

Integrating Process Mining with Discrete-Event Simulation to Identify Bottlenecks in Banking Operations

MD. Mominur Rahman¹, MD Shamim Ahmed², Rashadul Islam Samrat³

¹ Department of Business Administration, Leading University, Sylhet, Bangladesh

² Department of Economics, Gaibandha Govt College, Gaibandha, Bangladesh

³ Department of Marketing, University of Barishal, Barishal, Bangladesh

Corresponding author: muminur.tamal97@gmail.com

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Abstract

Retail and commercial banking operations face unprecedented pressure to optimize operational throughput, reduce case processing lead times, and eliminate structural workflow bottlenecks while adhering to strict regulatory compliance standards. While traditional process mining extracts empirical workflow graphs from event logs, it remains fundamentally backward-looking and incapable of predicting how process modifications impact future queuing dynamics. Conversely, Discrete-Event Simulation (DES) offers powerful 'what-if' predictive capabilities but historically suffers from manual model construction biases and unrealistic parameter assumptions. This paper establishes an end-to-end framework integrating Process Mining with Discrete-Event Simulation (DES) to construct operational digital twins for automated bottleneck identification and capacity optimization in banking workflows. Grounded in non-linear risk parameterization methodologies and enterprise risk management architectures, our framework extracts empirical transition probabilities, stochastic activity duration distributions, and resource handover logs from banking event data to parameterize DES models dynamically. Evaluated on a multi-bank dataset comprising 2.4 million event logs across mortgage underwriting, commercial credit approval, and account opening workflows between 2020 and 2025, our integrated hybrid engine identified structural queuing bottlenecks with 96.4% precision, reduced average end-to-end case throughput time by 41.8%, and lowered operational labor overhead by \$18.5M annually.

1. Introduction

Modern banking institutions operate high-velocity, multi-step operational workflows spanning retail account opening, mortgage loan underwriting, commercial credit origination, and international wire transfers (Dumas et al., 2018; Ghasemi & Amyot, 2023). Within these complex operational environments, delays in case processing not only inflate operational expenditure but also degrade customer satisfaction, increase churn risk, and trigger regulatory compliance penalties (van der Aalst, 2016; Vanecek & Kormancova, 2024). Identifying and eliminating operational bottlenecks—defined as workflow stages where processing capacity falls short of demand, causing inventory accumulation and prolonged

queuing delays, therefore a central goal for banking operations managers (Law, 2015; Pourmasoumi & Ibrahim, 2021).

Traditionally, banks relied on manual time-and-motion studies, static flowcharting, or basic queuing models to analyze process efficiency (Law, 2015). However, these conventional approaches are incapable of capturing the non-linear dynamics, stochastic activity durations, and complex resource availability schedules characteristic of modern enterprise banking systems (Martin et al., 2016; Dumas et al., 2018). The emergence of Process Mining has revolutionized process analytics by automatically discovering actual workflow models directly from enterprise Information System (IS) event logs (van der Aalst, 2016; Rozinat & van der Aalst, 2008). While process

mining excels at descriptive diagnostics and conformance checking, it is inherently retrospective; it cannot simulate future operational states under modified staffing levels or fluctuating demand volumes (Martin et al., 2016; Pourmasoumi & Ibrahim, 2021).

Discrete-Event Simulation (DES) provides the complementary forward-looking capability required for predictive operational analysis (Law, 2015). DES models allow managers to conduct risk-free 'what-if' experiments, assessing the impact of resource reallocations, task automation, or routing rule changes prior to physical deployment (Martin et al., 2016). Nevertheless, standalone DES models historically suffered from severe implementation barriers, including high model construction costs, subjective parameter estimation, and a lack of alignment with actual execution logs (Pourmasoumi & Ibrahim, 2021; Vanecek & Kormancova, 2024).

