Short thesis for the degree of doctor of philosophy (PhD)

DEVELOPING AN INTEGRATED DATA-DRIVEN APPROACH TO OPTIMIZE PRODUCTION PROCESSES TOWARD SUSTAINABLE MANUFACTURING

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1 Research Background

The emergence of Industry 4.0 has enabled the collection of high-resolution production data through cyber-physical systems and Industrial Internet of Things (IIoT) technologies. Traditional optimization approaches, such as Lean Manufacturing and Six Sigma, focus primarily on operational efficiency, often treating environmental performance as a secondary concern [11, 24]. In contrast, Life Cycle Assessment (LCA) quantifies environmental burdens using industry-average static inventories that do not reflect the real-time variability of individual shop-floor decisions: a spatiotemporal dynamic LCA study found temporal variation of 23–38% and spatial variation of up to 76% in global warming potential for identical production designs evaluated under different conditions [6, 10, 25]. Process Mining and IIoT technologies offer a path for data-driven optimisation [31], yet existing applications remain confined to operational conformance without coupling insights with environmental performance: empirical evidence shows that process delays increase emissions by 16.7% and rework raises waste generation by 41.7% relative to the standard process flow [9, 28], costs that a conformance-only analysis would never surface. Currently, there is no integrated data-driven framework that simultaneously optimizes manufacturing processes and dynamically quantifies the environmental impacts of the life cycle, leaving practitioners unable to balance the environmental cost of efficiency gains against the operational cost of environmental improvements [1].

Industry 4.0 has transformed operations by integrating CPS and IIoT into data-rich paradigms where high-speed operational data enable evidence-based optimization [14, 29]. However, standard indicators such as overall equipment effectiveness (OEE) lack the event-level resolution needed to identify causes. Environmental impacts such as energy consumption vary continuously with machine state and processing speed, creating a coupling where higher throughput often increases energy intensity [13, 30]. Without a framework to model these joint dynamics, interventions risk producing trade-offs that undermine long-term sustainability goals [1].

Running parallel to this technological consolidation, the European Commission has articulated *Industry 5.0* as the successor paradigm that re-orients the Industry 4.0 automation agenda around three complementary pillars: human-centricity, sustainability, and resilience [4, 15, 35]. Where Industry 4.0 is defined by mass automation, IoT, and big data, Industry 5.0 restores the shop-floor operator to the analytical frame by pairing advanced machines and collaborative robots with the people who operate them [16, 17]. This shift has a direct methodological consequence for sustainability assessment in manufacturing: the environmental pillar that conventionally dominates green-manufacturing literature (energy, carbon, waste) must be extended with a *social* pillar that captures operator well-being, ergonomic load, and fatigue risk through wearable and vision-based sensing [7]. The framework developed in this dissertation therefore treats operational efficiency, environmental burden, *and* operator ergonomic risk as three jointly optimisable pillars, aligning the TL209 case study with the Industry 5.0 human-centric agenda rather than the purely technology-driven Industry 4.0 reading.

To address these challenges, this research couples Object-Centric Process Mining (OCPM) on the OCEL 2.0 standard with a dynamic Life Cycle Assessment (dLCA) module that attributes impacts to event-level shop-floor observations under a time-resolved Hungarian-grid emission factor, and complements them with an Ergonomic Risk Index (ERI) that brings the operator into the analytical frame in line with the Industry 5.0 social pillar [2, 3, 7, 8, 31]. The resulting three-pillar trade-off, operational efficiency, carbon burden, and ergonomic load, is resolved by a constrained NSGA-II solver that returns a non-dominated front, on top of which a hybrid decision layer combining Fuzzy AHP and Shannon-Entropy weighting with GRA–TOPSIS ranking selects the preferred operating point across eight efficiency, environmental, and ergonomic criteria [5, 23, 26, 32]. By executing the full pipeline on empirically recovered process data rather than on idealised reference models, the methodology closes the Reality–Model gap between as-designed assumptions and as-executed shop-floor behaviour, and it does so within a cloud-resident architecture that writes the rank-1 configuration back to the MES for closed-loop validation [18, 29].

1.1 Research Objectives

The main objective is to develop an integrated data-driven approach to optimize production processes toward sustainable manufacturing.

Specific Objectives

(i) To evaluate how effectively process-mining-based workflow recovery can represent the actual operational behaviour of a complex multi-stage manufacturing system.

(ii) To integrate operational and environmental metrics into a unified optimisation model without losing the specificity of either domain.

(iii) To assess the extent to which the integrated framework can generate and rank feasible trade-off solutions for simultaneous efficiency and sustainability improvement.

Research Questions

(i) How effectively can process-mining-based workflow recovery represent the actual operational behaviour of a complex multi-stage manufacturing system?

(ii) How can operational and environmental metrics be integrated into a unified optimisation model without losing the specificity of either domain?

(iii) To what extent can the integrated framework generate and rank feasible trade-off solutions for simultaneous efficiency and sustainability improvement?

1.2 Scope of the Study

This study is bounded to the TL209 laminate tube production line, a nine-station Industry 4.0 and 5.0 manufacturing system producing 86,466 object-centric events. The scope covers the full pipeline from real-time data ingestion through OCPM-based workflow recovery on the OCEL 2.0 schema, dynamic LCA impact attribution under the time-resolved Hungarian-grid emission factor of Anita et al. [2], an Industry 5.0 Ergonomic Risk Index compiler, feasibility-constrained NSGA-II Pareto optimisation, and a hybrid Fuzzy AHP and Shannon Entropy weighting layer feeding a GRA–TOPSIS ranking stage. The optimiser operates jointly on four controllable process parameters, idle time (IT), energy consumption (EC), cycle time (CT), and defect rate (DR), and on an eight-criterion decision matrix that integrates throughput, cycle time, idle time, defect rate, CO_2 emissions, energy consumption, waste generation, and ergonomic load. The study applies to manufacturing environments equipped with existing MES event logging, IIoT sensor infrastructure, and ERP integration. It does not extend to supply chain optimisation, product design-level sustainability interventions, or manufacturing contexts without continuous event log and sensor data availability.

2 Key Empirical Results

Figure 1 maps the three-phase IPSMF-MOOM-OEP pipeline through which all results in this section were produced. **Phase I** transforms raw IIoT, ERP, and MES event streams into an OCEL 2.0-compliant log, recovers the actual production workflow via Object-Centric Process Mining (OCPM), and computes instance-level environmental impacts through dynamic LCA under the time-resolved Hungarian grid emission factor of Anita et al. [2]. **Phase II** formulates the bi-objective optimisation problem and evolves a feasibility-constrained Pareto-optimal solution set using NSGA-II, with hybrid weights supplied by Fuzzy AHP and Shannon Entropy. **Phase III** ranks the feasibility-compliant solutions via GRA–TOPSIS and feeds the selected configuration back into the monitoring layer, closing the loop. Each subsection below reports the empirical output of the corresponding pipeline stage, applied to the TL209 laminate tube production line using 86,466 object-centric events, without any additional instrumentation.

