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Simulation-Based Optimisation of ISNOO Manufacturing as a Decision Tool for Resource Efficiency

Michał Sąsiadek[1], Waldemar Woźniak[2], Sławomir Michalski[3], Jarosław Jabłoński[3], Krzysztof Glonek[3]*

[1]Department of Mechanics and Machine Design, Institute of Mechanical Engineering, University of Zielona Góra, Poland

https://orcid.org/0000-0002-7804-9459

[2]Department of Production and Transport Engineering, Institute of Materials and Biomedical Engineering, University of Zielona Góra, Poland

https://orcid.org/0000-0002-4703-6823

[3]RENZ Ltd., Gądki, Poland

**corresponding author's e-mail: m.sasiadek@iim.uz.zgora.pl*

Abstract: Environmental protection in sheet-metal manufacturing requires decisions that limit avoidable material consumption, waste generation and resource-intensive processing. This study presents a calibrated simulation model for resource-efficient manufacturing of an Innovative Dispatch-Receiving-Organisational System (ISNOO), a high-mix sheet-metal product. The model connects manufacturing optimisation with environmental performance through sheet nesting, overproduction avoidance, machine-state timing, buffer control and transport planning. It covers 11 production units, buffers, transport, three product variants and stochastic disturbances. A representative comparison of nesting and scheduling alternatives reduced the reported completion time from 1.33 to 1.07 days (19.5%). Shop-floor measurements were collected for a plan of 20 units per variant and an adjusted plan of 6 units per variant. Mean capability indices across eligible operation-product records were Cp = 1.142 and Cpk = 1.036 in the first campaign, and Cp = 1.615 and Cpk = 1.402 in the second. These differences reflect different production schedules and record sets; calibration improved the model representation but does not indicate improved physical process capability. The model identifies opportunities to prevent unnecessary sheet-metal processing, reduce potential scrap and rework, and convert idle-ready periods into planned shutdowns. Because direct material-loss, energy, and emission measurements were unavailable, these outcomes are proxies for resource efficiency and potential environmental benefits rather than quantified reductions in waste or greenhouse-gas emissions.

Keywords: discrete-event simulation, resource efficiency, sustainable manufacturing, OEE, process capability, nesting optimisation

1. Introduction

Environmental protection in manufacturing depends on preventing avoidable material losses and limiting the energy and auxiliary resources consumed in producing accepted products. In sheet-metal production, unnecessary components and rejected parts consume metal and may also require cutting, forming, welding, coating, and transport before becoming waste. Improving production flow can therefore support environmental performance by reducing these physical resource demands. This requirement is particularly important in high-mix production, where changes in product configuration propagate through cutting, forming, joining, coating, identification and assembly. A local improvement at one workstation can increase work in process or generate additional transport elsewhere. Environmental decision-making therefore requires a system-level representation of material flow, machine states, and operation timing. Simulation offers such a representation before changes are introduced on the shop floor and allows screening of resource-efficiency opportunities alongside delivery performance (Diaz-Elsayed et al., 2013; Sproedt et al., 2015).

Digital models and digital twins are used to connect physical production data with virtual experiments. Kritzinger et al. (2018) distinguish a digital model, a digital shadow, and a digital twin by the degree of automated data exchange. The system investigated here is best described as a calibrated digital model: shop-floor measurements were used to update processing-time distributions, but the data exchange was not fully automatic. This distinction matters because environmental claims should reflect the actual integration and measurement level, not the technological label alone.

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The case concerns production of an Innovative Dispatch-Receiving-Organisational System (ISNOO). Its modular structure creates three principal product variants and numerous component routes. Sheet-metal parts pass through laser cutting, bending, corner forming, welding and powder coating, after which selected parts are engraved, pressed and assembled. The process combines serial and parallel flows, shared equipment, intermediate storage and material handling. These characteristics make a single average cycle time insufficient for production and environmental decision-making.

The study aimed to develop and validate a simulation-based decision method that links manufacturing optimisation to resource efficiency and potential environmental performance. The specific aims were to: (i) model the routes and stochastic behaviour of 11 production units; (ii) evaluate disturbance and sheet-format scenarios; (iii) calibrate the model with direct measurements; and (iv) connect completion time, nesting, buffers, transport and process capability with mechanisms of material-loss prevention and energy-demand management. The environmental rationale is that avoiding unnecessary components prevents sheet consumption and downstream processing, while coordinated schedules can create opportunities to reduce powered idle time. Improved flow and quality-risk identification can also help target handling, scrap, and rework. The novelty lies in combining a detailed industrial flow model with an explicit boundary between measured production effects and environmental effects that require additional energy, material, and reject data. The study thus supports environmental protection by identifying preventive production decisions, while providing a framework for subsequent quantitative environmental assessment. A shorter completion time or higher capability index alone is not treated as proof of reduced emissions or waste.