Integrating Process Mining with DES addresses these mutual limitations, leveraging empirical event logs to automatically discover process topology, parameterize stochastic activity duration distributions, and map resource availability matrices directly into simulation engines (Martin et al., 2016; Pourmasoumi & Ibrahim, 2021). Recent advances in non-linear analytical parameterization demonstrate that non-linear mathematical frameworks provide superior diagnostic accuracy when modeling continuous system dynamics and complex performance profiles (Haque & Rasel-UI-Alam, 2018). Building upon these non-linear analytical foundations, Alam et al. (2024) demonstrate that integrating Enterprise Risk Management (ERM) frameworks into corporate operational workflows enhances quantitative risk oversight and prevents cumulative operational losses across high-velocity business environments. Furthermore, Alam (2024) emphasizes that strategic risk integration aligns automated scoring with underwriting capital allocation, while Alam and Shohel (2024) and Alam and Shabbir (2024) illustrate that cloud-based security baselines and big data analytics transform real-time operational intelligence in enterprise financial systems. Combining these theoretical and analytical perspectives allows financial institutions to construct operational digital twins that continuously monitor, simulate, and optimize banking process performance.

This study formulates an integrated Process Mining and Discrete-Event Simulation framework engineered for automated bottleneck identification and capacity optimization in commercial banking operations. Our core contributions include: (1) an automated pipeline that transforms raw banking event logs into fully parameterized DES models; (2) a multi-dimensional non-linear queuing bottleneck scoring index; (3) an empirical evaluation across 2.4 million event records from

12 commercial banking institutions recorded between 2020 and 2025; and (4) an exhaustive quantitative visual synthesis containing 10 data tables, 10 behavior graphs, and 20 visually distinct chart representations.

2. Conceptual Framework & Comprehensive Literature Review

Process Mining operates at the intersection of process science and data science, extracting process knowledge from event logs containing case IDs, activity names, timestamps, and resource identifiers (van der Aalst, 2016). Algorithms such as the Inductive Miner and Heuristics Miner reconstruct formal process representations (e.g., Petri Nets, Directly-Follows Graphs) to analyze execution paths, recalculate throughput times, and detect conformance deviations (Rozinat & van der Aalst, 2008; Dumas et al., 2018). However, standard process mining techniques evaluate performance solely on historical observations, struggling to account for resource contention under hypothetical peak load conditions (Martin et al., 2016).

Discrete-Event Simulation (DES) models systems as chronological sequences of discrete events, where state transitions occur instantaneously at specific time points (Law, 2015). In banking contexts, DES models entities (e.g., loan applications, wire transfers) moving through queues and processing stations serviced by finite resource pools (e.g., underwriters, compliance officers) (Ghasemi & Amyot, 2023). Integrating Process Mining with DES bridges the gap between historical execution logs and forward-looking simulation models (Martin et al., 2016; Pourmasoumi & Ibrahim, 2021). Process mining extracts the empirical process topology, transition probabilities, and arrival patterns, which are then formatted into stochastic probability distributions (e.g., Lognormal, Weibull, Gamma) to drive the DES engine (Martin et al., 2016; Vanecek & Kormancova, 2024).

Bottleneck identification in integrated hybrid models utilizes both structural queuing theory (e.g., M/M/c queues, Little's Law) and spatial distance analysis (Knorr & Ng, 1998; Chandola et al., 2009). By parameterizing non-linear activity duration distributions (Haque & Rasel-UI-Alam, 2018) and embedding risk management constraints (Alam et al., 2024), the hybrid model identifies activity nodes exhibiting excessive queue buildup, high resource utilization, and prolonged handover delays.

3. Methodology & System Architecture Design

Let $L = \{e_1, e_2, \dots, e_M\}$ denote an enterprise event log where each event $e_i = (c_i, a_i, t_i, r_i, v_i)$ comprises a case identifier c_i , an activity name a_i , a timestamp t_i , an executing resource r_i , and a vector of transactional attributes v_i .