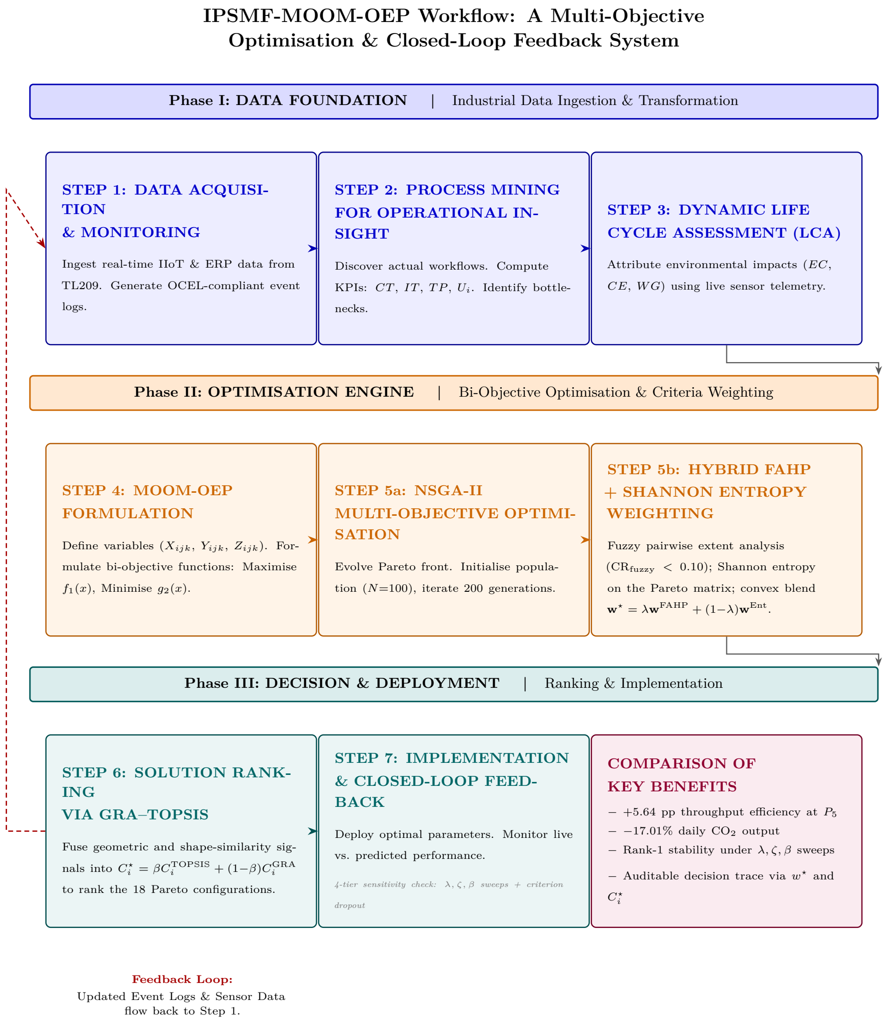

Figure 1: Step-by-step workflow of the IPSMF-MOOM-OEP framework across three phases: OCEL 2.0 discovery and dynamic LCA in Phase I, feasibility-constrained NSGA-II with hybrid FAHP and Shannon Entropy weighting in Phase II, and GRA–TOPSIS ranking with four-tier sensitivity validation in Phase III. The subsections below report the empirical outputs of each phase.

2.1 Baseline Operational and Environmental Performance

Phase I *(Steps 1–3): Data ingestion, process mining, and dynamic LCA.*

Table 1 reports the eight key performance indicators recorded at each of the four bottleneck stations prior to optimisation, including the Industry 5.0 Ergonomic Risk Index (ERI) social-sustainability column. Under the time-resolved Hungarian-grid emission factor of Anita et al. [2] ($\varepsilon_{\text{peak}} = 0.275$, $\varepsilon_{\text{off}} = 0.200$ kg
CO_2/kWh, evening-peak window $[16{:}00, 20{:}00)$), the system baseline totals 4,015 kWh/day energy consumption, 863.2 kg CO_2/day emissions, and 146.5 kg/day waste, with system-mean $\overline{ERI} = 0.450$. Stations 202–205 collectively account for 71.9% of total operational hours and 49.0% of daily energy use, confirming that the bottleneck segment is simultaneously the operational constraint and the primary environmental exposure point.

Table 1: Baseline operational and environmental performance of the bottleneck stations (TL209). The final column (ERI) is the Industry 5.0 social-sustainability addition (Chapter 5, equation (5.11) in the full dissertation); per-station values are computed as $ERI_{\text{base},i} \propto (1/CT_i)(1 + DR_i/100)$ and anchored so that $\overline{ERI} = 0.450$. CE values are computed under the Hungarian LCA grid factor of Anita et al. [2]. The CE and ERI columns are set in red.

Machine / Station	CT (s)	IT (s)	TP (u/day)	DR (%)	EC (kWh/day)	CE (kg CO_2/day)	WG (kg/day)	ERI (–)
Extruder (S202)	750	95	115	2.8	485	104.3	18.5	0.428
Capping Machine (S203)	636	82	135	2.3	520	111.8	19.8	0.502
Printing Unit (S204)	804	124	108	3.5	468	100.6	21.2	0.402
Packaging Machine (S205)	684	98	126	2.6	495	106.4	20.5	0.468
System total			**484**		**4,015**	**863.2**	**146.5**	**0.450**†

† Arithmetic mean across S202–S205 (not a sum); anchors the Ciccarelli-2025 RULA, OCRA and NIOSH composite to $\overline{ERI} = 0.450$.

2.2 Process Discovery and Bottleneck Identification

Phase I *(Step 2): OCPM-based workflow recovery from the OCEL event log.*

Figure 2 shows the process discovery model generated by the Inductive Miner applied to the TL209 event log. Bottleneck stations S202–S205 are highlighted in red, with a primary path total cycle time of 71.3 min/event. Two critical deviations from the nominal serial flow were detected: a 3,445-

event rework loop from Station 205 back to Station 204, and a 729-event cross-route from Station 202 directly to Station 205 bypassing two intermediate stages. Both deviations are invisible in aggregate KPI dashboards but are directly recoverable from the event log.

