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Development and Validation of the MANUPRAXA Framework for Integrating Manufacturing Productivity, Process Reliability and Operational Excellence in Industrial Production Systems

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Abstract

Industrial production systems are frequently evaluated through isolated measures of throughput, equipment effectiveness, maintenance efficiency, and continuous improvement. Such fragmented measurement can reward short-term output while concealing degradation in asset reliability or growth in avoidable operating cost. This article develops MANUPRAXA, an explicitly defined multi-criteria framework integrating manufacturing productivity, reliability, and operational excellence through a reliability-adjusted performance function and constrained operational decision rules. The research adopts a design-science and computational feasibility methodology using a reproducible, 180-day synthetic production panel with four competing intervention strategies: baseline practice, total productive maintenance, lean improvement, and the integrated MANUPRAXA policy. The model combines availability, performance, quality, renewal-process reliability indicators, cost, and a non-compensatory robustness constraint. Comparative indicators and six monochrome figures are reported, with perturbation analysis illustrating the sensitivity of estimated effects to specified assumptions. Simulated improvements support computational consistency of the proposed architecture but cannot establish factory-level causal effectiveness. Future validation requires prospective multi-plant data, independently recorded stoppages, prespecified operating cost definitions, and blinded outcome auditing.

Keywords: *Manufacturing Productivity; Process Reliability; Operational Excellence; Total Productive Maintenance; Overall Equipment Effectiveness; Computational Validation; Continuous Improvement.*

I. INTRODUCTION

Contemporary production facilities must deliver conforming output at competitive unit costs while limiting unplanned downtime, deterioration, and process variability. Conventional performance systems often separate operations, quality, and engineering maintenance. This division complicates root-cause analysis because a gain in one metric can conceal a loss elsewhere. Overall equipment effectiveness (OEE) is widely used to distinguish time loss, speed loss, and quality loss, although its interpretation depends on the accounting boundary and its treatment of planned stoppages (Nakajima, 1988; Hung et al., 2022).

Manufacturing improvement is also an organizational system rather than a single machine intervention. Lean practices address flow and waste, continuous improvement organizes improvement cycles, and reliability engineering studies failures and repair

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processes. Recent literature emphasizes the benefit of integrating these activities while identifying substantial implementation barriers related to data quality, employee capability, and governance (Vinodh et al., 2021; Macias-Aguayo et al., 2022; Terra et al., 2023).

The central research question is whether a coherent decision architecture can link production yield, equipment reliability and operational excellence without using a purely additive performance index that permits severe deterioration in one dimension to be offset by improvements elsewhere. The proposed answer, MANUPRAXA, supplies a common observation model, standardized decision variables, and explicit constraints on unacceptable losses.

This paper offers three contributions. First, it formalizes a reproducible measurement architecture that connects OEE with repairable-system metrics and unit-cost behavior. Second, it develops a non-linear, reliability-adjusted manufacturing utility with risk-sensitive constraints. Third, it supplies reproducible computational comparison, providing an auditable protocol for later empirical validation. The February 2024 date is treated as a strict evidence cutoff; later sources are deliberately excluded.

➢ *Research Questions and Objectives*

- RQ1: How can productivity, reliability, and operational excellence be integrated into a common measurement architecture while preserving the distinct meaning of each construct?
- RQ2: Under explicitly stated hypothetical intervention effects, does the integrated MANUPRAXA policy dominate isolated TPM and lean policies on conforming output and operating cost?
- RQ3: How sensitive are any modeled advantages to uncertain uptake, non-linear interactions, and unavoidable disruption shocks?

II. LITERATURE REVIEW AND THEORETICAL FOUNDATION

➢ *Overall Equipment Effectiveness and Productivity*

Manufacturing-oriented TechConnect proceedings illustrate why indicator quality must be established before drawing conclusions about productivity. Triltsch and Büttgenbach (2008) described integrated design and process planning with cost and workflow constraints, while Strandman et al. (2015) examined at-line measurement for quality control in food production. Their contributions concern specific manufacturing processes, rather than the plant-wide effectiveness of MANUPRAXA; they nevertheless support using traceable operational measurements rather than throughput totals alone.

OEE has an established role in documenting availability, performance, and conforming quality. Yet different interruption classifications can change its apparent level, and comparison across plants is unreliable unless accounting rules are harmonized. The operational-excellence measurement model reported in 2022 emphasized the distinction between target and actual production time, and classified changeover and material loading losses as important sources of inefficiency (see the 2022 IFAC-PapersOnLine development and validation study).

Hung et al. (2022) identified hidden capacity limits in OEE management: improving the ratio of effective to scheduled machine time does not automatically expand production beyond cycle-time or bottleneck limits. Accordingly, MANUPRAXA tracks not only OEE but also good units, utilization constraints, and the yield-adjusted production rate. OEE serves as a diagnostic input rather than a final welfare objective.

➢ *Reliability Engineering and Maintenance Policy*

TechConnect publications provide complementary engineering examples of reliability and robustness. McCluskey and Pecht (1999) proposed early reliability assessment supported by failure-physics models, and Reh et al. (2000) used probabilistic analysis to represent manufacturing uncertainty in microelectromechanical systems. These studies are application-specific and do not independently validate the reliability constraints proposed here, but they reinforce the value of modelling failure mechanisms and uncertainty explicitly.

Reliability concerns the probability that an asset or process performs its required function for a stated duration under specified conditions. For repairable equipment, mean time between failures (MTBF) and mean time to repair (MTTR) summarize distinct aspects of the renewal and restoration processes. Their ratios can be informative for operational planning but should not be interpreted as evidence that failure-time distributions are exponential without diagnostic testing (Rausand & Høyland, 2004; Barlow & Proschan, 1965).

Industrial maintenance policies include reactive maintenance, preventive scheduling, condition-based action, and reliability-centred prioritization. A 2023 pharmaceutical manufacturing study integrating maintenance and operational excellence illustrates the practical relevance of the combination, but site-specific improvements cannot be transported directly into another production context (as reported in a 2023 Heliyon maintenance case study). MANUPRAXA therefore treats maintenance effectiveness as a scenario parameter to be estimated empirically.

