

A System Dynamics Approach to Inventory Optimization for Reducing Overstock in a Remote Mining Warehouse: A Case Study of a Spare-Parts Warehouse at a Large Mining Operation in Indonesia

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Abstract—Spare-parts warehouses in remote mining operations often carry rising inventory value even while reservations remain overdue, a pattern that points to a structural planning problem rather than a stock-availability shortage. Although previous inventory optimization studies have emphasized EOQ based optimization and forecasting techniques, limited research has examined how dynamic feedback among inventory replenishment parameters, lead-time delays and issuance performance drivers overstock condition in a remote mining warehouse with intermittent demand. This paper addresses the gap and reports a mixed-methods system dynamics case study of a spare-parts warehouse operated by a large nickel/copper mining company in Indonesia. Stock-on-hand grew from US\$56.7 million in 2020 to US\$77.0 million in 2024, while 3,066 of 4,652 reservation lines (66%) were overdue, 84% of which had stock already available. A causal-loop and stock-and-flow model, calibrated on 2020-2024 SAP data and semi-structured interviews, was simulated in Vensim through 2030. The baseline model projects inventory rising from US\$39.9 million (2025) to US\$81.9 million (2030), concentrated in slow- and non-moving items whose replenishment is driven 72% by static reorder-point/maximum (ROP/Max) settings rather than reservation demand. Three intervention scenarios were tested: reducing ROP/Max by 50%, raising the outgoing (issuance) rate to 0.5, and combining both. The combined scenario cut projected 2030 inventory to US\$55.2 million, a 32.6% reduction, outperforming either single-lever intervention. The study concludes that overstock in intermittent-demand mining warehouses should be addressed through segmented, service-level-based replenishment policies rather than uniform stock-reduction targets.

Keywords—inventory optimization; system dynamics; spare-parts inventory; reorder point and maximum (ROP/Max) policy; intermittent-demand forecasting; mining warehouse operations

I. INTRODUCTION

Remote mining operations depend on continuous availability of spare parts to avoid costly equipment downtime, yet the same operations frequently accumulate spare-parts inventory far beyond what operational consumption justifies. The tension between availability and overstock is well documented in capital-intensive industries: excessive inventory ties up working capital, consumes storage capacity, and increases obsolescence risk, while insufficient inventory risks production-stopping downtime [1], [2]. This paper examines that tension at a spare-parts warehouse (referred to here as the case warehouse) operated by a large copper/gold mining company in Papua, Indonesia, which supplies materials for both lowland processing and highland mining operations.

Between 2020 and 2024, stock-on-hand at the case warehouse increased from approximately US\$56.7 million to US\$77.0 million, a rise of 54%. Total inventory value including in-transit stock rose from US\$61.6 million to US\$90.4 million over the same period. As of January 2025, 3,066 of 4,652 open reservation lines (66%) were overdue; of those overdue lines, 84% already had stock available and only 4% were genuinely out of stock. This combination — rising inventory value alongside a large volume of overdue-but-fulfillable reservations — indicates that the warehouse's problem is not a shortage of material but a structural mismatch between how inventory is replenished, stored, and released.

The problem addressed in this research is therefore: how should the case warehouse's inventory be structured to minimize overstock while maximizing on-time material availability? This is investigated through four research questions: (1) what is the current state of inventory performance; (2) what factors cause overstock and fulfillment delay; (3) what inventory policy would reduce overstock while preserving service level; and (4) what operational impact would a recommended policy produce. The study uses a mixed-methods system dynamics (SD) approach, combining five years of enterprise resource planning (SAP) data with semi-structured interviews, to build and simulate a causal-loop

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and stock-and-flow model of the warehouse system through 2030.

II. LITERATURE REVIEW

Spare-parts inventory differs fundamentally from finished-goods inventory because its purpose is to sustain equipment reliability rather than to generate direct sales revenue; consequently, spare-parts policy should weight service level and operational risk alongside cost [3], [4]. Effective spare-parts management is widely identified as a major lever for cost-effective availability, since spares can represent a substantial share of a capital asset's lifecycle cost while their absence risks expensive unplanned downtime [2].