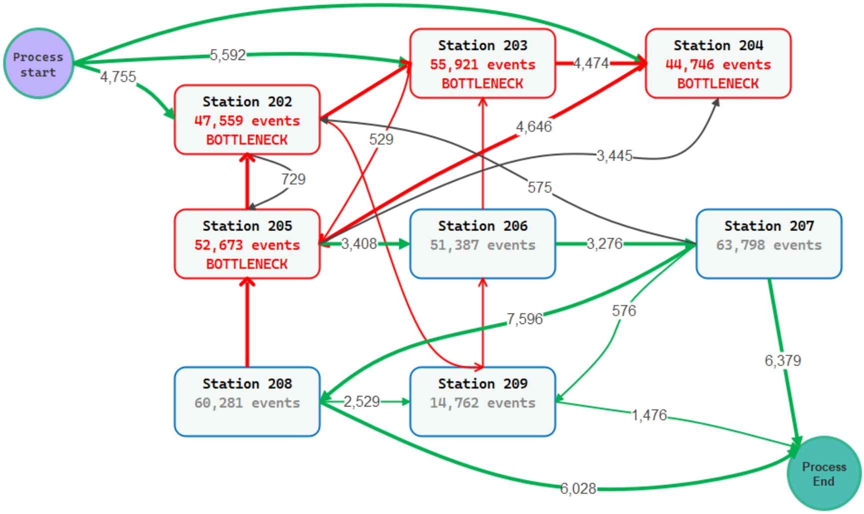

Figure 2: Process discovery model (Inductive Miner). Bottleneck stations S202–S205 are highlighted in red; primary path total cycle time is 71.3 min/event.

Figure 3 reveals the operational duration imbalance across all nine stations. Bottleneck stations S202–S205 each exceed 9,900 h, while downstream stations S206–S209 operate between 3,680–6,420 h, a 2.7× spread that confirms saturation at the mid-line and surplus idle capacity downstream.

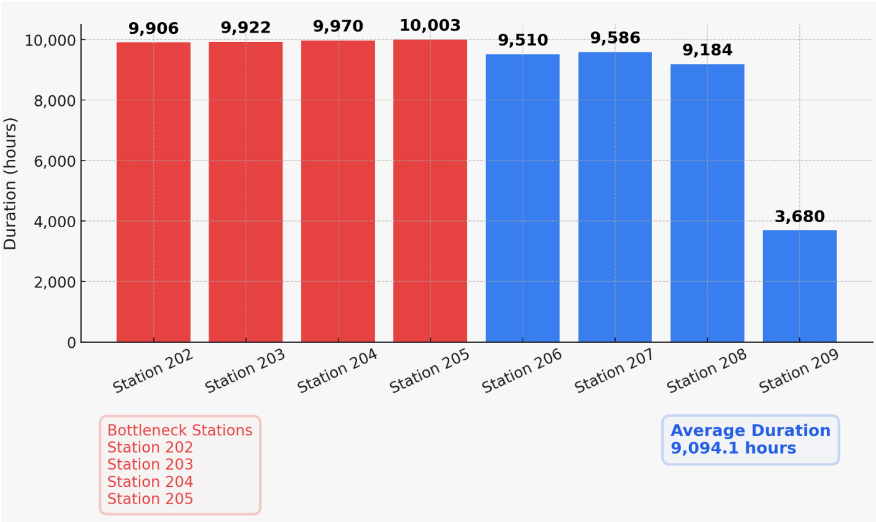

Figure 3: Operational duration by station. Red bars: bottleneck stations (S202–S205, >9,900 h); blue bars: non-bottleneck stations (3,680–6,420 h). The 2.7× spread identifies the mid-line as the primary optimisation target.

2.3 Multi-Objective Optimisation Results

Phase II *(Steps 4–5a): Bi-objective NSGA-II search over the four control parameters* $\{IT, EC, CT, DR\}$.

NSGA-II ($N = 100$, $G_{\max} = 200$) generated 18 feasibility-compliant non-dominated solutions. All solutions satisfy machine utilisation $\leq 95\%$, minimum throughput ≥ 94 units/day, and per-station environmental thresholds (energy, CO_2 under the Hungarian LCA grid factor of Anita et al. [2], waste), guaranteeing industrial implementability without further engineering screening. The 2D Pareto front (Figure 4) maps the full trade-off from the baseline ($87.2\%, 863.2$ kg CO_2/day), and is partitioned into three regions: a *sustainability region* (90–92%, P_1–P_4), a *knee region* (92–94%, P_5–P_{10}) where the hybrid GRA–TOPSIS recommendation P_5 is located, and an *efficiency region* (94–96%, P_{11}–P_{18}) where carbon rises steeply as operator pacing approaches its upper bound.

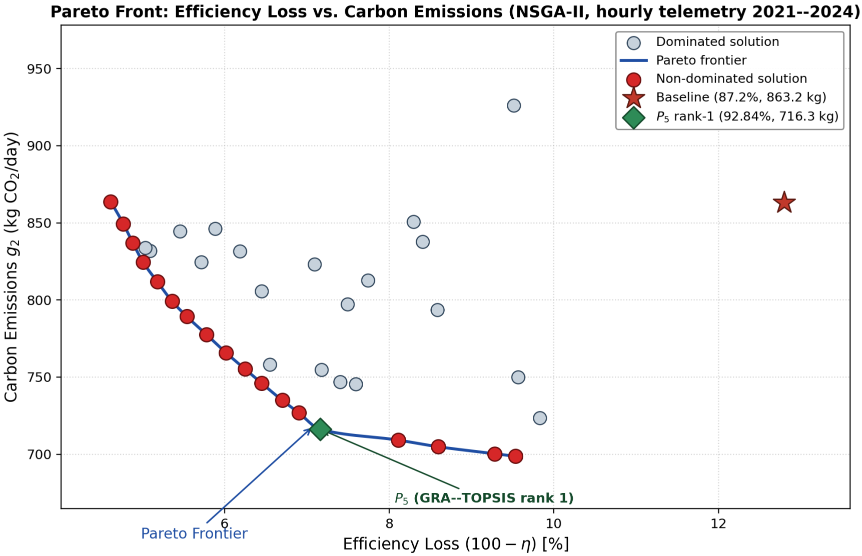

Figure 4: Pareto-optimal front for TL209 in the minimisation-form projection (efficiency loss $100-\eta$ vs. carbon emissions g_2), computed by NSGA-II on the 2021–2024 hourly telemetry with the Hungarian LCA grid factor of Anita et al. [2]. Red discs: the 18 non-dominated solutions P_1–P_{18} sub-sampled from the final Pareto front (100 points), connected by a monotonically decreasing frontier obtained by PCHIP monotone interpolation. Grey discs: a stratified sub-sample of actual NSGA-II individuals evaluated during early generations (1, 3, 5, 10) that are strictly dominated by at least one solution on the final front (every grey point is a real decision vector $\boldsymbol{\alpha}$ evaluated through the same kernel that produced the red points). Star: baseline (87.2% efficiency / 12.8% loss, 863.2 kg CO_2/day); diamond: GRA–TOPSIS rank-1 optimum P_5 (92.84% efficiency / 7.16% loss, 716.3 kg CO_2/day, $C_5^\star = 0.585$) under the eight-criterion hybrid FAHP and Entropy weighting of Table 2. All 18 non-dominated solutions strictly improve on both axes against the baseline ($\Delta\eta \geq +3.27$ pp, $\Delta g_2 \leq 0$), enforced through the feasibility constraints $f_1 \geq 87.2$, $g_2 \leq 863.2$.