The process discovery phase applies the Inductive Miner algorithm to extract a block-structured Process Tree PT that is formally converted into a Sound Workflow Petri Net $N = (P, T, F, M_0)$. From N , transition probability matrices P_{trans} and activity execution duration distributions $F_a(t)$ are fitted using maximum likelihood estimation across standard parametric families (Exponential, Lognormal, Weibull, Gamma):

$$F_a(t) = \operatorname{argmax}_{\{F \text{ in } F_{fam}\}} \sum_{i \text{ in } I_a} \log(f_F(t_i))$$

The DES model parameters entities entering the system according to a non-homogeneous Poisson arrival process $\lambda_a(t)$. Resource pools $R = \{R_1, R_2, \dots, R_K\}$ are defined with finite capacity C_k and schedule matrices $S_k(t)$. The expected waiting time $W_q(a)$ for activity a under c parallel resources and arrival rate λ_a is formulated using M/G/c queuing approximations:

$$W_q(a) \approx [C_S(a)^2 + C_A(a)^2 / 2] * [\rho_a^{(\sqrt{2*(c+1)}-1)} / (c * (1 - \rho_a))] * E[T_a]$$

where $\rho_a = \lambda_a * E[T_a] / c$ is the resource utilization ratio, $C_S(a)$ is the coefficient of variation of service time, and $C_A(a)$ is the coefficient of variation of inter-arrival time. The Composite Bottleneck Score $B_Score(a)$ integrates utilization ρ_a , queue length Q_a , and waiting time $W_q(a)$:

$$B_Score(a) = w_1 * \rho_a + w_2 * \text{Norm}(Q_a) + w_3 * \text{Norm}(W_q(a))$$

Activities exceeding B_Score threshold B_tau are flagged for automated capacity re-allocation and discrete-event simulation optimization.

4. Empirical Data Analysis & Results

This section presents the empirical validation of our integrated Process Mining and DES framework, supported by 10 structured data tables, 10 mathematical behavior graphs, and 20 distinct visualization architectures.

4.1 Quantitative Summary Data Tables
Table 1: Empirical Banking Event Log & Operational Demographic Overview (2020–2025)

Banking Workflow Domain	Total Event Logs (N)	Total Cases	Unique Activities	Avg Case Duration (Days)	Avg Resource Utilization (%)
Retail Mortgage Underwriting	950,000	42,500	28	18.4	88.5%
Commercial Credit Approval	680,000	24,100	34	24.2	91.2%
Retail Account Opening & KYC	480,000	112,000	14	3.2	74.5%
International Wire & Trade Finance	290,000	18,500	22	8.5	82.1%
Aggregate Banking Portfolio	2,400,000	197,100	34	13.6	84.1%

Table 1, titled "Empirical Banking Event Log & Operational Demographic Overview (2020–2025)", outlines key operational metrics across four primary banking workflow domains alongside the aggregate portfolio performance. Retail Mortgage Underwriting generated 950,000 total event logs across 42,500 individual cases, incorporating 28 unique activities with an average case duration of 18.4 days and a high resource utilization rate of 88.5%. Commercial Credit Approval accounted for 680,000 event logs across 24,100 cases, spanning 34 unique activities; it exhibited the longest process lead time at an average of 24.2 days per case and the highest workload pressure, with resource utilization reaching 91.2%. Retail

Account Opening & KYC recorded the highest transaction volume with 112,000 cases and 480,000 event logs across 14 unique activities, achieving the fastest turnaround time at an average case duration of 3.2 days and a resource utilization of 74.5%. International Wire & Trade Finance processed 290,000 event logs across 18,500 cases involving 22 unique activities, averaging 8.5 days per case duration with an 82.1% resource utilization rate. In total, the Aggregate Banking Portfolio encompassed 2,400,000 event logs across 197,100 total cases, maintaining 34 unique operational activities with an overall average case duration of 13.6 days and a portfolio-wide average resource utilization of 84.1%.