2. Materials and Methods

2.1. Industrial System and Model Boundary

The system boundary began with sheet-metal cutting and ended when a completed ISNOO unit reached the finished-goods store (Table 1). Eleven designated industrial technology units (DITs) were represented. DT01 was the entry process; DT02–DT10 were processing or assembly resources with inter-operation buffers; and DT11 represented final assembly. The model included scheduled transport between workstations, loading and unloading, intermediate storage, setup time, run time, calendar availability and disturbance parameters (Figure 1). It did not include embodied impacts of machinery, building services, supplier transport, or the product's use phase.

Table 1. Production units represented in the ISNOO model

Unit	Operation	Primary resource-efficiency mechanism
DT01	Laser cutting	Sheet nesting, setup sequencing, overproduction avoidance
DT02–DT04	Bending and corner forming	Batch balance, buffer control, reduced waiting
DT05–DT06	Robotic welding	Route selection, setup and idle-time control
DT07	Powder coating	Batch formation, colour sequencing, shared-capacity planning
DT08–DT09	Laser and mechanical engraving	Selective routing and utilisation control
DT10	Eccentric pressing	Shared-resource scheduling
DT11	Final assembly	Synchronisation of converging component streams

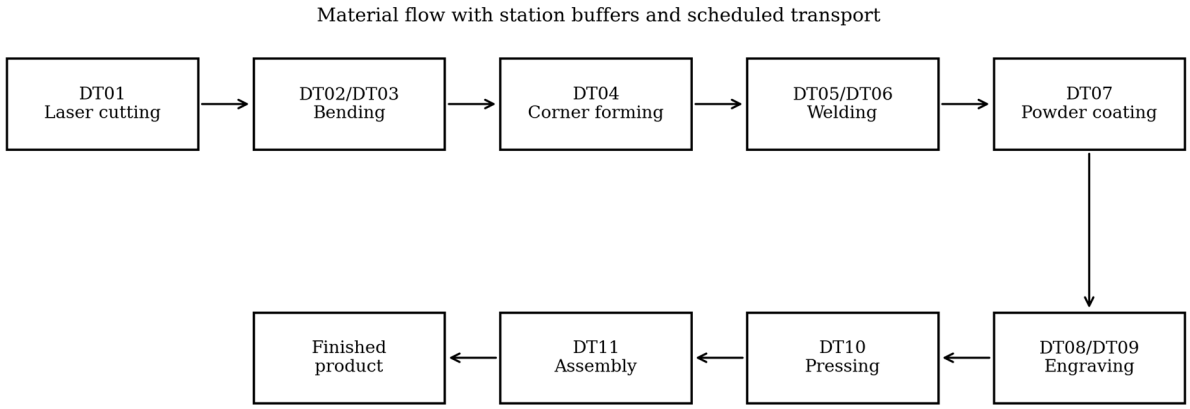

Fig. 1. Simplified process boundary and material flow used in the simulation model

2.2. Mathematical and Simulation Structure

Each production unit was defined by its processing capacity, setup time, run time, and reliability behaviour. For a constant cycle time, capacity was represented as its reciprocal. Machine operation was described by up and down states, while mean time to failure (MTTF) and mean time to repair (MTTR) controlled disturbance generation. The system was implemented as a discrete-event sequence because components move to the next buffer only after the relevant technological operation is completed. This representation preserves blocking, starvation and route-dependent waiting, which are lost when only annual or monthly averages are considered.

The principal performance variables were throughput, production rate, work in process, residence time, blocking and starvation probabilities, setup time and equipment utilisation. Overall Equipment Effectiveness (OEE) was calculated from availability, performance and quality. Two time bases were retained: total calendar availability and the working shifts assigned to a given operation. The shift-based value was more informative for shared equipment because the analysed ISNOO orders occupied only part of its available production time. Quality Buy Rate was initially set at 95% for all DITs because workstation-specific reject data were unavailable. OEE was therefore used as a diagnostic utilisation measure, not as direct evidence of environmental improvement.