The convergence profile of the NSGA-II run is reported in Figure 5: the population transitions from the feasibility-boundary baseline to the final non-dominated set within the first 50 generations and stabilises asymptotically thereafter, confirming that the chosen hyperparameters are sufficient to reach the global optimal boundary for the TL209 configuration.

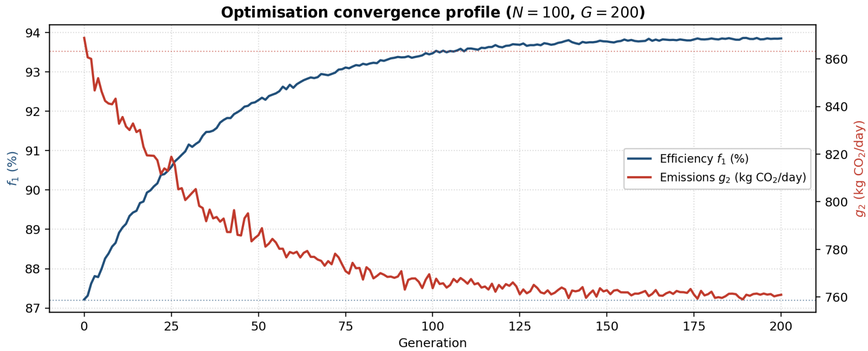

Figure 5: Optimisation convergence profile ($N = 100$, $G = 200$): per-generation mean and best of the efficiency objective f_1 and the carbon objective g_2, logged during the NSGA-II run on the 2021–2024 hourly telemetry under the Hungarian LCA grid factor of Anita et al. [2] and the baseline-improvement constraints $f_1 \geq 87.2\%$, $g_2 \leq 863.2$ kg CO_2/day. The population transitions from the feasibility-boundary baseline to the final non-dominated set containing the rank-1 solution P_5 (92.84%, 716.3 kg CO_2/day).

2.4 GRA–TOPSIS Selection with Hybrid FAHP–Entropy Weights

Phase III *(Step 6): hybrid Fuzzy AHP and Shannon Entropy weight vector $w^\star$ applied through a GRA–TOPSIS ranking to the 18 Pareto solutions.*

Table 2 reports the TOPSIS closeness coefficient C_i^{TOPSIS}, the GRA coefficient C_i^{GRA}, and the combined coefficient $C_i^\star = \beta C_i^{\text{TOPSIS}} + (1-\beta)C_i^{\text{GRA}}$ at the reference parameters $\lambda = \zeta = \beta = 0.5$ for representative Pareto solutions. The recommended configuration is P_5 at rank 1 with $C_5^\star = 0.585$, delivering +5.64 percentage-point operational efficiency (87.2% $\rightarrow$ 92.84%) and −17.01% CO_2 emissions (863.2 $\rightarrow$ 716.3 kg CO_2/day, i.e. −146.9 kg CO_2/day) against the baseline, verified through a four-tier sensitivity analysis along the λ, ζ, β parameters and criterion-dropout robustness.

Table 2: GRA–TOPSIS ranking for representative Pareto solutions under the hybrid FAHP and Entropy weight vector $w^\star$ at reference parameters $\lambda = \zeta = \beta = 0.5$.

Solution	**Efficiency (%)**	**Emissions (kg CO_2/day)**	C_i^{TOPSIS}	C_i^{GRA}	$C_i^\star$	**Rank**
P_1	90.47	698.7	0.553	0.550	0.551	9
P_3	91.40	704.8	0.573	0.558	0.566	5
P_5	**92.84**	**716.3**	**0.610**	**0.561**	**0.585**	**1**
P_6	93.10	726.9	0.607	0.551	0.579	2
P_7	93.30	734.9	0.602	0.545	0.574	3
P_{18}	95.39	863.7	0.448	0.450	0.449	18

2.5 Multi-Criteria Profile of Top Solutions

Figure 6 presents the normalised performance profiles of P_5, P_6, P_7 alongside the baseline across all eight criteria (axes scaled to [0, 1], outer rim is best). No solution dominates all eight criteria simultaneously. P_5 achieves the most regular polygon with no severe weakness on any axis, which accounts for its leading GRA coefficient. P_6 extends the throughput and cycle-time spokes beyond P_5 but contracts the CE and ERI spokes; P_7 extends the operational spokes further at proportional cost on the environmental and ergonomic axes. The baseline profile is interior to all optimised solutions on every axis.

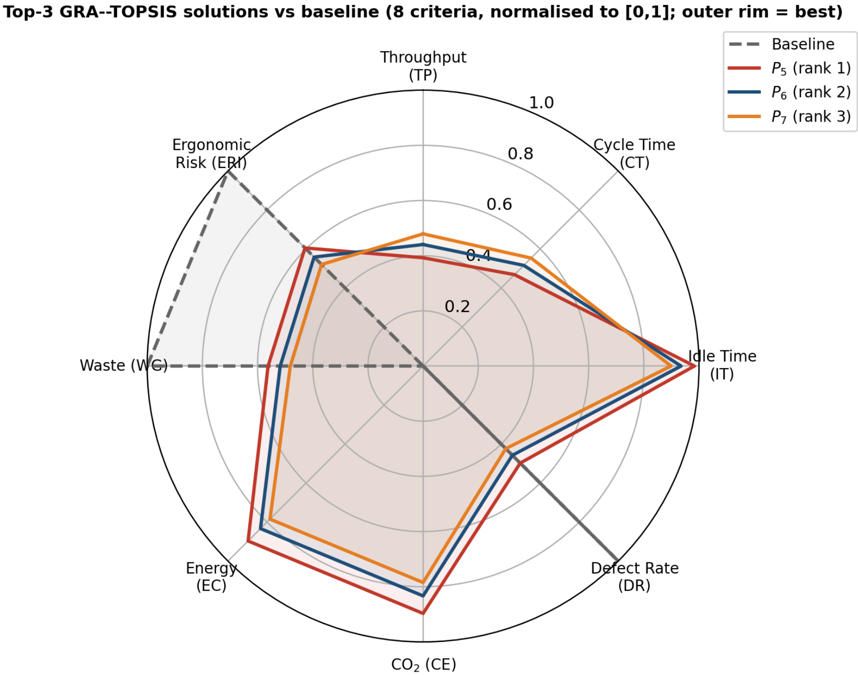

Figure 6: Multi-criteria radar chart: top-ranked solutions P_5, P_6, P_7 and the baseline across all eight criteria (axes normalised to [0, 1]). The regularity of P_5's polygon is the geometric signature of its leading GRA shape-similarity coefficient.