➢ *Lean, Continuous Improvement and Cost*

Additional TechConnect process studies show how quality and economic consequences can be assessed together: Porzio et al. (2014) examined resource-constrained industrial water-system optimisation, and Pupek (2018) described continuous-flow nanomaterial processing as a route to lower batch variability and more scalable production. Such case studies motivate extending a performance framework beyond narrow machine-

efficiency ratios; their process-specific findings should not be generalized to all industrial plants.

Lean approaches focus on material flow, variation reduction, and removal of non-value-added work. Womack and Jones (1996) argued for a system view of customer value, while Deming (1986) emphasized management of the overall process and the dangers of unstable performance evaluation. For MANUPRAXA, lean practices enter not as a label attached to a plant but as measurable changes in cycle time, scrap rate, queue length, and unit-level resource consumption.

The equipment cost-efficiency literature demonstrates why OEE can improve without equivalent financial benefit when additional maintenance or equipment expenditures exceed the value created (Liew et al., 2023). Consequently, cost is modeled independently and retained in a constraint system. This design prevents the mistaken conclusion that an intervention is operationally superior simply because its reported OEE is higher.

➢ *Integration Architecture and Implementation Capacity*

The manufacturing case evidence also shows that the unit of analysis matters. Kim et al. (2007) coupled numerical modelling with process-condition studies for nanoimprint lithography, and Triltsch and Büttgenbach (2008) connected engineering data models to process planning. These examples support the proposed MANUPRAXA emphasis on integrating technical process data with managerial decisions, without claiming that they establish causal effectiveness for the proposed framework.

Syntheses of continuous improvement and advanced manufacturing identify meaningful contact points between data acquisition and traditional quality management. Skalli et al. (2023), Komkowski et al. (2023), and Pongboonchai-Empl et al. (2023) point to integration mechanisms spanning diagnostic analytics, workflow redesign, and workforce capability. The research also records impediments involving skill availability, incomplete operational standards, and organizational resistance.

Berhe et al. (2023) presented a structured integrated Kaizen model, supporting the idea that improvement routines require defined governance and verification. Pansare et al. (2024); Ogundola, (2022) examined operational excellence and reconfigurable systems in an issue available by January 2024. These publications support the architectural premise of MANUPRAXA but do not validate the model itself.

➢ *Conceptual Gap and Propositions*

Prior studies offer strong arguments for maintenance integration and performance measurement, but the practical problem of compensation remains: a model may aggregate better yield and lower cost into a positive score even while reliability falls below an acceptable threshold. This motivates a non-compensatory design with hard constraints on availability, safety-relevant failure intensity, and minimum service capability (Abolade, et al., 2024).

The propositions to be subjected to future empirical testing are that (P1) an integrated intervention improves conforming throughput relative to isolated strategies, (P2) reliability gating reduces the probability of undesirable high-output/high-failure solutions, and (P3) the marginal benefit of integrated management depends on baseline asset condition and implementation fidelity. The computational experiments below test feasibility of these propositions, not their truth in industrial populations.

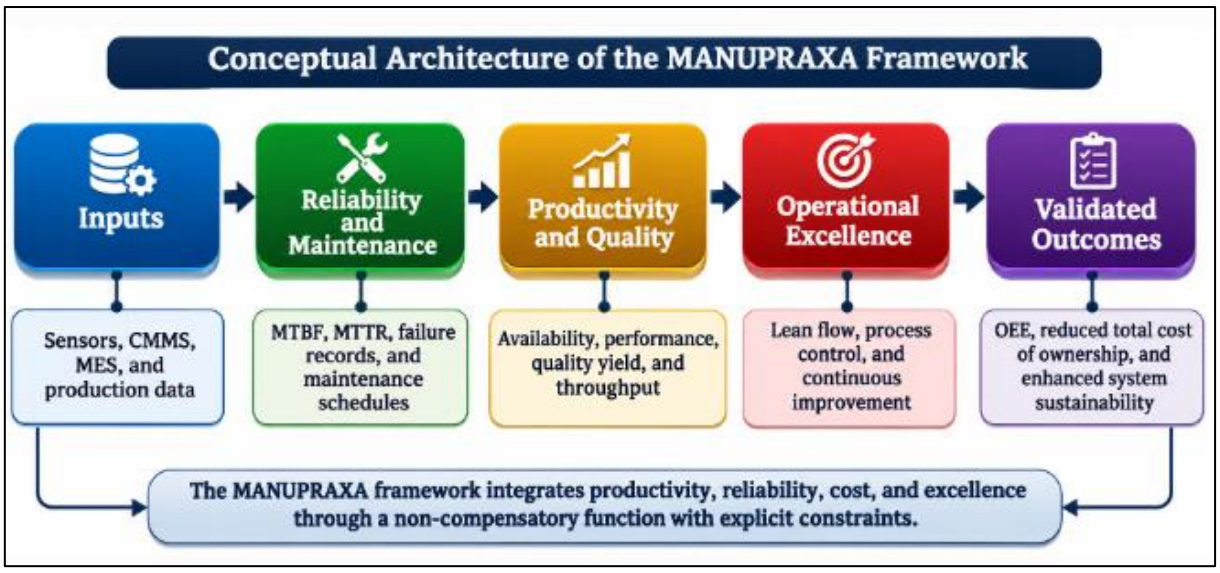

Fig 1 Conceptual Structure of MANUPRAXA Linking Plant Data Inputs, Reliability Analysis, Productivity Assessment, Operational Excellence Routines and Validated Decision Outcomes.

The conceptual framework in Figure 1 summarizes the theoretical integration advanced in Section 2. It shows how plant data streams support reliability analysis, productivity measurement, operational excellence routines, and a constrained decision layer that together produce validated intervention choices for industrial production systems.

III. MATERIALS AND METHODS

This section describes an original methodological proposal and a fully synthetic proof of concept. All formulas are operational definitions or candidate mathematical models; they have not been fitted to real production measurements. A deterministic random seed of 202402 permits computational replication. Twelve classes of variables are distinguished to avoid double counting and to support subsequent field validation.

➢ *Design and Experimental Units*

The numerical design contains 180 simulated daily records for each of four competing improvement policies. A shared baseline disturbance sequence is reused in every arm, a common-random-numbers technique that decreases Monte Carlo noise in paired contrasts. Scenario intensities are chosen transparently as assumptions, not reported intervention effect sizes. This provides a fair computational test but not randomized causal identification (Law, 2015).