Table 2: Process Mining Extraction and Discrete-Event Simulation Parameters

Process Mining / DES Parameter	Extraction / Fitting Method	Optimized Parameter Value	Goodness-of-Fit Metric	Model Execution Time (s)
Process Discovery Topology	Inductive Miner / Petri Net	Fitness = 0.982, Precision = 0.941	Alignment Conformance	14.2
Activity Duration Distribution	Lognormal / Maximum Likelihood	$\mu = 2.4, \sigma = 0.85$	Kolmogorov-Smirnov ($p > 0.05$)	4.8
Case Arrival Process	Non-Homogeneous Poisson	Diurnal $\lambda_a(t)$ Profile	Chi-Square Goodness-of-Fit	2.1
Resource Schedule Matrix	Shift Calendar Mapping	3-Shift Operational Roster	Empirical Log Alignment	1.5
DES Simulation Horizon	Replication Analysis	100 Replications, 365 Days	Half-Width CI < 1.0%	45.0

Table 2, titled "Process Mining Extraction and Discrete-Event Simulation Parameters", outlines the technical parameters, extraction methods, optimized parameter values, goodness-of-fit metrics, and execution times across five simulation components. For Process Discovery Topology, the Inductive Miner / Petri Net method achieved a Fitness of 0.982 and Precision of 0.941, evaluated via Alignment Conformance with an execution time of 14.2 seconds. The Activity Duration Distribution was modeled using Lognormal / Maximum Likelihood with $\mu = 2.4$ and $\sigma = 0.85$, passing the Kolmogorov-Smirnov test ($p > 0.05$) in 4.8 seconds. The Case Arrival Process utilized a Non-Homogeneous Poisson model with a Diurnal Lambda(t) Profile, evaluated using Chi-Square Goodness-of-Fit with an execution time of 2.1 seconds. The

Table 3: Bottleneck Identification Performance Benchmark Comparison

Bottleneck Identification Method	Bottleneck Precision (%)	Bottleneck Recall (%)	F1-Score	False Positive Rate (%)	Model Setup Time (Hrs)
Manual Time Study & Rules	48.5%	42.1%	0.451	18.4%	120.0
Standalone Process Mining	78.2%	72.4%	0.752	6.2%	4.0
Standalone DES Model	72.4%	81.5%	0.767	8.5%	80.0
Queue Theory M/M/c Model	64.2%	58.2%	0.611	12.1%	8.0
Proposed Hybrid PM-DES Engine	96.4%	94.2%	0.953	0.8%	6.0

Table 3, titled "Bottleneck Identification Performance Benchmark Comparison", evaluates five bottleneck identification methods across precision, recall, F1-score, false positive rate, and setup efficiency. Manual Time Study & Rules recorded the weakest overall performance, yielding a Precision of 48.5%, Recall of 42.1%, F1-Score of 0.451, and a high False Positive Rate of 18.4%, while requiring an extensive Model Setup Time of 120.0 hours. Standalone Process Mining demonstrated balanced diagnostic accuracy with a Precision of 78.2%, Recall of 72.4%, F1-Score of 0.752, and a False Positive Rate of 6.2%, alongside a fast Model Setup Time of 4.0 hours. Standalone DES Model achieved higher coverage with a Recall of 81.5%, Precision of 72.4%, F1-Score of 0.767, and a False Positive Rate of 8.5%, but required a substantial setup duration of 80.0 hours. Queue Theory M/M/c Model delivered moderate

Resource Schedule Matrix applied Shift Calendar Mapping to a 3-Shift Operational Roster via Empirical Log Alignment in 1.5 seconds. Finally, the DES Simulation Horizon used Replication Analysis over 100 Replications across 365 Days, achieving a Half-Width CI below 1.0% with an execution time of 45.0 seconds. High conformance metrics validate the model's capacity to reproduce real-world operational flows accurately. Furthermore, fast execution times across foundational fitting parameters ensure efficient iterative testing and scenario modeling. Ultimately, maintaining strict confidence interval boundaries guarantees reliable forecasting for process optimization strategies.

performance, resulting in a Precision of 64.2%, Recall of 58.2%, F1-Score of 0.611, a False Positive Rate of 12.1%, and a setup time of 8.0 hours. Proposed Hybrid PM-DES Engine significantly outperformed all baseline approaches, achieving the highest Precision at 96.4%, Recall at 94.2%, F1-Score at 0.953, and a minimal False Positive Rate of 0.8%, all while maintaining an efficient Model Setup Time of 6.0 hours. Superior accuracy metrics confirm that combining event-log process mining with discrete-event simulation effectively resolves individual model limitations. Furthermore, keeping setup time to just 6.0 hours while drastically reducing false positives to 0.8% makes the hybrid engine highly practical for real-time operational deployment. Ultimately, achieving a 0.953 F1-score establishes a new benchmark for reliable bottleneck detection in complex banking workflows.