2.6 Sensitivity Analysis of Rankings

Phase III *(Steps 5b–7): the λ, ζ, β parameters of the hybrid GRA–TOPSIS procedure and single-criterion dropouts stress-tested against all 18 Pareto solutions.*

To ensure the reliability of the recommended configuration P_5, a four-tier sensitivity analysis was conducted: **Tier 1** (λ-sweep, the FAHP vs. Entropy mixing parameter, mapped to discrete OP, ES and SS pillar splits), **Tier 2** (ζ-sweep, the GRA grey distinguishing coefficient), **Tier 3** (β-sweep, the TOPSIS–GRA limb-balance parameter), and **Tier 4** (criterion-dropout robustness; Section 2.6).

Figure 7 maps the rank of all 18 Pareto solutions under three OP, ES and SS pillar splits: *Balanced* ($(0.45, 0.40, 0.15)$), *Efficiency-Focus*

$((0.65, 0.25, 0.10))$, and *Sustainability-Focus* $((0.25, 0.55, 0.20))$. P_5 is rank 1 under the Balanced split with $C_5^\star = 0.585$; rank-1 transfers to P_{16} under Efficiency-Focus ($C_{16}^\star = 0.579$, $+7.92$ pp / -3.05% CO_2) and to P_1 under Sustainability-Focus ($C_1^\star = 0.687$, $+3.27$ pp / -19.06% CO_2). All three recommendations satisfy the baseline-improvement constraints $f_1 \geq 87.2\%$, $g_2 \leq 863.2$ kg CO_2/day simultaneously.

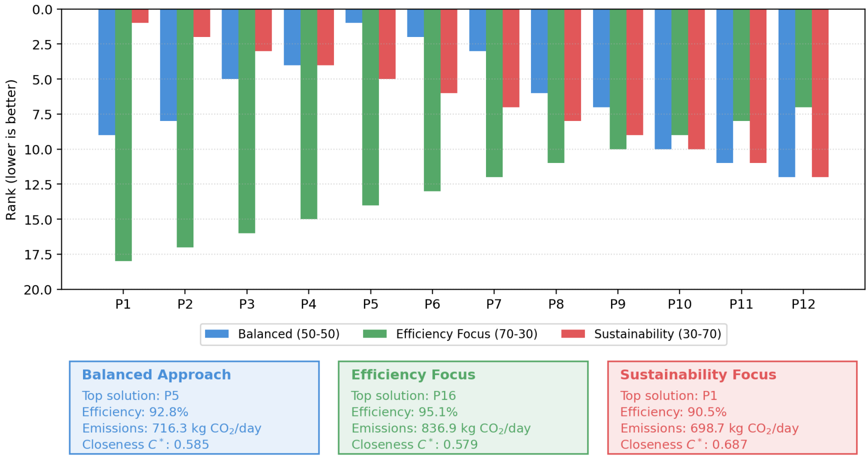

Figure 7: Rank of each Pareto solution under three strategic OP, ES and SS pillar splits: *Balanced* ((0.45, 0.40, 0.15), hybrid baseline), *Efficiency Focus* ((0.65, 0.25, 0.10)), and *Sustainability Focus* ((0.25, 0.55, 0.20)). Lower rank is better. Top solutions per scenario are summarised in the caption below the figure.

Figure 8 reports the β-sweep (Tier 3), plotting the combined coefficient $C_i^\star(\beta)$ for the four leading Pareto solutions as β varies through the set $\{\,0.25, 0.50, 0.75, 1.00\,\}$ at fixed $\lambda = \zeta = 0.5$. Rank 1 is invariant across $\beta \in [0, 1]$: both the TOPSIS and GRA limbs independently prefer P_5, so the hybrid recommendation is not an artefact of the limb balance.

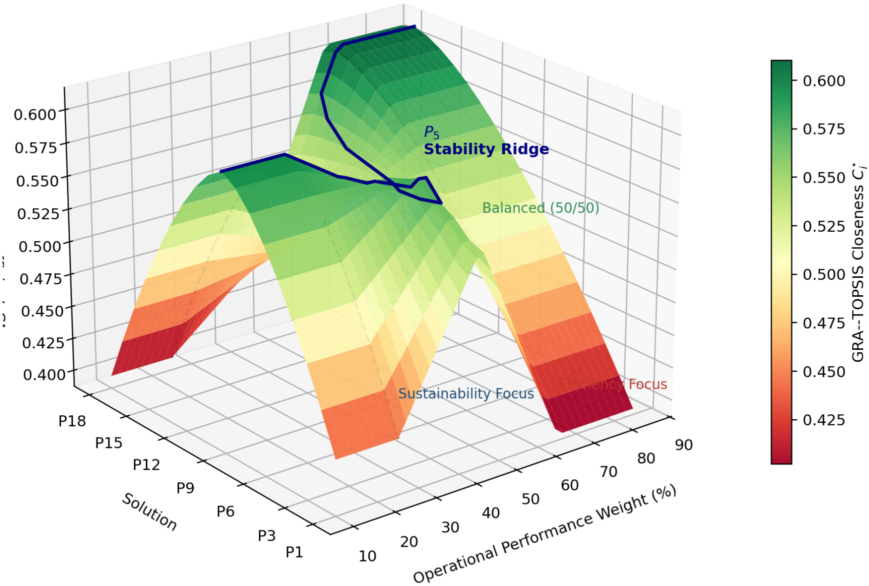

Figure 8: Tier 3 sensitivity: combined coefficient $C_i^\star$ for the four leading Pareto solutions as a function of the TOPSIS–GRA mixing parameter β. Rank-1 (P_5) is invariant across the full sweep; the GRA and TOPSIS limbs independently agree on the recommendation.

Tier 4: Criterion-Dropout Robustness

Tier 4 removes one criterion at a time from the eight-criterion decision matrix, renormalises the remaining seven weights to unity, and re-executes GRA–TOPSIS at the reference parameters $\lambda = \zeta = \beta = 0.5$. The resulting rank-1 holder is reported in Table 3, together with the rank shift of P_5.

