison matrix satisfied the CR < 0.10 threshold at CR = 0.043, confirming acceptable consistency in expert judgment and validating the reliability of the derived weight vector.

Table 3. AHP Priority Weight Results for Green Metrics Dimensions

Green Metrics Dimension	AHP Weight	Rank	CI	CR
Greenhouse Gas Emissions	0.342	1	0.048	0.043
Solid Waste Management	0.261	2	0.048	0.043
Energy Efficiency	0.198	3	0.048	0.043
Water Consumption	0.124	4	0.048	0.043
Material Toxicity	0.075	5	0.048	0.043

Note: CI = Consistency Index; CR = Consistency Ratio. CR = 0.043 < 0.100 indicates acceptable judgment consistency.

Greenhouse gas emissions received the highest priority weight (0.342), reflecting the expert panel's consensus that this dimension carries the greatest environmental and regulatory significance in the current policy landscape, particularly given Indonesia's commitment to a 41% unconditional GHG reduction by 2030 under the Enhanced Nationally Determined Contribution (NDC) framework. Solid waste management ranked second (0.261), a priority alignment consistent with the substantial waste volumes documented in the baseline assessment and with tightening Indonesian solid waste regulations under Government Regulation No. 22 of 2021 Government Regulation No. 22 of 2021. Energy efficiency (0.198) ranked third, reflecting both its direct economic cost implications and its indirect contribution to GHG emissions through purchased electricity and on-site thermal energy generation. Water consumption (0.124) and material toxicity (0.075) ranked fourth and fifth, respectively, consistent with the wood-processing industry's relatively lower water intensity and the recent industry-wide transition from solvent-based to water-based coating systems.

Multi-Objective Model Development and Validation Results

The MOLP model was developed with 28 decision variables and 18 constraint functions, as described in Research Method. The model was calibrated using January–September 2023 production data and validated against October–December 2023 actuals. Validation results yielded a MAPE of 5.3% across all three objective function predictions, corresponding to a prediction accuracy of 94.7%. Sensitivity analysis confirmed parametric stability across the full ±15% parameter variation range, with no solution infeasibility or objective function rank reversal observed within this range. These results meet the validation criteria established in Section Model Validation Protocol and confirm the model's representational adequacy for production planning purposes.

The model's constraint structure successfully captured the principal operational realities of the production system, including shift-specific machine capacity limits for the five kiln dryers and twelve CNC cutting machines, timber species-specific raw material availability schedules, process-specific emission limits compliant with Government Regulation No. 22 of 2021, product dimension and moisture content quality specifications, and energy efficiency targets aligned with the company's ISO 50001 energy management framework. The incorporation of these diverse constraint types into a unified mathematical model represents a significant methodological contribution to green production planning in the wood-processing sector.

Post-Implementation Environmental and Operational Performance

Following staged implementation across all production lines during January–June 2024, comprehensive performance measurement was conducted. Table 4 presents the comparison of baseline and post-implementation performance across all monitored indicators.

Table 4. Comparative Performance Before and After Model Implementation

Performance Indicator	Baseline (2023)	Post-Implementation (2024)	Change (%)	Initial Target
CO_2eq Emissions (ton/yr)	4,782.0	3,412.8	−28.6%	−25%
Solid Waste (ton/yr)	1,467.4	965.8	−34.2%	−30%
Energy Consumption (MWh/yr)	7,518.3	5,831.0	−22.4%	−20%
Production Output (m^3/yr)	62,400	73,823	+18.3%	+15%

Performance Indicator	Baseline (2023)	Post-Implementation (2024)	Change (%)	Initial Target
Operating Costs (IDR million/yr)	48,620	40,980	−15.7%	−12%
Emission Intensity (kg CO_2eq/m³)	76.6	46.2	−39.7%	−27%*

** Emission intensity target was revised upward from the initial 27% to 25% during planning; the achieved result of 39.7% substantially exceeded both target levels. Reference benchmarks: Southeast Asian industry average = 58.3 kg CO_2eq/m³; Global best practice = 38.5 kg CO_2eq/m³ (UNIDO, 2023).*

All six performance indicators exceeded their predetermined targets, with the emission intensity indicator achieving the most dramatic improvement: a 39.7% reduction from 76.6 to 46.2 kg CO_2eq/m³. This achievement positioned the company below the Southeast Asian industry benchmark (58.3 kg CO_2eq/m³) and within 20% of the global best practice standard (38.5 kg CO_2eq/m³), representing a significant competitive repositioning in terms of environmental performance.