Overstock is a recurring finding in comparable mining and industrial contexts. A study of a large Indonesian aluminum smelter found spare-parts inventory value exceeding US\$35 million against an achieved service level of only 62% versus a 95% target, with optimized policies estimated to reduce inventory by more than half while preserving service [3]. Similar results are reported in system-dynamics studies of production-disruption and shipping-equipment supply chains, where reinforcing feedback between replenishment policy and inventory growth produces persistent overstock unless structurally corrected [5], [6].

A second stream of literature addresses demand character. Spare-parts demand is frequently intermittent — long stretches of zero demand punctuated by irregular usage — for which conventional forecasting methods such as moving averages tend to perform poorly [7], [8]. Specialized approaches such as the Croston method and the Syntetos-Boylan Approximation are recommended for such demand patterns [7], [9]. Related work on safety-stock strategy shows that low inventory turnover correlates strongly with excessive carrying cost and material aging [10], reinforcing the case for differentiated, movement-based replenishment rather than uniform reorder rules across an entire parts catalogue [11], [12].

System dynamics (SD) is used here because inventory behavior in a warehouse of this kind is generated by feedback among replenishment policy, lead time, congestion, and issuance rather than by any single variable in isolation. Industrial-dynamics theory holds that inventory accumulates whenever inflow exceeds outflow over time, and that delayed feedback within a system causes balancing mechanisms to over correct, producing overshoot [6], [13]. This framing motivates the causal-loop and stock-and-flow modeling approach adopted in Section III, and distinguishes the present study from purely statistical or optimization-based inventory studies by explicitly representing the reinforcing loop between reorder-point settings, incoming flow, congestion, and issuance delay.

III. METHODOLOGY

This study uses a mixed-methods system dynamics case-study design. Quantitative data consist of five years (2020-2024) of SAP transactional records — stock-on-hand, in-transit value, incoming and outgoing rates, reservation status, and lead time — for materials at the

case warehouse. Qualitative data consist of semi-structured interviews with warehouse leadership and inventory controllers, analyzed thematically to surface causal relationships and operational bottlenecks not visible in the transactional data alone.

Quantitative and qualitative data serve distinct roles in the SD workflow. Interview data inform the causal-loop diagram (CLD), which maps the qualitative structure of the system — for example, how procurement lead time is perceived to affect reorder behavior. SAP data then parameterize the corresponding stock-and-flow diagram (SFD), providing initial stock levels, flow rates, and lead-time distributions. The two data streams are triangulated: where interviews identified a bottleneck (e.g., yard congestion limiting issuance), the SAP data were used to quantify its magnitude, and vice versa.

Semi-structured interviews were conducted with warehouse managers and senior inventory controllers to cover both perspective of replenishment policy and regular replenishment process. The interview focused on four themes: how ROP/Max parameters are set and reviewed over time; perceived drivers of reservation delay and yard congestion; how procurement lead time can influence reorder behavior; and informal workarounds used when reservations remain overdue despite available stock. Recurring themes from these interviews — in particular, the perceived link between rising congestion, slower issuance, and planners' tendency to sustain or raise safety stock and ROP/Max even after non-movement was evident — were translated directly into the reinforcing (R1) and balancing (B1) loops shown in Fig. 2, with each loop variable and causal link cross-checked against informants before being carried into the SAP-parameterized stock-and-flow model.

Materials were segmented by moving code (MC), a turnover classification ranging from MC 0 (non-moving) to MC 6 (superfast-moving), and grouped into three analytical segments: superfast/fast-moving (MC 4-6), medium (MC 2-3), and slow/non-moving (MC 0-1). The SD model was built and simulated in Vensim, projecting inventory behavior from 2025 to 2030 under the existing replenishment structure and under three alternative policy scenarios described in Section IV. Model verification compared simulated stock trajectories for 2020-2024 against the corresponding historical SAP values before the model was used for forward projection.

Consistent with Sterman's (2000) System Dynamics testing framework, the model was subjected to both structure validation and behavioral validation before it was used for policy analysis. Structure validation assessed whether the model's causal architecture corresponds to the real warehouse system: stock, flow, and auxiliary variable was checked for dimensional consistency, and each causal link included in the CLD (Section IV-B) was cross-checked against the semi-structured interview transcripts and SAP process documentation described in Section III, so that a link was retained only if it reflected a mechanism practitioners recognized rather than a purely statistical association. Behavioral validation assessed whether the model accurately replicates the observed behavior of the system: the simulated 2020-2024 stock trajectory was compared against the corresponding historical SAP values, and the model was accepted for forward projection only after the simulated pattern of inventory accumulation tracked the historical trend across the

moving-code segments summarized in Table I. These two evaluations distinguish a model that merely fits historical data by coincidence from one whose behavior is supported by empirical evidence.