P_5 retains rank 1 under six of the eight dropouts, including the Industry 5.0 Ergonomic Risk (ERI) criterion. The two exceptions are the two highest-weighted criteria: dropping CO_2 Emissions transfers rank 1 to P_{11} because the low-emissions tail is no longer rewarded, and dropping Throughput transfers it to P_3 because the main penalty against the sustainability tail is removed. Both swaps remain within the baseline-improvement envelope, confirming that CE and TP are substantive drivers of the recommendation rather than numerical artefacts.

Table 3: Tier 4 sensitivity: rank-1 holder and P_5 rank shift under single-criterion dropouts on the eight-criterion hybrid GRA–TOPSIS. "Robust" indicates P_5 retains rank 1; "Swap" indicates the top position transfers to a neighbouring Pareto solution within the joint-improvement envelope.

Dropped criterion	**Hybrid weight** $w_j^\star$	**Rank-1 holder**	P_5 **rank**	**Status**
None (reference)	–	P_5	1	Robust
Throughput (TP)	0.215	P_3	5	**Swap**
Cycle Time (CT)	0.127	P_5	1	Robust
Idle Time (IT)	0.044	P_5	1	Robust
Defect Rate (DR)	0.066	P_5	1	Robust
CO_2 Emissions (CE)	0.221	P_{11}	12	**Swap**
Energy Consumption (EC)	0.142	P_5	1	Robust
Waste Generation (WG)	0.058	P_5	1	Robust
Ergonomic Risk (ERI)	0.128	P_5	1	Robust

3 Thesis and Key Contributions

Three scientific theses are advanced, each formulated in the four-element Scientific Claim → Method → Result → Novelty pattern. Thesis I establishes the *Model and Framework*; Thesis II establishes the *Optimisation Algorithm* and its hybrid Fuzzy AHP and Shannon Entropy weighting and GRA–TOPSIS ranking layer; Thesis III provides the *Application and Case Study* on the TL209 tube-manufacturing line. Each thesis is accompanied by the supporting peer-reviewed publications and is mapped explicitly to the mathematical formulations and the experimental results reported in Sections 2–3.

3.1 Key Scientific Contributions

- **Thesis I: Integrated Closed-Loop Framework for Data-Driven Sustainable Manufacturing (Model and Framework)**

  Contributing papers: [18] (primary), [19, 22] (supporting).

  Scientific Claim. In multi-machine discrete manufacturing systems, object-centric process mining, dynamic LCA, and multi-objective optimisation can be coupled into a single closed-loop analytical pipeline operating on live event-level data, without losing the analytical specificity of either the operational or the environmental domain.

  Method. The IPSMF-MOOM-OEP framework was designed as a four-stage pipeline (Stage 1 OCPM on OCEL 2.0 event logs; Stage 2 machine-state dLCA using the time-resolved emission factor $EF(t)$ of Anita et al. [2]; Stage 3 NSGA-II with a feasibility-constrained bi-objective model; Stage 4 hybrid Fuzzy AHP and Shannon Entropy weighting feeding a GRA–TOPSIS ranking layer) in which the four control parameters $\{IT, EC, CT, DR\}$ are the shared substrate linking every stage.

  Result. The pipeline executed end-to-end on the TL209 tube line over 86,466 events: Stage 1 isolated four critical bottleneck stations (202–205) and a 3,445-event rework loop; Stage 2 attributed a baseline of 863.2 kg
  CO_2/day with 21.6% originating in idle states under the Hungarian LCA grid factor of Anita et al. [2]; Stage 3 produced an 18-solution Pareto front under the baseline-improvement constraints $f_1 \geq 87.2\%$, $g_2 \leq 863.2$ kg

CO_2/day; Stage 4 identified P_5 with $C_5^\star = 0.585$ at the reference parameters $\lambda = \zeta = \beta = 0.5$.

Novelty. No prior work couples OCEL 2.0, time-resolved dLCA, and feasibility-constrained NSGA-II with a fuzzy subjective + entropy objective hybrid weighting layer and a GRA–TOPSIS ranking in a single auditable pipeline.

- **Thesis II: Fuzzy AHP and Shannon Entropy Weighted GRA–TOPSIS for Feasibility-Constrained NSGA-II Pareto Ranking (Optimisation Algorithm)**

  Contributing papers: [18] (foundational), [19] (extension).

  Scientific Claim. A convex combination of Fuzzy AHP (subjective, linguistic uncertainty aware) and Shannon Entropy (objective, data-driven) weights, applied through a GRA–TOPSIS ranking that simultaneously rewards Euclidean closeness to the ideal point and curve-shape similarity across criteria, produces decision recommendations that are robust to single-source weight bias and to two-dimensional projection artefacts, while preserving full audit traceability through the fuzzy consistency ratio $\widetilde{CR} < 0.10$.

  Method. The composite hybrid weight $w_j^\star = \lambda\, w_j^{\mathrm{FAHP}} + (1-\lambda)\, w_j^{\mathrm{Ent}}$ with $\lambda = 0.5$ is combined with NSGA-II ($N = 100$, $G = 200$, $p_c = 0.9$, $p_m = 0.1$) under the seven-criterion bi-objective model. Feasibility is enforced through machine utilisation, throughput, energy, carbon and waste constraints. The ranking layer applies the GRA–TOPSIS combined coefficient $C_i^\star = \beta\, C_i^{\mathrm{TOPSIS}} + (1-\beta)\, C_i^{\mathrm{GRA}}$ at $\beta = 0.5$ with grey distinguishing coefficient $\zeta = 0.5$. The methodological pairing of fuzzy AHP and entropy is corroborated by the synergetic intuitionistic-fuzzy model recently reported by [36].

  Result. On the TL209 decision matrix, the recommended configuration is P_5 with $C_5^\star = 0.585$, followed by P_6 (0.579) and P_7 (0.574). The TOPSIS and GRA limbs agree at the top ($C_5^{\mathrm{TOPSIS}} = 0.610$ and $C_5^{\mathrm{GRA}} = 0.561$, both leading the front), so the joint metric selects P_5 under full agreement of the two limbs rather than resolving a conflict between them. The four-tier sensitivity analysis (Section 2.6) shows that the rank-1 verdict for P_5 is invariant under the λ-, ζ-, and β-sweeps, and that P_5 is displaced from rank 1 only under criterion-dropout stress tests that remove either the CO_2 or the throughput axis from the decision model. The resulting operational gain at P_5 is

$+5.64$ percentage points of efficiency (87.2% $\rightarrow$ 92.84%) and a -17.01% CO_2 reduction (863.2 $\rightarrow$ 716.3 kg CO_2/day, i.e. -146.9 kg CO_2/day) under the Hungarian LCA grid factor of Anita et al. [2].