Table 1 Proposed Data Dictionary for Factory Validation.

Construct	Operational Record	Unit	Source in Real Study
Equipment availability	Run time / planned time	Proportion	MES / downtime log
Speed performance	Actual versus ideal cycle rate	Proportion	PLC / takt records
Quality yield	Conforming units / total units	Proportion	Quality register
Failure recurrence	Operating hours between failure events	Hours	CMMS / failure log
Restoration duration	Time between outage and qualified return	Hours	CMMS / technician audit
Operational cost	Resource spending per period	Indexed / currency	Cost ledger

The production observation window, measurement frequency, failure-event classification and exclusion policy should be preregistered. Design decisions must be defined before examining outcome trends, particularly when the same operational manager both implements an intervention and certifies its performance.

$$OEE_t = A_t \times P_t \times Q_t = (T_{r,t} / T_{p,t}) \times (\tau^* N_t / T_{r,t}) \times (G_t / N_t) \quad (1)$$

Where OEE_t is total equipment effectiveness for period t; A_t is availability; P_t is performance; Q_t is quality yield; $T_{r,t}$ is running time; $T_{p,t}$ is planned production time; τ^* is ideal time per unit; N_t is total output; and G_t is conforming output.

Equation (1) defines the production-side reference metric. MANUPRAXA requires a documented definition of planned time so that changes in scheduling policy are not incorrectly classified as technological efficiency gains.

➢ *Reliability Function and Temporal Dynamics*

$$R(t \mid x) = exp\{-\int_0^t \lambda_0(u)\, exp(\beta^{\mathrm{T}} x(u))\, du\} \quad (2)$$

Where $R(t \mid x)$ is conditional survival probability over duration t; $\lambda_0(u)$ is baseline failure hazard at time u; β is a vector of covariate coefficients; $x(u)$ is the vector of time-dependent operating conditions; and u is integration time.

Equation (2) allows covariate-dependent equipment deterioration and does not impose a constant failure hazard. The hazard parameters would require equipment event-history data and a separate statistical estimation protocol.

$$A_\infty = MTBF / (MTBF + MTTR);\ MTBF = \Sigma U_j / J;\ MTTR = \Sigma D_j / J \quad (3)$$

Where A_∞ is steady-state repairable-system availability under renewal assumptions; U_j is uptime before failure j; D_j is corresponding repair duration; J is the counted failure events; MTBF is mean time between failures; MTTR is mean time to repair.

Equation (3) is useful as a consistency check and is not substituted for directly logged operational availability where planned stoppages are present.

$$\lambda_t = \lambda_0\, exp\{\gamma_1 v_t + \gamma_2 s_t^2 - \gamma_3 m_t + \gamma_4 (v_t m_t)\} \quad (4)$$

Where λ_t is period-specific failure intensity; λ_0 is reference hazard; v_t is load severity; s_t is operating-condition variability; m_t is maintenance intensity; and γ_1–γ_4 are coefficients governing individual and interactive effects.

Equation (4) captures a possible non-linear load-maintenance interaction: under high load, a superficially improved machine can remain vulnerable to accelerated failure. The model parameters must be learned with measured condition and failure data before operational application.

➢ *Integrated Decision Function and Constraints*

$$U(\theta) = [\prod_{k=1}^{3} (z_k(\theta) + \varepsilon)^{w_k}]\, exp\{-\rho\, CVaR_\alpha(L(\theta))\} - \kappa C(\theta) \quad (5)$$

Where $U(\theta)$ is MANUPRAXA decision utility for intervention vector θ; z_k are normalized productivity, reliability, and excellence indices; ε is a small positive numerical offset; w_k are non-negative weights summing to

one; ρ is risk-aversion weight; CVaRα is conditional value at risk at probability α; L is operational loss; κ is cost penalty; and C is normalized intervention cost.

Equation (5) combines complementary outcomes multiplicatively, so a near-zero score cannot easily be compensated by another dimension. The downside-risk penalty discourages strategies that appear attractive only in favorable simulations.

$$\theta * = arg\ max\theta \in \Theta\ U(\theta)\ subject\ to\ R(\Delta|\theta)\ \geq\ r\square_{i}\square\ ;\ C(\theta)\ \leq\ B\ ;\ q(\theta)\ \geq\ q\square_{i}\square \quad (6)$$

Where θ is the optimal decision vector; Θ is the feasible policy set; R(Δ|θ) is mission-time reliability over horizon Δ; r_{min} is minimum reliability; C is policy cost; B is the budget ceiling; q is conforming yield; and q_{min} is required minimum quality.*

Equation (6) states the non-compensatory logic explicitly. No amount of throughput improvement is admissible if an essential reliability or quality constraint is violated.

$$z\square(\theta)\ =\ [x\square(\theta)\ -\ \ell\square]\ /\ [u\square\ -\ \ell\square]\ ;\ \Sigma\square w\square\ =\ 1\ ;\ w\square\ \geq\ 0 \quad (7)$$

Where z_k is the normalized score for domain k; x_k is its raw indicator; ℓ_k and u_k are prespecified minimum and maximum reference limits; and w_k is the domain weight. Limits are fixed before observing scenario outcomes.

Equation (7) standardizes domains with different units. Fixed scaling limits are preferable to arm-specific extrema, which could change a policy ranking simply because the comparison set changes.

➢ *Intervention Response and Production Process*

$$A\square(\theta)\ =\ min\{0.99, A\square^{0}\ +\ a^{\mathrm{T}}\theta\}\ ;\ P\square(\theta)\ =\ min\{0.995, P\square^{0}\ +\ b^{\mathrm{T}}\theta\} \quad (8)$$

Where A_t^0 and P_t^0 are baseline availability and performance; θ is the intervention vector; a and b are assumed domain-response coefficients; and min enforces physically interpretable upper limits.

Equation (8) implements bounded policy effects within the simulation. These are not estimated from plant intervention data and should not be interpreted as clinically or industrially observed treatment effects.

$$G\square(\theta)\ =\ D\square\ A\square(\theta)\ P\square(\theta)\ Q\square(\theta)\ ;\ Q\square(\theta)\ =\ min\{0.998, Q\square^{0} + c^{\mathrm{T}}\theta\} \quad (9)$$

Where G_t is simulated conforming units; D_t is theoretical period capacity under demand; A_t, P_t and Q_t are intervention-specific ratios; Q_t^0 is baseline quality; c is the assumed quality response vector.