IV. FINDINGS AND DISCUSSION

A. Baseline Condition

The baseline analysis confirms a structural rather than availability-driven overstock problem. Materials were distributed across moving-code segments: slow- and

non-moving items (MC 0-1) accounted for 52% of the material catalogue but only an average outgoing rate of 0.34 — equivalent to inventory turning over roughly once every three years. Medium-moving items (MC 2-3) represented 30% of materials with an outgoing rate of 1.02, while superfast-moving items (MC 4-6) represented only 18% of materials but turned over more than three and a half times per year on average. Table I summarizes the 2024 segment profile.

Table I.
2024 Inventory Profile by Moving-Code Segment

Segment	2024 Value (US\$M)	% of Total Value	% of Total Items	Avg. Incoming Rate	Avg. Outgoing Rate	Demand Signal
Superfast (MC 4–6)	28.1	31%	18%	10.02	3.78	41% ROP/Max
Medium (MC 2–3)	29.9	33%	30%	9.14	1.02	53% ROP/Max
Slow/Non-moving (MC 0–1)	32.4	36%	52%	7.76	0.34	72% ROP/Max

As Table I shows, the slow/non-moving segment held the largest share of 2024 inventory value (36%) despite representing the weakest operational movement, and its replenishment was driven predominantly (72%) by static ROP/Max parameters rather than open reservation demand — nearly the reverse of the super fast segment, where reservations drove a majority of replenishment signals. This asymmetry indicates that the warehouse's planning logic treats slow-moving and fast-moving materials similarly despite fundamentally different demand behavior, consistent with the literature's caution against uniform replenishment rules for intermittent-demand items [7]–[9].

B. Root Causes

Simulation of the existing (unmodified) system structure through 2030 shows inventory value rising from US\$39.9 million in 2025 to US\$81.9 million in 2030 if current parameters persist. Four interacting root causes were identified. First, incoming flow structurally exceeds outgoing flow: across all materials the average incoming rate (8.30) was roughly 6.2 times the average outgoing rate (1.33), widening to approximately 22:1 for the slow/non-moving segment alone. Second, replenishment is dominated by static ROP/Max parameters rather than reservation-based demand signals, particularly for slow-moving items. Third, lead times for slow/non-moving materials (approximately 242–259 days on average) are substantially longer than for superfast items (approximately 123 days), and because reorder points are calculated from lead time and safety-stock assumptions, longer lead times mechanically inflate both reorder points and pipeline inventory. Fourth, issuance performance is weak relative to available stock: interviews attributed part of this to yard congestion — with the majority of yard space occupied by slow/non-moving material — and to logistics constraints on delivery to remote highland sites.

These four factors reinforce one another in a feedback loop: high ROP/Max settings increase incoming flow, which raises inventory and yard congestion; congestion

slows issuance, which is interpreted by planners as elevated supply risk; and that perceived risk sustains or increases safety stock and reorder points, regenerating the cycle. Interview data corroborate this structural account: inventory controllers reported that the volume of ROP/Max parameters requiring periodic review exceeds available review capacity, meaning aggressive settings persist even after non-movement is evident in the data — a resourcing constraint rather than a parameter-design oversight.

Figure 1 maps this account onto a causal-loop diagram. The reinforcing loop (R1) runs from incoming rate to inventory to yard congestion to issuance efficiency to lead time and back to safety stock and ROP/Max, so that each pass around the loop raises the reorder point that started it, consistent with the overshoot behavior reported for delayed balancing structures in the literature [6], [13]. The balancing loop (B1), by contrast, is the mechanism planners rely on to draw inventory down through issuance, but its correction acts on a lag long enough (242–259 days for slow/non-moving items) that R1 dominates system behavior over the simulation horizon. This is why Model 1 and Model 2, which each intervene on only one arm of the loop, under-perform Model 3 in Section IV-C: cutting ROP/Max alone weakens the reinforcing loop's input without strengthening B1's correction, while raising the outgoing rate alone strengthens B1 without removing the structural trigger that keeps regenerating R1.