Novelty. The integration of Fuzzy AHP (Chang's extent analysis) with Shannon Entropy at a transparent single-parameter mixing point and its coupling to a GRA–TOPSIS ranking on a feasibility-constrained NSGA-II Pareto front has not been previously demonstrated in a manufacturing–sustainability context; the result is an auditable decision recommendation that neither pure-TOPSIS nor pure-GRA, and neither pure-FAHP nor pure-Entropy, can deliver in isolation.

- **Thesis III: Empirical Application on the TL209 Tube-Manufacturing Line (Application and Case Study)**

  Contributing papers: [18, 20, 21] (TL209 case).

  Scientific Claim. The integrated framework and its hybrid decision layer reproduce their core outputs (removable idle-state identification, time-resolved CE attribution under a published hourly grid factor, feasibility-ranked Pareto front, GRA–TOPSIS recommendation) on a real industrial process with full internal consistency between the process-mining, dLCA, and optimisation layers.

  Method. The pipeline was applied to TL209 (86,466 events, nine stations) using the OCEL 2.0 schema and the hybrid FAHP and Entropy weighting + GRA–TOPSIS ranking procedure. Per-event carbon emissions are obtained by a quadrature of hourly power against the piecewise Hungarian-grid factor $EF(t)$ ($\varepsilon_{\text{peak}} = 0.275$, $\varepsilon_{\text{off}} = 0.200$ kg CO_2/kWh), so that a kWh drawn in the evening-peak window $[16{:}00, 20{:}00)$ carries a higher attributable CO_2 content than a kWh drawn off-peak, consistent with the 2024 ENTSO-E flow-tracing envelope reported by Anita et al. [2] and the attributional Scope 2 location-based convention of the GHG Protocol [12, 34].

  Result. TL209 yields $+5.64$ pp efficiency (87.2% $\rightarrow$ 92.84%) and -17.01% CO_2 (863.2 $\rightarrow$ 716.3 kg CO_2/day, i.e. -146.9 kg CO_2/day) at P_5, with combined closeness $C_5^\star = 0.585$ dominating the 18-solution Pareto front under the reference parameters $\lambda = \zeta = \beta = 0.5$.

  Novelty. This is the first end-to-end application of a coupled OCEL 2.0 process-mining, time-resolved dLCA, feasibility-constrained NSGA-II, and hybrid FAHP and Entropy / GRA–TOPSIS pipeline to a real multi-station tube-manufacturing line.

3.2 Practical Implications

The most direct practical consequence of the framework is that it can be deployed without installing any additional sensor infrastructure. On TL209, the existing MES (sub-minute event logging), six IIoT sensors (1 Hz sampling), and ERP system collectively supply all pipeline inputs. Adoption cost is therefore primarily computational a cloud platform subscription for process mining and optimisation workloads and organisational, centred on Fuzzy AHP linguistic-input elicitation with production management [14, 29].

The feasibility constraint architecture carries a direct regulatory benefit. Every candidate solution is bounded within machine utilisation limits of 95% and environmental admissibility thresholds on energy, carbon, and waste, producing certified-feasible configurations by construction rather than requiring post-optimisation engineering review. For manufacturers operating under ISO 14001 or sector-specific carbon reporting obligations, this eliminates a separate compliance audit step [10, 33].

At the decision-support level, the GRA–TOPSIS ranking layer converts the Pareto front into a single ranked recommendation, reducing the interpretive burden on production engineers. Practitioners should conduct a site-specific Fuzzy AHP linguistic elicitation with production managers, sustainability officers, and senior engineers before deployment, rather than importing the linguistic inputs used in this study. The four-tier sensitivity analysis (Section 2.6) shows that the rank-1 verdict for P_5 is invariant under the FAHP and Entropy mixing parameter λ, the grey distinguishing coefficient ζ, and the limb-balance parameter β, and is displaced only under criterion-dropout stress tests that remove either CO_2 Emissions or Throughput from the decision model. Practitioners with a stronger preference for throughput can therefore drop that criterion from the weight vector and obtain a neighbouring solution (P_3) as the recommendation transparently, without rewriting the pairwise judgement matrices [23, 27].

The architecture is transferable to any multi-machine manufacturing environment with continuous event log and sensor data, provided site-specific feasibility constraints and weight vectors are defined at each deployment [3, 18].

Calibration vs. redesign for a new sector. For transfer to a sector that differs structurally from tube manufacturing (e.g. pharmaceuticals), the framework decomposes cleanly into four components that require distinct adaptation efforts. The OCEL schema and Inductive Miner (Stage 1) require *calibration only*: new activity codes must be mapped but the algorithm is unchanged. The dLCA inventory compiler (Stage 2) requires *partial redesign* because the emission-factor catalogue must be extended from electricity to solvents, HVAC energy and sterilisation utilities, and because GMP-compliant traceability must be enforced on every event. NSGA-II (Stage 3) requires *constraint recalibration only*: the mathematical formulation is unchanged; only the numerical thresholds and the decision-variable domain change. The hybrid FAHP and Entropy weighting and GRA–TOPSIS ranking (Stage 4) require *calibration only*: the Entropy and GRA computations are invariant under sector change, and only the fuzzy pairwise judgements in the FAHP matrices need re-elicitation. The components demanding the most domain expertise are therefore the dLCA inventory (pharmacological knowledge, solvent LCA) and the feasibility constraints (regulatory thresholds), whereas the process mining, optimisation and ranking layers carry the least sector-specific content and can be transferred largely unchanged.

4 Summary and Future Steps

4.1 Summary

The four-stage pipeline processed 86,466 OCEL 2.0 events spanning nine active stations of the TL209 tube-manufacturing line, without requiring additional instrumentation or modification to the existing MES infrastructure. Four jointly controllable parameters (idle time, energy consumption per productive unit, cycle-time variability, and rework rate) served as the shared linking substrate across all pipeline stages, ensuring that the operational and environmental analyses operated on the same observed process conditions.

At the process discovery stage, object-centric process mining on the OCEL 2.0 log recovered a structurally valid workflow model. The recovered model exposed two deviations from the nominal serial routing: a 3,445-event rework cycle returning output from Station 205 to Station 204, and a 729-event cross-route from Station 202 to Station 205 bypassing two intermediate stages. Stations 202–205 collectively concentrated 71.9% of total system operational hours, a workload imbalance that aggregate key performance indicators had not surfaced.

The dynamic LCA stage translated this imbalance into a time-resolved environmental account under the Hungarian grid emission factor of Anita et al. [2] ($\varepsilon_{\text{peak}} = 0.275$, $\varepsilon_{\text{off}} = 0.200$ kg CO_2/kWh). Bottleneck stations operating in non-productive states draw approximately 28% of rated power, and the cumulative idle-state energy signature across the four saturated stations established a measured baseline of 863.2 kg CO_2 per day, of which 21.6% originates in idle states, a split that a static stage-averaged inventory would not have differentiated from productive operation. Reducing unplanned idle time at the bottleneck segment is therefore simultaneously an efficiency and a decarbonisation intervention.