Equation (9) generates the primary productivity outcome. Consistent with Hung et al. (2022), a deployment study should explicitly test bottleneck capacity before replacing theoretical capacity with a realized production forecast.

$$C\square(\theta)\ =\ C\square^{0}(1 - d^{\mathrm{T}}\theta)\ +\ C^{\mathrm{I}}(\theta)\ ;\ \Pi\square(\theta)\ =\ pG\square(\theta)\ -\ C\square(\theta) \quad (10)$$

Where C_t^0 is baseline operating cost; d is the cost-reduction response vector; C^I is direct intervention investment; Π_t is daily contribution; and p is marginal contribution per conforming unit. The demonstration records only an indexed operating-cost proxy and does not estimate C^I from accounts.

Equation (10) shows why the simulated cost comparison is incomplete as an investment appraisal. Payback, discounting, training cost, lifecycle maintenance, and operational disruption require observed financial data (Liew et al., 2023).

➢ *Robustness, Causal Evaluation and Uncertainty*

$$\Delta\square\ =\ E[Y\square(\theta\square) - Y\square(0)]\ ;\ \Delta\square\ =\ N^{-1}\ \Sigma\square[Y\square(\theta\square) - Y\square(0)] \quad (11)$$

Where Δ_m is the average modeled effect of policy m; Y_t is a specified outcome such as OEE or conforming output; θ_m is the policy; 0 represents baseline; N is the number of days; and E denotes expectation under the simulation mechanism.

Equation (11) computes only a model-implied scenario contrast. A real factorial or randomized stepped-wedge trial would additionally require assignment documentation, pre-intervention trends, and a treatment identification strategy.

$$V(\Delta\square)\ =\ (N - 1)^{-1}\ \Sigma\square[(\delta\square - \delta)^{2}]/N\ ;\ \delta\square\ =\ Y\square(\theta\square) - Y\square(0) \quad (12)$$

Where $\hat{V}$ is an illustrative sampling-variance estimator; δ_t is each paired-day difference; $\bar{\delta}$ is its mean; and N is the panel length. Serial dependence means this expression should be replaced by block-bootstrap or HAC estimates in real daily series.

Equation (12) documents a simple uncertainty starting point while making its limitations explicit. For factory data, block lengths should reflect equipment repair cycles and the degree of temporal autocorrelation.

$$CVaR\alpha(L) = min\eta \{\eta + [1/(1-\alpha)]\, E[max(L-\eta, 0)]\} \quad (13)$$

Where CVaRα is expected loss in the upper tail; L is the random operational loss; α is a prespecified upper-tail probability; η is the candidate loss threshold; and E is the expectation operator.

Equation (13) provides a mathematically explicit method for penalizing low-frequency, high-consequence operating states. Tail metrics are only meaningful when sufficiently long or well-founded failure scenarios are available.

$$S\square = [U(\theta + he\square) - U(\theta - he\square)]/(2h) \quad (14)$$

Where S_j is a central finite-difference sensitivity score for policy component j; U is the utility defined in Equation (5); h is a prespecified perturbation step; and e_j is the unit vector corresponding to component j.

Equation (14) allows managers to identify which assumptions most influence the decision ranking. The demonstration figure uses a single, collective intensity parameter; full multi-parameter global sensitivity is reserved for later empirical work.

- *Computational Protocol, Comparison Groups and Validation Criteria*

Table 2 Prescribed Synthetic Intervention Response Assumptions (Not Measured Effects).

Scenario	Availability Shift	Performance Shift	Quality Shift	Cost Index Reduction
Baseline	0.000	0.000	0.000	0.0%
TPM only	0.045	0.010	0.006	7.0%
Lean only	0.012	0.035	0.016	4.5%
MANUPRAXA	0.068	0.043	0.023	13.0%

A 180-day reference sequence is constructed from bounded seasonal processes and shared Poisson disruption shocks. The policy effects in Table 2 are applied to the same baseline sequence for all four strategies. Good units and indexed cost are derived according to the computational definitions. The full simulated data panel and a runnable Python program accompany this manuscript. These parameters are deliberately described as assumed changes, not external findings.

Three validation layers are proposed. Code verification checks bounds, time indexing, random-seed reproducibility, and consistency of Equation (1). Construct validation evaluates whether measures and failure classifications agree with MES and CMMS records. External validation compares prespecified predictive errors and intervention performance at independent plants. This paper completes only the code and conceptual demonstration layers, not field validation.

The planned empirical primary endpoint is conforming output per scheduled production hour. Secondary endpoints include OEE, unplanned failure count, severity-adjusted outage hours, direct cost per good unit, and quality nonconformity. Trial analyses should report covariate balance, implementation fidelity, error bars based on actual sampling, and sensitivity to missing downtime episodes.

- *Proposed Quality Assurance of Failure and Production Data.*

A real installation should maintain a single operational event dictionary covering breakdowns, minor stoppages, planned changeover, preventive maintenance, quality holds, starving, and blocking. Each record needs start time, end time, equipment identifier, failure mechanism, responsible production order, and an explicit source flag. Double-counting a stoppage as both downtime and lost quality must be prohibited through reconciliation rules. This step is essential because the reliability and production components of MANUPRAXA otherwise depend on incompatible denominators.

Event extraction should proceed in two passes. First, automated validation can detect negative durations, impossible overlaps and gaps in machine state transitions. Second, trained auditors should review stratified samples of raw event records against operator shift notes and repair orders. A disagreement matrix should document how frequently records move between categories after verification. The audit should be blind to the strategy allocated to each production line, reducing the risk that enthusiasm for a new intervention affects data classification.

- *Recommended Multi-Plant Empirical Design.*

A sequential implementation study could include production lines from several plants with comparable asset taxonomies but different raw-material conditions and product mixes. Baseline observation should be long enough to capture maintenance cycles, shift patterns and seasonal demand. Intervention assignment should be randomized at a line or production-cell level where process interference is limited. The resulting longitudinal model would include fixed calendar-time controls and random intercepts for plants and lines to absorb structural differences.