The simultaneous achievement of environmental improvement and production output growth (18.3% increase) and operating cost reduction (15.7% decrease) provides empirical refutation of the frequently cited trade-off hypothesis—the assumption that environmental performance improvements necessarily come at the expense of economic performance. These results are consistent with the Porter Hypothesis (Porter & van der Linde, 1995), which posits that well-designed environmental constraints stimulate innovation and efficiency gains that generate net economic benefits, and extend this hypothesis's empirical validation to the Indonesian wood-processing sector.

The reduction in solid waste (34.2%) was substantially driven by the model's optimized routing of production volumes to minimize defect-generating process combinations, the implementation of real-time process parameter control based on G-VSM-identified waste generation thresholds, and the introduction of wood dust biomass recovery for on-site kiln fuel supplementation—a circular economy intervention identified through G-VSM that simultaneously reduced both waste disposal costs and purchased fuel costs. Energy consumption reduction (22.4%) was primarily achieved through production schedule optimization that improved kiln utilization efficiency, reducing the proportion of heating cycles operated at sub-optimal load factors, and through the installation of kiln exhaust heat recovery systems identified as a high-impact intervention in the G-VSM future-state mapping.

Critical Success Factors in Model Implementation

Qualitative analysis of the implementation process, combined with quantitative performance tracking, identified five critical success factors that collectively determined the implementation outcome:

First, top management commitment was the foundational enabling condition. The company's board of directors allocated a dedicated green initiative budget equivalent to 2.3% of total operational costs, established environmental performance indicators in executive and managerial key performance indicator (KPI) frameworks, and mandated monthly green metrics performance reviews at director level. Djatnika et al. (2023) identified this pattern of active, resource-backed management commitment as the primary predictor of environmental management system implementation success in Indonesian manufacturing enterprises, a finding directly validated by this study's experience.

Second, measurement data quality proved critical to model reliability. Analysis showed that emission and waste measurement deviations exceeding 5% from calibrated values produced significant degradation in model prediction accuracy, potentially reducing optimization efficacy. The procurement and maintenance of SNI-certified measurement instruments, combined with a monthly calibration protocol, was therefore a prerequisite for sustained model performance.

Third, technical human resource development was essential for operational-level model implementation. A structured 40-hour training program delivered to 24 production operators and technicians covering green manufacturing concepts, G-VSM waste identification, and green metrics dashboard operation produced an 87% improvement in production process compliance rates with green metrics targets. This result is consistent with broader findings in organizational change management literature that skill development is a necessary condition for sustained behavioral change in complex operational environments.

Fourth, real-time information system integration proved critical for responsive production control. Integration of smart meter energy monitoring, Manufacturing Execution System (MES) production tracking,

and the green metrics optimization dashboard into a unified real-time data architecture enabled production supervisors to detect and respond to environmental performance deviations within 15 minutes of occurrence. Sensitivity analysis of the data latency effect showed that delays exceeding 15 minutes in emission and waste data availability reduced production control intervention effectiveness by approximately 34%, demonstrating the quantitative value of real-time data infrastructure investment.

Fifth, environmental performance-based incentive systems amplified employee engagement and catalyzed continuous improvement beyond model-specified targets. The introduction of team and individual recognition and financial bonus programs tied to green metrics achievement generated over 40 employee-initiated process improvement suggestions during the implementation period, of which 18 were implemented and contributed measurably to performance outcomes. This finding is consistent with self-determination theory's prediction that intrinsic and extrinsic motivation alignment amplifies the adoption and sustainability of complex behavioral change programs.

Financial Analysis of Model Implementation

The total implementation investment comprised instrument procurement (IDR 0.92 billion), optimization software development (IDR 0.78 billion), human resource training (IDR 0.31 billion), and process adjustment capital expenditures (IDR 0.83 billion), totaling IDR 2.84 billion. Annual economic benefits were generated from three sources: energy cost savings of IDR 3.12 billion/year (from the 22.4% reduction in energy consumption), incremental revenue from recovered waste material valorization of IDR 0.84 billion/year, and waste management cost avoidance of IDR 0.62 billion/year, yielding total annual benefits of IDR 4.58 billion.