Operation-time capability was described using Cp and Cpk. These indices quantify dispersion and centring relative to specification limits; they do not independently establish statistical process stability. Cp compares the allowable interval between the upper and lower specification limits with six standard deviations, whereas Cpk additionally accounts for displacement of the mean. The project acceptance condition was $Cp > 1$ and $Cpk > 1$. In the first digital simulation, operation times were sampled from a normal distribution centred on the normative run time, with an initial standard deviation parameter of 0.2. Direct measurements were then used to replace this common assumption with DIT- and item-specific standard deviations. Records with fewer than six measurements were excluded from the capability calculation. Model calibration changes how operation-time variability is represented, whereas any change in physical process capability must be established from comparable shop-floor measurements.

Inter-operation buffer requirements were derived from cumulative inflow and outflow. For every analysed time point, the buffer content was calculated as accumulated arrivals minus accumulated departures; the maximum positive difference defined the required capacity. Transport duration combined route distance with preparation, loading, unloading, and loaded-travel parameters. The material-handling model used a pallet truck with a nominal travel speed of 4.5 km/h and a lifting capacity of 1000 kg. Logistic units included plastic containers and two pallet formats.

2.3. Simulation Scenario Design, Calibration and Validation

The study analysed alternative production plans using the mathematical model and ISNOO simulator, then verified them on the complete demonstration manufacturing installation. Numerical experiments were used to develop production schedules for three ISNOO variants and assess the utilisation of individual installation modules. Two plans were selected for verification under actual production conditions: 20 units of each variant, totalling 60 ISNOO units, and 6 units of each variant, totalling 18 units. The plans served different research purposes and were not replications of the same experiment (Table 2).

The first industrial trial aimed to confirm the feasibility of repeatable production of three product configurations and verify technological operation times at individual installation modules. Operation times were determined from production and measurement plans and used to assess process parameters and verify the model's timing assumptions. Based on the experience gained from the first trial, a representative batch comprising 6 units of each of the three ISNOO variants was defined. Its production plan was developed using the mathematical model and simulator. This trial aimed to assess the Cp and Cpk indices and equipment utilisation, expressed as OEE.

Table 2. Model development and validation sequence

Stage	Input and experiment	Decision output
Structural model	Three product variants, component routes and 11 DITs	Process topology and precedence
Scenario model	Alternative production plans and disturbance and nesting assumptions	Completion time, setup and utilisation
Digital campaign	Numerical experiments using the ISNOO model and simulator	Sensitivity to disruptions and nesting
Validation 1	20 units of each of three variants (60 units total), with direct timing	Corrected flow and variability assumptions
Adjustment	DIT- and item-specific deviations and buffer sizes	Revised schedule and WIP control
Validation 2	6 units of each of three variants (18 units total)	Descriptive Cp, Cpk and OEE assessment under a different production schedule

2.4. Environmental Interpretation

The environmental interpretation followed a lean-and-green logic: time and flow indicators were first connected to physical resource mechanisms, and only effects supported by available data were quantified. Four pathways were considered. First, improved nesting reduces unused sheet area and prevents production of components not required by the order. Second, shorter setup and completion times reduce the time machines and auxiliary systems must remain ready. Third, correctly sized buffers reduce excess work in process, handling, and storage. Fourth, operation-time capability can identify departures from timing specifications that may require process investigation. These timing indices do not directly measure product defects, scrap or rework; such environmental links require separate quality and material-loss measurements. Similar simulation-based links between lean actions and environmental performance have been proposed by Herrmann et al. (2011), Diaz-Elsayed et al. (2013) and Sproedt et al. (2015).

Data on direct electricity, compressed air, coating materials, and scrap mass were not available. Consequently, the study did not calculate kWh, kg CO_2 equivalent, or life-cycle impacts. The model nevertheless provides the activity times needed for a later inventory. For each DIT, electricity can be calculated by multiplying the sum of run, setup, idle, and off-state durations by their measured power levels. Transport energy can be added based on distance and load, while material loss can be calculated as sheet mass minus accepted component mass. This extension would complement OEE with Overall Environmental Equipment Effectiveness (Domingo & Aguado, 2015) and a life-cycle assessment consistent with ISO 14040 and ISO 14044.