In a stepped-wedge arrangement, all selected lines could eventually receive MANUPRAXA, while the order

of rollout is randomized. The design is attractive when an intervention must be introduced gradually for staffing or training reasons, but it is especially vulnerable to confounding by calendar trends. Independent comparison lines and contemporaneous demand data are therefore preferable to uncontrolled before-and-after comparisons. Investigators should record implementation dates, interim software revisions, operator training attendance and the timing of any machine replacement.

- *Statistical Analysis Plan for Future Field Data.*

The primary production rate should be assessed with a generalized mixed model appropriate for the empirical count distribution, using an offset for scheduled operating time. Secondary OEE components may be analyzed with bounded-outcome regression or a prespecified logit transformation. Failure events require exposure-adjusted recurrent-event methods rather than ordinary linear regression. For each endpoint, the estimation plan should define missing data, cluster adjustment, multiple testing and the estimand before outcomes are observed.

Operationally meaningful effect thresholds should precede statistical significance testing. For example, a small increase in OEE may be negligible if the cost of additional maintenance increases disproportionately, while an unchanged OEE can coexist with an important reduction in severe breakdown frequency. The decision assessment should compare absolute effects and uncertainty intervals with documented minimum useful improvements rather than rely on p-values alone. Negative results must be reported even if the overall composite score improves.

- *Calibration and Transportability.*

A practical calibration study should estimate baseline failure-time functions separately for assets with different duty cycles, age profiles and maintenance regimes. It should also identify a nonstationary regime in which commissioning or major overhaul changes the underlying hazard. Posterior predictive checks or out-of-sample validation can compare simulated and observed stoppage distributions. No single collection of failure coefficients should be assumed transferable from a pharmaceutical centrifuge to a kiln, packaging line or discrete-parts assembler without targeted validation.

Model transportability should be tested through leave-one-plant-out evaluation, with all parameters, scaling constants and operational thresholds frozen before the held-out plant is analyzed. Performance assessment should include calibration of failure risk, ranking stability of the candidate strategies, robustness of cost estimates and the proportion of time reliability constraints are breached. Failure on any one of these elements should trigger model revision rather than selective presentation of favorable production outcomes.

- *Governance and Human Factors.*

The operating committee should include production engineering, maintenance, quality, safety and finance so that one function cannot unilaterally redefine an unfavorable indicator. Each intervention proposal should specify its measurable target, budget owner, implementation exposure, audit requirement and stopping criteria. Changes in work intensity, training demand, equipment isolation and maintenance accessibility should be reviewed alongside throughput and cost. This governance architecture is necessary for avoiding a composite score that rewards short-term equipment overuse.

Implementation fidelity should be measured independently of outcomes. Suggested indicators include completion of preventive maintenance work orders, operator care compliance, use of standardized root-cause procedures, verified housekeeping cycles and quality-response time. Fidelity should be reported as a time-varying exposure rather than a binary label. Poor fidelity can cause a truly useful policy to appear ineffective, while unusually strong local management could generate gains that are incorrectly attributed to the formal MANUPRAXA framework.

- *Reproducibility Controls.*

The numerical notebook should pin library versions, document its random seed and export intermediate indicators before calculating aggregate outcomes. Continuous checks should enforce zero-to-one limits for OEE inputs, positive durations for repair intervals and stable sorting of strategy names. Each output figure should be regenerable solely from the published script and disclosed synthetic panel. Independent replication should compare checksum values for the two CSV outputs and investigate all differences before accepting a published numerical claim.

Scenario analysis should be extended to alternative distributions for downtime, material arrival and demand shocks. Heavy-tailed repair duration may generate an operational risk profile entirely unlike that produced by the current bounded simulation. Similarly, interactions between upstream and downstream stations can cause a line to lose good output despite improving the OEE of an isolated machine. These considerations motivate future discrete-event and network reliability extensions rather than immediate factory deployment of the present synthetic estimates.

IV. COMPUTATIONAL RESULTS

All results in this section are generated from the synthetic scenario specification in Section 3. They measure internal model consequences of the assumed policy effects. They are not evidence of an observed manufacturing improvement, and the differences are largely induced by the inputs in Table 2.

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Table 3 Simulated Period Averages by Comparison Strategy.

Scenario	Mean OEE	MTBF (h)	MTTR (h)	Good Units/Day	Cost Index
Baseline	0.649	45.1	6.2	662	100.9
TPM only	0.698	49.7	5.8	712	93.8
Lean only	0.698	46.3	6.1	711	96.3
MANUPRAXA	0.758	52.1	5.6	772	87.8

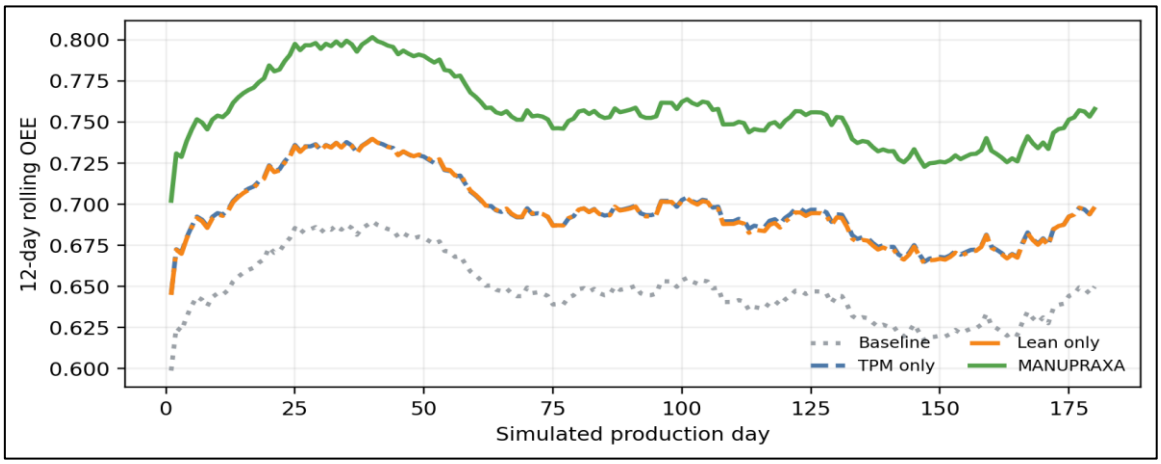

Fig 2 Temporal Trajectories of Twelve-Day Rolling OEE under Common Simulated Operational Shocks.