Financial analysis yielded a simple payback period of 7.4 months, a Net Present Value of IDR 18.9 billion over a five-year horizon at an 8% discount rate, and an Internal Rate of Return of 156.2%. These metrics confirm that the implementation is financially superior by a substantial margin relative to the company's hurdle rate, and that the environmental and economic value propositions are mutually reinforcing rather than competing.

Beyond direct financial returns, the implementation generates three categories of strategic option value: first, eligibility for ISO 14001 environmental management system certification, which is a prerequisite for penetrating environmentally regulated export markets in the EU, Japan, and Australia; second, access to green financing instruments, including Indonesia's green bond market and international development finance institution concessional lending programs; and third, potential carbon credit revenue under Indonesia's Emission Trading System established through Presidential Regulation No. 98 of 2021, which assigns a carbon unit value to verified emission reductions.

CONCLUSION

This study has developed, validated, and implemented a green metrics-integrated multi-objective production control optimization model for a wood-processing manufacturing enterprise in Kalimantan, Indonesia. The model represents a methodological advance over prior single-objective or sequentially optimized green production planning approaches by simultaneously optimizing three objective functions—emission minimization, waste minimization, and output maximization—within a unified mathematical framework informed by AHP-weighted green metrics priorities and G-VSM-identified environmental waste streams.

The principal findings and contributions of this research are threefold. First, the MOLP model comprising 28 decision variables and 18 constraint functions achieved a validation accuracy of 94.7% (MAPE = 5.3%) and maintained parametric stability across ±15% parameter variation, confirming its reliability as a production planning decision-support tool. Second, staged implementation over six months produced environmental performance outcomes—28.6% CO_2eq emission reduction, 34.2% solid waste reduction, 22.4% energy consumption reduction—that systematically exceeded all predetermined targets and repositioned the company's emission intensity (46.2 kg CO_2eq/m^3) below the Southeast Asian regional industry benchmark (58.3 kg CO_2eq/m^3). Simultaneously, production output increased by 18.3% and operating costs decreased by 15.7%, providing robust empirical evidence for the environmental-economic performance

complementarity hypothesis in the wood-processing context. Third, financial analysis confirmed a payback period of 7.4 months and NPV of IDR 18.9 billion over five years, demonstrating that green metrics-integrated production control is not merely environmentally beneficial but constitutes a financially superior investment relative to conventional production management approaches.

The convergence of five critical success factors—top management commitment, measurement data quality, technical human resource capability, real-time information system integration, and environmental performance incentive systems—was identified as necessary for implementation effectiveness. The absence or weakness of any single factor was observed to materially constrain realization of the model's theoretical performance potential, underscoring the importance of holistic organizational readiness assessment prior to implementation.

Recommendations

For manufacturing companies considering adoption of green metrics-integrated production control, the following implementation pathway is recommended: initiate with AHP-guided green metrics dimension prioritization to focus initial measurement and improvement efforts on highest-impact indicators; deploy G-VSM as the primary environmental waste identification tool before model development to ensure comprehensive baseline characterization; invest in SNI-certified measurement infrastructure and real-time data integration as prerequisite conditions for model reliability; and develop a phased human resource capacity building program concurrent with technical implementation to ensure operational-level adoption.

For future research, three directions are identified as priorities. First, extension of the emission accounting boundary to include Scope 3 emissions from upstream supply chain and downstream product distribution activities—following the GHG Protocol Corporate Value Chain Standard—would enable more comprehensive and internationally comparable environmental performance measurement. Second, integration of reinforcement learning algorithms into the optimization architecture would enable adaptive real-time production scheduling that responds to dynamic input parameter changes more rapidly than the current static MOLP approach. Third, replication of the model in other resource-intensive Indonesian manufacturing sectors—including mining, palm oil processing, petrochemicals, and cement production—would enable the development of sector-specific emission factors and benchmarks, expanding the model's generalizability and supporting the development of a national sustainable manufacturing performance reference database.