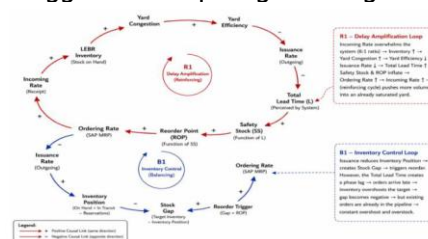


Figure 1.
Causal-loop diagram of the reinforcing (R1) and balancing (B1) feedback identified as the root cause of overstock.

Having established the causal structure, Figure. 2 translates the causal-loop diagram in Figure. 1 into the stock-and-flow structure underlying the baseline and scenario simulations discussed below. The model represents LEBR inventory as a stock accumulating between an incoming rate (procurement, shaped by ROP/Max policy and total lead time) and an outgoing rate (issuance to end users), with in-transit material forming a second stock between order placement and warehouse receipt. This structure operationalizes reinforcing loop R1 and balancing loop B1 into a form suitable for numerical simulation, and is the mechanism that produces the segment profile in Table I and the root causes discussed above.

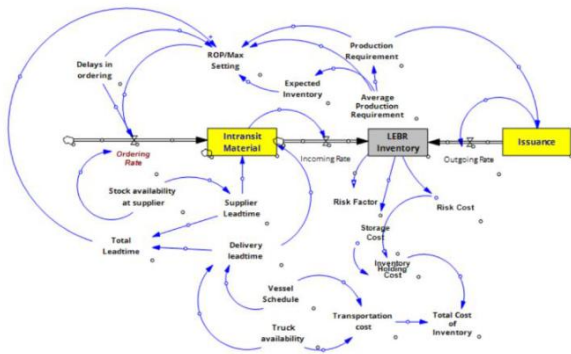


Figure. 2.
Stock-and-flow diagram of the case warehouse inventory system.

C. Simulation Scenarios

Three intervention scenarios were simulated against the slow/non-moving segment, holding demand assumptions constant across all scenarios so that any inventory reduction reflects policy change rather than reduced consumption. Model 1 reduced ROP/Max by 50%; Model 2 raised the outgoing (issuance) rate from 0.34 to 0.5; Model 3 combined both interventions. Table II and Fig. 4 summarize projected 2030 inventory value under each scenario.

Table II.
Projected 2030 Inventory Under Alternative Scenarios

Scenario	Intervention	Projected 2030 Value (US\$M)	Reduction vs. Baseline
Existing model	None (status quo)	81.90	—
Model 1	ROP/Max –50% (slow/non-moving)	75.49	7.8%
Model 2	Outgoing rate raised to 0.5	60.50	26.1%
Model 3	ROP/Max –50% + outgoing rate 0.5	55.19	32.6%

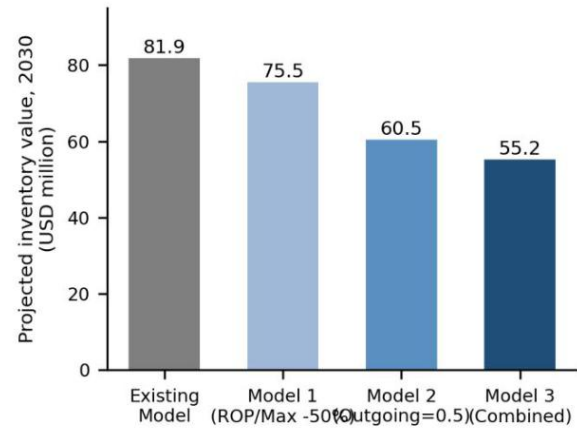


Figure 3.
Projected 2030 inventory value under the existing model and three intervention scenarios.

Model 1 slowed inventory growth (US\$75.49 million by 2030, a 7.8% reduction) but did not reverse it, because incoming flow was reduced while the outgoing rate remained unchanged at 0.34. Model 2 produced a larger reduction (US\$60.50 million, 26.1%) by narrowing the gap between incoming and outgoing flow without changing replenishment policy, confirming that issuance performance is at least as important as reorder-point calibration. Model 3, combining both interventions, produced the strongest result: projected 2030 inventory of US\$55.19 million, a reduction of approximately US\$26.7 million (32.6%) relative to the existing model. Applying an indicative 15-25% carrying-cost assumption, this reduction corresponds to approximately US\$4.0-6.7 million in potential annual carrying-cost savings, before accounting for yard-space recovery or avoided write-offs.