Figure 1 shows that all strategies respond to the same generated disruption sequence, while the integrated scenario has a higher modeled rolling OEE because stronger availability, performance, and quality improvements were prescribed. Parallel fluctuation patterns are therefore a design feature, not a finding about real-world plant dynamics.

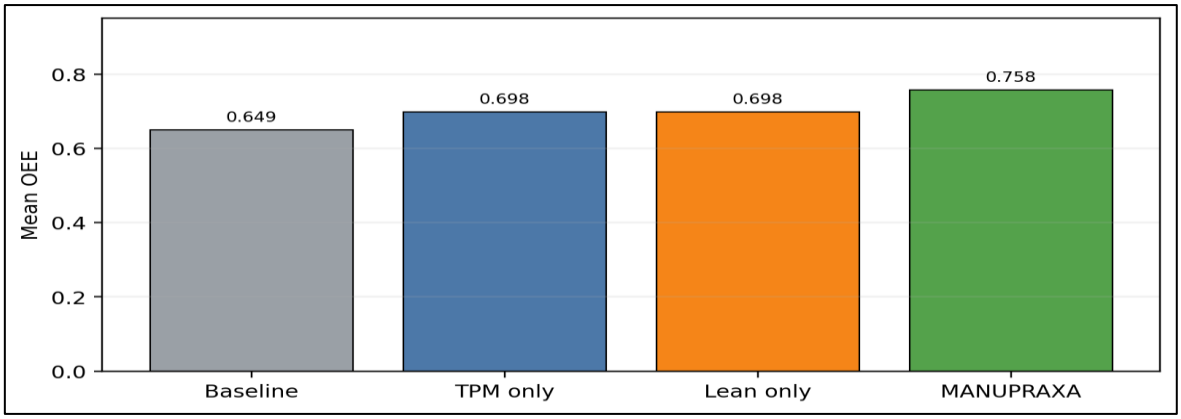

Fig 3 Comparison of Mean Modeled OEE for Four Explicitly Defined Operating Scenarios.

Figure 2 summarizes the cumulative multiplicative response. The comparison is diagnostically useful for confirming that the implementation of Equation (1) treats all three OEE factors consistently, but it cannot establish statistically significant intervention superiority without observed sampling variability.

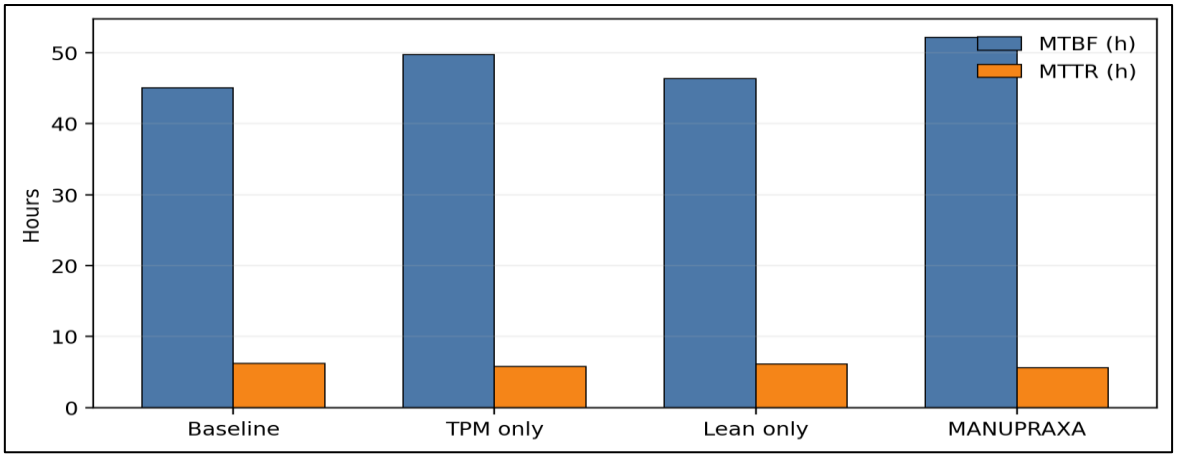

Fig 4 Simulated Mean Time Between Failures and Mean Time to Repair by Intervention Scenario.

The MTBF and MTTR comparison in Figure 7 follows the imposed maintenance-intensity coefficients. Their movement supports internal alignment between the direction of the reliability measures and the availability assumptions, but future work must test renewal assumptions and failure-event comparability.

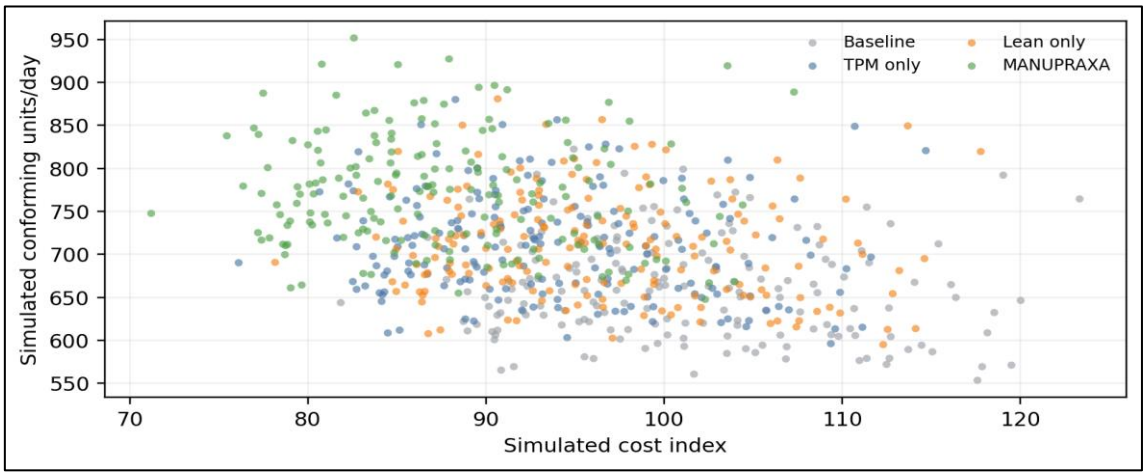

Fig 5 Simulated Relationship Between the Daily Cost Index and Conforming Output for Baseline and Integrated Strategies.