3. Results

3.1. Scenario Screening and Production Completion Time

A representative comparison reported a completion time of 1.33 days for a reference production scenario and 1.07 days for the optimised undisturbed scenario. The 0.26-day difference corresponds to a 19.5% reduction relative to the reference scenario. This result does not represent an energy saving of the same magnitude: the relationship depends on the power required in running, setup, idle, and off states. It does show that the same production demand can be completed within a shorter operating window, creating an opportunity to shut down equipment and supporting systems earlier or to avoid an additional shift.

The laser-cutting algorithm selected the number of nests for each item while minimising component overproduction. This is the clearest material-efficiency mechanism in the model because sheet use is determined before downstream operations begin. The source data did not include sheet area or scrap mass for each nesting

alternative, so a mass-based waste reduction could not be calculated. For implementation, the optimisation objective should therefore be expanded from the number of nests and completion time to a joint objective containing sheet utilisation, scrap mass, setup time and energy per accepted component.

3.2. Utilisation and Bottleneck Structure

For the validation plan of 20 units per variant, the highest reported shift-time OEE values occurred at DT01 (68.04%), DT08 (63.33%), DT09 (57.90%) and DT03 (55.51%). In the adjusted plan of 6 units per variant, DT01 and DT08 increased to 87.22% and 85.50%, respectively, while several shared resources remained lightly loaded. Figure 2 presents all values. The two campaigns differ in order size and schedule; the bars should therefore be interpreted as workload maps rather than a causal before-after comparison. Their environmental management value is practical: high-load resources deserve priority in energy monitoring, whereas low-load resources are candidates for automatic standby or consolidation into shorter operating windows.

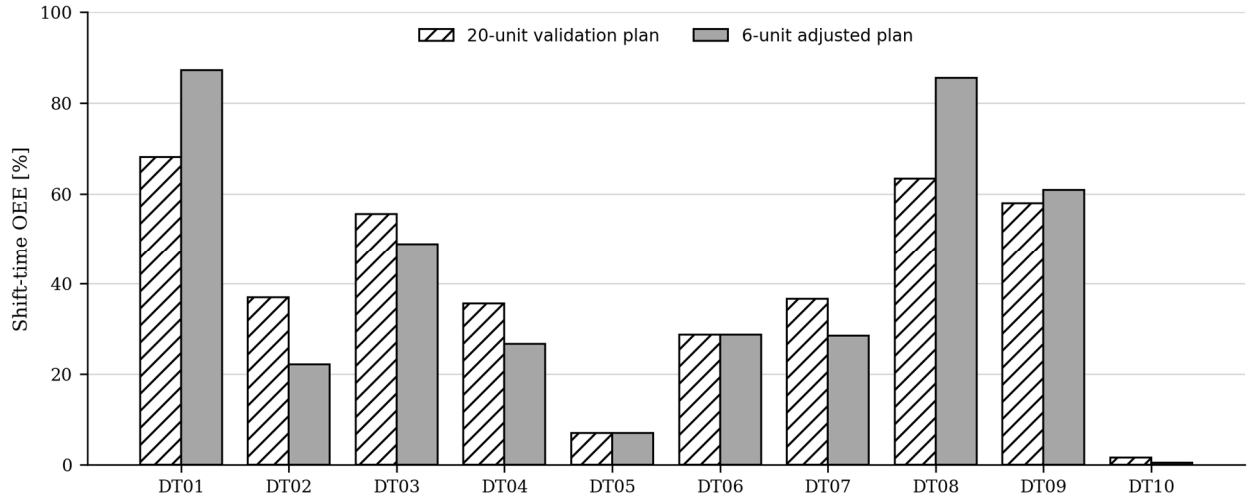

Fig. 2. Shift-time OEE reported for the two validation plans; order size and schedule differed between campaigns. The labels "20-unit validation plan" and "6-unit adjusted plan" denote quantities per variant (60 and 18 ISNOO units in total, respectively).

3.3. Process Capability and Buffer Calibration

The first validation campaign included 118 operation-product records with enough observations to calculate process capability. The mean Cp was 1.142, with a range of 1.01–1.46, and the mean Cpk was 1.036, with a range of 1.01–1.09. All eligible records exceeded the project threshold of 1, but the small margin of Cpk above the limit indicated that centering and variability still required attention. The direct measurements showed that a single variability value for all operations was not adequate (Table 3).