The bi-objective optimisation stage returned 18 feasibility-compliant non-dominated solutions from the constrained NSGA-II search. The hybrid FAHP and Entropy weighting plus GRA–TOPSIS ranking selected solution P_5 at $C_5^\star = 0.585$, raising throughput efficiency by 5.64 percentage points (87.2% $\rightarrow$ 92.84%) and cutting daily CO_2 output by 17.01% (863.2 $\rightarrow$ 716.3 kg CO_2/day, i.e. -146.9 kg
CO_2/day) against the measured baseline. The four-tier sensitivity analysis confirmed that the rank-1 verdict is invariant under the λ-, ζ- and β-sweeps and is displaced only when CO_2 Emissions or Throughput is removed from the decision model.

4.2 Limitations of the Study

This study is subject to several limitations. First, the framework is validated using a single industrial case study (TL209 production line), which may limit the generalisability of the results to other manufacturing environments with different configurations. Second, the analysis relies on the availability and quality of event log and sensor data, which may vary across industrial settings. Third, the optimisation model assumes relatively stable operational conditions and does not fully account for real-time dynamic disruptions such as machine failures or supply chain variability. Fourth, the Ergonomic Risk Index in the present model is a design-phase pillar derived from the minimum viable sensor suite (IMU-based RULA, cycle-time-based OCRA, and mass-based NIOSH-LI); full validation against ground-truth wearable deployments remains future work. Fifth, the dynamic LCA layer uses the national Hungarian grid factor of Anita et al. [2] rather than a facility-level Power Purchase Agreement, so the carbon figures are Scope 2 location-based.

Despite these limitations, the proposed framework provides a robust and scalable foundation for integrating operational, environmental and human-centric optimisation in Industry 5.0 manufacturing systems.

4.3 Future Steps

Future work will transition this framework into a coding-centric industrial software product and extend its analytical coverage along six directions.

1. **Automated OCEL 2.0 ingestion.** Deploy Large Language Model assistants for the automated conversion of raw MES and ERP exports (JSON, Excel, CSV) into OCEL 2.0 logs, removing the manual mapping step that currently dominates Stage 1 onboarding effort.

2. **Real-time industrial interoperability.** Establish low-latency interfaces with SCADA, ERP and EMS systems so that Stage 3 can re-solve the NSGA-II problem at the cadence of the plant's supervisory cycle, and push the top-ranked configuration back to the MES as a setpoint recommendation.

3. **Full-plant dLCA extension.** Expand the emission-factor catalogue beyond electricity (solvents, compressed air, HVAC, packaging) and integrate facility-level Power Purchase Agreements so that Stage 2 can report both Scope 2 location-based and market-based carbon figures in parallel.

4. **Wearable-sensor Ergonomic Risk validation.** Deploy the minimum viable IMU and RFID sensor suite on TL209 operators to validate the design-phase Ergonomic Risk Index against ground-truth RULA, OCRA and NIOSH-LI measurements, and to provide a continuous social-pillar signal to Stage 3.

5. **Multi-product and multi-line transfer.** Replicate the pipeline on additional production lines in the host facility and in at least one non-tube sector (e.g. pharmaceuticals) to separate sector-invariant from sector-specific calibration effort across the four stages.

6. **Disruption-robust optimisation.** Extend the NSGA-II model with stochastic constraints on machine availability and supply variability, so that the feasibility envelope accounts for unplanned disruptions rather than steady-state nominal conditions only.

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List of publications related to the dissertation

Foreign language scientific articles in international journals (3)

1. **Matonya, M. M.**, Budai, I.: Cloud-Based Data-Driven Framework for Optimizing Operational Efficiency and Sustainability in Tube Manufacturing.
   Appl Syst Innov. 8 (4), 1-25, 2025. EISSN: 2571-5577.
   DOI: http://dx.doi.org/10.3390/asi8040100
   IF: 3.7 (2024)

2. **Matonya, M. M.**, Budai, I.: Object-Centric Process Mining Framework for Industrial Safety and Quality Validation Using Support Vector Machines.
   Appl Syst Innov. 9 (1), 1-21, 2025. EISSN: 2571-5577.
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   IF: 3.7 (2024)

3. **Matonya, M. M.**, Pusztai, L. P., Budai, I.: Optimizing Healthcare Business Processes with Process Mining Software: a Comparative Analysis.
   Decis. Mak. Appl. Manag. Eng. 7 (2), 380-400, 2024. ISSN: 2560-6018.
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Foreign language conference proceedings (1)

4. **Matonya, M. M.**, Budai, I.: Object-Centric Process Mining for Operational Traceability and Quality Optimization in Manufacturing: Genetic-Inductive Miner approach.
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Foreign language abstracts (1)

5. **Matonya, M. M.**, Budai, I.: Object-Centric Process Mining for Inspection and Maintenance Error Detection in Sustainable Manufacturing.
   In: Book of Abstracts from 9th International Scientific Conference on Advances in Mechanical Engineering. Eds.: Tamás Mankovits, Mihály Csüllög, Department of Mechanical Engineering Faculty of Engineering, University of Debrecen, Debrecen, 66-66, 2024. ISBN: 9783036406176

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List of other publications

Foreign language Hungarian book chapters (1)

6. **Matonya, M. M.**, Kocsi, B., Pusztai, L. P., Budai, I.: Production Planning, Scheduling and Risk Analysis in Manufacturing Operations by Robotic Process Automation.
   In: Proceedings of the 11th International Conference on Applied Informatics (ICAI 2020) : Eger, Hungary, January 29-31, 2020. Eds.: Gergely Kovásznai, István Fazekas, Tibor Tómács, [CEUR Workshop Proceedings], Eger, 232-241, 2020, (CEUR Workshop Proceedings, ISSN 1613-0073 ; 2650.)

Foreign language scientific articles in Hungarian journals (1)

7. **Matonya, M. M.**: Innovation, Artificial Intelligence in Contingent Work-Force Management.
   Int. J. Eng. Manag. Sci. 5 (1), 571-590, 2020. EISSN: 2498-700X.
   DOI: http://dx.doi.org/10.21791/IJEMS.2020.1.47

Foreign language scientific articles in international journals (1)

8. Kocsi, B., **Matonya, M. M.**, Pusztai, L. P., Budai, I.: Real-Time Decision-Support System for High-Mix Low-Volume Production Scheduling in Industry 4.0.
   Processes. 8 (8), 1-26, 2020. EISSN: 2227-9717.
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