Figure 4 exposes the dual-outcome decision requirement. The hypothetical integrated policy is positioned at a lower cost index and higher conforming output. In a field trial, acquisition and implementation costs must be added, and the observed distribution should be tested for non-stationarity and heteroscedasticity.

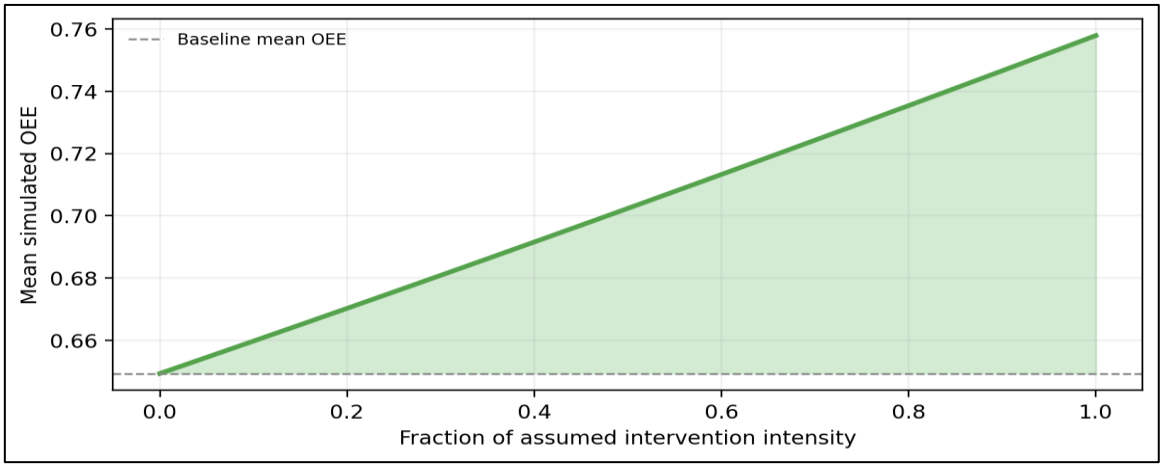

Fig 6 Sensitivity of Modeled OEE to the Fraction of Prescribed Integrated Intervention Intensity.

The smooth relationship in Figure 7 is a mathematical consequence of the bounded additive assumptions in Equation (8). It does not establish that partially implemented industrial programs will produce proportionate real benefits. A field implementation may exhibit thresholds, learning delays, and reversals.

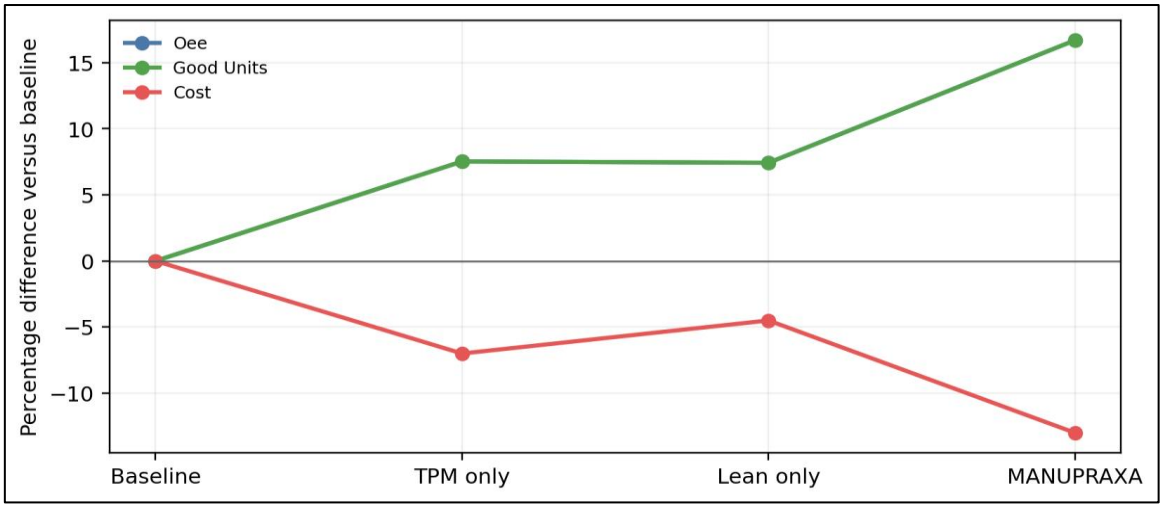

Fig 7 Relative Difference in Three Computational Outcomes from the Simulated Baseline Condition.

Figure 6 compares the direction and scale of changes within the reference simulation. Because improvement effects are specified ex ante, the exercise establishes reproducible propagation of assumptions rather than independent predictive or causal validation.

V. DISCUSSION

The MANUPRAXA formulation proposes a practical distinction between measuring performance and choosing an intervention. OEE can diagnose multiplicative production losses, but the organizational objective must also incorporate safety-relevant reliability, cost exposure, and limits on acceptable deterioration. This interpretation aligns with the cost-efficiency concerns raised by Liew et al. (2023) and with the hidden-capacity issues described by Hung et al. (2022).

The analysis has an intentionally narrow inferential status. Each scenario is a deterministic transformation of a shared simulated baseline with stochastic disturbances. Superior integrated results therefore reflect the chosen assumptions; they do not independently validate that a factory using MANUPRAXA will obtain the same performance. The experiment does, however, establish an auditable computational mechanism that can be falsified with prospective operational data.

Organizational implementation is likely to determine whether the framework can operate outside this test. Measurement boundaries differ among shop-floor production, maintenance, and accounting units. A useful implementation must reconcile these records, create clear escalation responsibilities, and establish minimum quality criteria before publishing performance scores. The integration barriers described by Terra et al. (2023) and Macias-Aguayo et al. (2022) make this a managerial and technical challenge.