In the second campaign, using the calibrated model with item- and DIT-specific standard deviations and revised inter-operation buffer parameters, 128 eligible records yielded a mean Cpk of 1.402 (range 1.35–1.45) and a mean Cp of 1.615 (range 1.36–2.61). The number of buffer-flow inconsistencies also decreased qualitatively, and the observed operation-time variation was closer to the digital model. The capability indices describe the records collected under the adjusted 6-unit-per-variant production schedule; they reflect that campaign, not effects caused by calibration. Calibration improved the correspondence between the model and measured operation times and buffer flows. It did not, by itself, change the physical manufacturing process's capability. Because the 20- and 6-unit-per-variant campaigns differed in schedule, order size, mix, and eligible record sets, their aggregate Cp and Cpk values are descriptive summaries and cannot establish a causal improvement or a matched before-and-after effect. Both sets of eligible records exceeded the project threshold.

Table 3. Summary of reported and derived validation results

Indicator	20 units per variant	6 units per variant	Environmental interpretation
Eligible records	118	128	Evidence base for variability and quality-risk control
Mean Cp	1.142	1.615	Timing dispersion relative to specification limits; no quantified scrap reduction
Mean Cpk	1.036	1.402	Timing centring and dispersion; no causal calibration effect or measured rework reduction
Capability range	Cp 1.01–1.46; Cpk 1.01–1.09	Cp 1.36–2.61; Cpk 1.35–1.45	All eligible records remained above 1
Buffer behaviour	Flow inconsistencies observed	Fewer inconsistencies observed	Improved flow representation; handling and WIP benefits require measurement

3.4. Resource-efficiency Effects

The combined results identify three levels of environmental action. At the operation level, measured run-time distributions improve the prediction of active and idle duration. At the flow level, buffer trajectories and the transport matrix reveal where parts wait or require additional movement. At the system level, nesting and schedule selection reduce the completion window and prevent avoidable production. These levels should not be collapsed into a single efficiency percentage: each requires different physical inventory and may involve trade-offs. For example, a smaller buffer can reduce stored material but increase starvation and repeated transport if it is undersized.

The model therefore supports a decision hierarchy. The priority is to eliminate overproduction at DT01 because every unnecessary component consumes sheet, laser time, and downstream capacity. Second, investigate operations with low timing Cpk and combine this assessment with product-conformity checks before resource-intensive coating or engraving. The third is to schedule shared resources so that low utilisation becomes planned off time rather than unproductive powered idle time. The fourth is to set buffers using cumulative flow rather than fixed customary values. This hierarchy converts the simulation from a delivery-date tool into an environmental decision-support structure.

4. Discussion

4.1. Contribution to Sustainable Manufacturing

The case confirms that a production model can contribute to environmental protection even before a complete life-cycle inventory is available. This contribution does not replace energy or emission measurement. It identifies where and when those flows occur, and which control decisions can change them. This aligns with energy-oriented manufacturing simulation, where machine states and production schedules are necessary to explain energy demand (Kuczynski et al., 2021) that cannot be captured by multiplying annual output by an average intensity (Herrmann et al., 2011; Seow & Rahimifard, 2011).

This result also aligns with research showing that production scheduling can reduce energy use without requiring new machinery (May et al., 2015). In the ISNOO case, the 19.5% shorter representative completion time, combined with a map of station-specific utilisation, provides the temporal information required to test power-down policies. Whether the policy is beneficial depends on restart energy, thermal constraints, maintenance requirements and the availability of a sufficiently long idle interval. These variables should be added explicitly rather than assuming that every minute saved is an equal environmental gain.

Process capability offers further guidance for resource-efficient operation, but its environmental interpretation depends on the characteristic being measured. Scrap and rework carry the cumulative material and energy inputs of preceding operations. In this study, however, Cp and Cpk describe operation-time records rather than dimensional conformity or measured reject rates. Higher timing-capability indices in the second campaign therefore cannot be converted into avoided scrap, rework, material loss, or energy consumption. The values were observed under a different production schedule after the model parameters had been updated; calibration improved the model representation and does not demonstrate an improvement in physical process capability. The results help identify operations requiring investigation and more reliable scheduling. Establishing an envi-

ronmental quality benefit would require comparable production plans and workstation-specific records of accepted, reworked, and rejected components, together with the material and energy inputs accumulated before rejection.