The scenario comparison indicates that overstock at the case warehouse cannot be resolved by adjusting either replenishment policy or issuance performance alone; both sides of the inventory equation must be addressed jointly. This is consistent with the reinforcing-loop structure identified in Section IV-B: reducing ROP/Max alone weakens inflow but leaves the underlying issuance bottleneck intact, while improving issuance alone leaves excessive replenishment signals unaddressed.

D. Managerial Implications

The findings support a segmented, service-level-based replenishment policy rather than a uniform inventory-reduction target. Super fast and operationally critical items should retain high service targets with tight, frequently reviewed reorder points linked closely to reservation demand. Medium-moving items warrant moderate service levels with periodic (e.g., quarterly) review. Slow- and non-moving items should be split further: those with continued criticality should retain a protected minimum buffer with materially reduced Max/ROP and manual replenishment review, while non-critical, long-dormant items should move to approval-based or periodic-review replenishment, with procurement freezes and disposal review triggered after extended inactivity.

Because the SD model represents stock, flow, and delay variables rather than fill-rate or service-level outcomes directly, the projected inventory reductions

should not be read as guaranteed service-level improvements. Interview evidence and the structural model both suggest service should improve as the issuance bottleneck is relieved, but this expectation should be validated through a pilot implementation using reservation-aging key performance indicators before broader roll-out.

E. Limitations

Since this is a single-site case study based on SAP records and interview data from one warehouse, these results are directly relevant to similar remote mining operations but should be validated through pilot implementation prior to generalization to other sites. Four further limitations apply. First, the model depends on the completeness and accuracy of SAP transactional records and interview accounts; any inaccuracy in stock, reservation, or lead-time data would affect calibration and interpretation. Second, because the model represents stock, flow, and delay structure at the segment level rather than item-level demand variability, it may understate heterogeneity among individual slow- and non-moving materials and as noted in Section IV-D, does not itself simulate fill-rate or service-level performance. Third, interview evidence reflects role-based perceptions that may be subject to recall bias or social-desirability effects. Finally, the carrying-cost savings reported in Section IV-C are indicative, based on a general 15-25% assumption rather than a verified financial rate, and the 2025-2030 projection assumes current policy and demand structures persist, so the forward results should be re-verified as conditions change.

V. CONCLUSION

Returning to the four questions that framed this study, the current state of inventory performance at the case warehouse is one of simultaneous overstock and delay: stock-on-hand rose from US\$56.7 million in 2020 to US\$77.0 million in 2024, a 54% increase, and by January 2025, 66% of open reservation lines were overdue even though 84% of those overdue lines already had stock available, indicating a fulfillment problem rather than a material shortage. This condition caused by four factors: replenishment mostly controlled by static ROP/Max settings rather than reservation demand, particularly for the slow/non-moving segment, where 72% of replenishment signals originated from ROP/Max rather than open reservations; lead times for slow-moving materials long enough (242-259 days on average) to mechanically inflate reorder points; weak issuance performance driven by yard congestion and remote-site logistics constraints; and a reinforcing feedback loop (R1) in which these factors regenerate one another faster than the balancing loop (B1) provided by issuance can correct. Addressing this structure calls for a policy that intervenes on both arms of the loop at once rather than pursuing a single uniform target: the combined scenario (Model 3), which paired a 50% ROP/Max reduction for slow/non-moving items with a higher outgoing rate of 0.5, is recommended over either lever alone because it weakens the reinforcing loop's input while strengthening the balancing loop's correction simultaneously. The operational impact of this recommended policy is substantial: projected 2030

inventory falls from US\$81.9 million under the status quo to US\$55.2 million, a 32.6% reduction equivalent to approximately US\$4.0-6.7 million in annual carrying-cost savings, although these gains should be read as inventory-value reductions rather than confirmed service-level improvements until validated through pilot implementation. Taken together, the findings support the conclusion that inventory optimization in intermittent-demand mining warehouses requires simultaneous, segment-differentiated adjustment of replenishment parameters and issuance performance, rather than reliance on any single lever, sustained through periodic parameter review and intermittent-demand forecasting methods.

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