REFERENCES

Alfarisi, R., Herdiyanto, D., & Nurokhim, A. (2023). Multi-Objective Production Optimization in Cement Industry: Integrating Carbon Emission and Waste Minimization. *Journal of Industrial Engineering*, *25*(1), 45–62.

Badan Pusat Statistik. (2023). *Produk Domestik Bruto Indonesia Triwulanan 2023*. BPS-Statistics Indonesia.

Brown, A., Amundson, J., & Badurdeen, F. (2014). Sustainable Value Stream Mapping (Sus-VSM) in Different Manufacturing System Configurations: Application Case Studies. *Journal of Cleaner Production*, *85*, 164–179. https://doi.org/10.1016/j.jclepro.2014.05.101

Chandrahadinata, D., & Fadilah, R. N. (2025). Minimalisasi pemborosan menggunakan metode lean manufacturing dan green manufacturing di UKM Asela. *Jurnal Kalibrasi*, *23*(1), 49–59. https://doi.org/10.33364/kalibrasi/v.23-1.1600

Djatnika, E., Kurniasih, D., & Rahayu, S. (2023). The Role of Top Management Commitment in the Successful Implementation of Environmental Management Systems in the Indonesian Manufacturing Industry. *Journal of Management and Organization*, *14*(2), 112–128.

Government Regulation No. 22 of 2021 on the Implementation of Environmental Protection and Management (2021).

Hardini, R., Purnomo, H., & Siswanto, N. (2022). Implementation of green value stream mapping in the Jepara furniture industry: Identification and elimination of environmental waste. *Journal of Industrial Systems Engineering*, *11*(3), 189–204.

Hartini, S., & Ciptomulyono, U. (2015). The Relationship Between Lean and Sustainable Manufacturing on Performance: Literature Review. *Procedia Manufacturing*, *4*, 38–45.

https://doi.org/10.1016/j.promfg.2015.11.012

Intergovernmental Panel on Climate Change. (2022). *Climate Change 2022: Mitigation of Climate Change*. Cambridge University Press. https://doi.org/10.1017/9781009157926

International Organization for Standardization. (2006a). *ISO 14040:2006 Environmental Management: Life Cycle Assessment: Principles and Framework*. ISO.

International Organization for Standardization. (2006b). *ISO 14044:2006 Environmental Management: Life Cycle Assessment: Requirements and Guidelines*. ISO.

International Organization for Standardization. (2018). *ISO 50001:2018 Energy Management Systems: Requirements With Guidance for Use*. ISO.

Krisi, S. A., Jami'in, M. A., & Apriani, M. (2022). Potensi dampak lingkungan pada industri minyak goreng sawit dengan metode life cycle assessment. *Jurnal Ilmu Lingkungan*, *20*(3), 672–677. https://doi.org/10.14710/jil.20.3.672-677

Kusumawati, R., Prasetyo, A., & Hidayat, W. (2022). Environmental Management System Adoption in Kalimantan Manufacturing Enterprises: Barriers, Drivers, and Implementation Gaps. *Journal of Environmental Management and Sustainability*, *11*(2), 45–62.

Pedersen, E., & Remmen, A. (2022). Challenges with product environmental footprint: A systematic review. *The International Journal of Life Cycle Assessment*, *27*(2), 342–352. https://doi.org/10.1007/s11367-022-02022-3

Porter, M. E., & van der Linde, C. (1995). Toward a New Conception of the Environment-Competitiveness Relationship. *Journal of Economic Perspectives*, *9*(4), 97–118. https://doi.org/10.1257/jep.9.4.97

Rajak, S., Vinodh, S., & Singh, A. R. (2022). Optimization of sustainable manufacturing metrics using multi-objective decision-making. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *44*, 217.

Regulation (EU) 2023/956 Establishing a Carbon Border Adjustment Mechanism (2023).

Saaty, T. L. (1980). *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*. McGraw-Hill.

United Nations Industrial Development Organization. (2024). *Industrial Development Report 2024: Turning Challenges Into Sustainable Solutions: The New Era of Industrial Policy*. UNIDO.

Womack, J. P., & Jones, D. T. (2003). *Lean Thinking: Banish Waste and Create Wealth in Your Corporation* (2nd ed.). Free Press.