For environmental protection, the main relevance lies in sustainable development, resource efficiency, and circular-economy implementation in industrial practice. The model makes material loops and losses measurable at the point where decisions are made: sheet nesting, batch creation, routing, intermediate storage and quality control. It can also support the use of recycled sheet or reprocessed coating material by adding material-specific process times, quality limits, and environmental factors (Lenort et al., 2019). In this way, the same model can compare whether a circular material option shifts burdens through longer processing, higher reject risk, or additional transport (Staniuk et al., 2022).

4.2. Limitations and Future Work

The principal limitation is the absence of direct environmental inventory data. No claims are made about absolute energy savings, carbon footprint, or waste mass. The assumed 95% quality rate is applied to all DITs and should be replaced with measured good-part rates. Sheet-format scenarios should record input sheet mass, accepted component mass, skeleton scrap, recoverable offcuts and overproduced parts. Powder coating requires separate measurement of electricity, gas, compressed air, powder consumption and overspray recovery. Transport should record actual distance, load and empty return journeys.

Table 4 defines a minimum, not an exhaustive, inventory. Its purpose is to preserve the event resolution already present in the production model. Aggregating electricity or waste only at monthly level would prevent attribution to a product variant, machine state or scheduling decision and would weaken the environmental interpretation.

Table 4. Minimum measurement set for environmental extension of the model

Process area	Measured variables	Model output	Environmental indicator
All DITs	Power in run, setup, idle-ready and off states	State duration by order and item	Electricity per accepted component
DT01 laser cutting	Sheet input, skeleton scrap, offcuts and overproduction mass	Nesting plan and cutting time	Material yield and scrap mass
DT07 powder coating	Electricity, gas, compressed air, powder input and recovered overspray	Batch, colour and loading time	Energy and coating loss per batch
Transport	Loaded and empty distance, load mass and handling time	Scheduled route and trip count	Transport energy per order
Buffers	Peak inventory and component residence time	Time-dependent WIP	Material-time in storage
Quality	Accepted, reworked and rejected quantities by DIT	Route-specific quality rate	Avoided cumulative material and energy loss
Energy supply	Time-dependent electricity and fuel emission factors	Timestamped machine demand	kg CO_2 equivalent per product variant

The validation data were collected during two industrial campaigns with different plan sizes. Capability statistics for records based on six observations are sensitive to distributional assumptions, and no uncertainty interval was reported. Future experiments should use replicated plans, a predefined sampling frequency, and statistical tests for model error. Validation should compare predicted and measured completion time, queue length, and utilisation with confidence intervals. A sensitivity analysis should then determine whether energy and waste conclusions remain stable under uncertainty in failure, repair and processing-time distributions.

A practical next step is to install sub-metering on DT01, DT07 and DT08, which were frequently among the most heavily loaded resources, and to measure at least four power states: processing, setup, idle-ready and off. Each simulated event can then be assigned energy, carbon, and cost factors. The resulting model could simultaneously optimise makespan, material loss, and greenhouse-gas emissions. Linking these outputs with product-level life-cycle assessment would allow dynamic allocation of manufacturing impacts to individual ISNOO variants (Löfgren & Tillman, 2011; Rödger et al., 2021).

5. Conclusions

A calibrated discrete-event model was developed for a high-mix ISNOO manufacturing system comprising 11 production units, intermediate buffers, transport and three product variants. In a representative comparison, the optimised program reduced completion time from 1.33 to 1.07 days, a 19.5% reduction.

Direct shop-floor measurements supported updates to DIT- and item-specific variability and buffer parameters and improved the model representation. The first campaign produced mean Cp = 1.142 and Cpk = 1.036 across 118 eligible operation-product records; the second, conducted under an adjusted 6-unit-per-variant production schedule, produced mean Cp = 1.615 and Cpk = 1.402 across 128 eligible records. Both descriptive summaries exceeded the project threshold. The campaigns differed in plan size, schedule, mix, and record sets, so differences in their indices do not show that model calibration improved physical process capability. Fewer buffer-flow inconsistencies support improved model correspondence, while a controlled comparison would be required to establish changes in the manufacturing process.

The model's environmental value lies in its ability to target material overproduction, avoidable setup and idle time, excess work in process, transport, and quality losses. The available data justify conclusions about resource-efficiency opportunities, not absolute reductions in energy or emissions. Adding machine-state power, scrap mass, coating consumption and transport measurements will convert the model into a quantitative environmental assessment and multi-objective optimisation tool.

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