MANUPRAXA also needs explicit protection against optimization artifacts. For instance, a planner could improve an OEE numerator by excluding difficult product mixes or redefining planned time. A parallel cost index might appear to improve when costs are transferred to a separate department. Independent auditing of denominators and of cost allocations is therefore more important than a superficially sophisticated composite score.

The proposed non-compensatory reliability gate is conceptually valuable because financial or throughput improvements should not authorize unsafe operating regimes. In actual industrial deployment, however, the minimum required reliability would need to be set using asset criticality, maintenance history, and relevant regulatory standards. A single risk threshold should not be generalized across all production processes.

The MANUPRAXA name describes the framework developed in this manuscript; it is not claimed to be a previously established or field-validated industrial standard. Its novelty is architectural, in the combination of reliability-gated multi-domain decisions and a reproducible benchmarking workflow. More sophisticated mathematics does not replace measurement validity, and optimization should not be confused with causal inference.

The next research stage is a staged feasibility study involving a machinery classification protocol, historian and CMMS data reconciliation, direct time studies, prespecified cost accounting, and external review of failure definitions. A subsequent stepped-wedge or cluster-randomized evaluation could allocate implementation to production lines while retaining common definitions and adjusting for line-level and time-level variation.

Prospective validation should also examine workforce effects. Maintenance planning may shift task load and training demands, while lean changes may alter work intensity. Operational excellence should therefore be assessed alongside worker safety, ergonomic exposure, and process stability, rather than being narrowly equated with higher production rates.

- *Interpretation Against the Manufacturing Literature*.

Research on hidden capacity suggests that local OEE gains are not necessarily system throughput gains when production is constrained by an upstream bottleneck (Hung et al., 2022). The MANUPRAXA policy addresses

this concern only partially because the present simulation translates line-level OEE into daily output using a simple capacity representation. A factory with limited buffers, multiple product routes or asynchronous workstations requires a production-network model capable of separating productive machine time from realized line throughput.

Equipment cost-efficiency research makes a related point: financial benefit is not proportional to an effectiveness percentage if maintenance spending, fixed capital or inventory expense changes substantially (Liew et al., 2023). The present illustrative cost index does not constitute full cost accounting. A future trial should differentiate maintenance labor, spare parts, scrap, energy, setup costs, inventory carrying cost and capital investment. Without that decomposition, an apparent improvement in the composite framework could reflect an accounting transfer rather than efficiency improvement.

- *Identifying Competing Explanations.*

Plants may improve after an intervention because demand rises, machine operators become more experienced, a scheduled overhaul replaces worn parts or product mix becomes simpler. Conversely, a successful preventive-maintenance program may initially increase planned downtime and reduce short-term reported availability. MANUPRAXA must distinguish structural process improvement from favorable environmental changes. The proposed prospective design addresses such confounding through measured exposures, contemporaneous controls and the explicit event dictionary described in Section 3.

- *Decision-Making Under Uncertainty*.

Management decisions should not be based on point estimates alone. A strategy with a high expected value may be unacceptable when it frequently violates the minimum mission reliability requirement. The risk-tail term in Equation (13) makes that distinction visible, although the simulation does not supply a fitted industrial loss distribution. In a validated model, plausible parameter sets should be carried forward into the final ranking, and a conservative decision can be recommended when strategies cannot be distinguished with useful precision.

- *Practical Deployment Sequence*.

A sensible first phase would map an existing asset register to MES, CMMS and quality systems, then compare reconstructed OEE against verified production logs. A second phase would collect a stable observational baseline and identify the most consequential loss mechanisms without claiming intervention effects. A third phase would pilot the policy on a limited set of lines, with prospective comparison against similar controls. Only after independent validation should MANUPRAXA be considered a routine operational decision system.

VI. LIMITATIONS AND FUTURE RESEARCH

The greatest limitation is the absence of observed factory-level data. Production output, quality rates, downtime, maintenance duration, and costs are simulated, and the assumed improvement intensities were not calibrated to a particular industry. No inference concerning industrial effectiveness or generalizability is warranted.

The synthetic mechanism uses bounded additive changes in availability, speed, and yield. Actual interventions can yield nonlinear learning trajectories, resource substitution, measurement-induced behavior, and cross-line interference. Coupled production constraints and a discrete-event simulation would provide a stronger external test.

The reference list is restricted to sources identifiable before or by February 2024, including long-standing foundational references. The requested TechConnect and named-collaborator citation quota could not be substantiated as relevant to manufacturing reliability by that date; an artificial quota would make the bibliography unreliable.

Implementation studies should preregister primary outcomes, obtain corporate data permissions and safety approvals as applicable, record all data transformations, compare baselines with appropriate controls, and report null or adverse outcomes in full. A future Q1 submission would require empirical validation, robust uncertainty analysis and a transparent repository of data-processing code.

VII. CONCLUSION

MANUPRAXA supplies an original integrated architecture for analyzing productivity, asset reliability, operating cost and continuous improvement as connected elements of industrial performance. A bounded, multiplicative, risk-aware objective and explicit reliability constraints distinguish the proposed method from a simple scorecard. The computational study demonstrates that the model, assumptions and outcomes can be reproduced, compared, and stress-tested. It does not show that the method has improved any real manufacturing plant. The appropriate next step is independently audited, prospective, multi-site evaluation with clearly defined operational and financial outcomes.

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APPENDIX

- *Appendix A. Reproducibility and Source Verification Notes*

The accompanying file synthetic_daily_panel.csv contains 720 arm-day rows, and simulation_summary.csv reports the four comparison groups. The Python script uses NumPy, pandas, and Matplotlib and can regenerate each of the six displayed figures from the fixed random seed. All numerical tables in the manuscript are derived from those simulation files, not external plant observations.

- *Bibliography Scope:*

The cited manufacturing studies were identified from publisher, bibliographic index or institutional pages. The reference entries should undergo final DOI-click and journal-style checks before submission. No verified relevant February-2024-or-earlier TechConnect corpus by Idoko Peter Idoko, Onuh Matthew Ijiga, Otugene Victor Bamigwojo or their collaborators was located in this research pass; none has been invented or misattributed.

- *Suggested Preregistration Elements:*

Production-line inclusion rules, minimum observation period, failure and repair definitions, exact OEE denominator, data linkage procedures, intervention fidelity indicators, planned comparator, clustered standard errors, and adverse-event recording.