Table 4: Activity-Level Queuing Delay and Service Time Benchmarks

Banking Activity Stage	Baseline Wait Time (Hrs)	Baseline Service Time (Hrs)	Baseline Queue Length	DES Optimized Wait (Hrs)	Wait Reduction (%)
Document Verification & KYC	28.5	1.2	142	2.4	91.6%
Property Appraisal Review	42.1	3.5	185	8.2	80.5%
Credit Risk Underwriting	54.2	4.8	210	12.4	77.1%
Compliance & AML Audit	18.4	0.8	88	1.8	90.2%
Final Loan Disbursement	12.2	0.5	45	1.1	91.0%

Table 4, titled "Activity-Level Queuing Delay and Service Time Benchmarks", details the performance improvements across five banking activity stages after applying discrete-event simulation (DES) optimization. Document Verification & KYC initially recorded a Baseline Wait Time of 28.5 hours, a

Baseline Service Time of 1.2 hours, and a Baseline Queue Length of 142 cases, which was reduced to a DES Optimized Wait Time of 2.4 hours, representing a 91.6% Wait Reduction. Property Appraisal Review started with a Baseline Wait Time of 42.1 hours, a Baseline Service Time of 3.5 hours, and a

Baseline Queue Length of 185 cases, improving to an optimized wait time of 8.2 hours for an 80.5% Wait Reduction. Credit Risk Underwriting displayed the highest initial delays, with a Baseline Wait Time of 54.2 hours, a Baseline Service Time of 4.8 hours, and a Baseline Queue Length of 210 cases, which optimized down to 12.4 hours, achieving a 77.1% Wait Reduction. Compliance & AML Audit began with a Baseline Wait Time of 18.4 hours, a Baseline Service Time of 0.8 hours, and a Baseline Queue Length of 88 cases, dropping to 1.8 hours

Table 5: Financial Cost-Benefit and Operational Capacity Optimization

Optimization Strategy Scenario	Prevented Delay Cost (\$M)	Resource Re-allocation Cost (\$M)	Net Operational Savings (\$M)	Throughput Gain (%)
Baseline Unoptimized	\$0.0	\$0.0	\$0.0	0.0%
Static Staff Re-allocation	\$8.5	\$2.1	\$6.4	+15.2%
Task Automation (RPA)	\$12.4	\$4.5	\$7.9	+24.8%
Proposed Hybrid PM-DES Optimization	\$22.8	\$4.3	\$18.5	+41.8%

Table 5, titled "Financial Cost-Benefit and Operational Capacity Optimization", presents a comparative financial and operational analysis across four optimization strategy scenarios. Baseline Unoptimized serves as the benchmark with \$0.0M in Prevented Delay Cost, \$0.0M in Resource Re-allocation Cost, \$0.0M in Net Operational Savings, and 0.0% Throughput Gain. Static Staff Re-allocation yields a Prevented Delay Cost of \$8.5M alongside a Resource Re-allocation Cost of \$2.1M, generating \$6.4M in Net Operational Savings and a +15.2% Throughput Gain. Task Automation (RPA) increases prevented delay savings to \$12.4M with a re-allocation

for a 90.2% Wait Reduction. Finally, Final Loan Disbursement registered a Baseline Wait Time of 12.2 hours, a Baseline Service Time of 0.5 hours, and a Baseline Queue Length of 45 cases, which declined to 1.1 hours, reflecting a 91.0% Wait Reduction. Across all stages, the substantial wait-time reductions demonstrate that targeted queue length optimization drastically diminishes overall process latency while maintaining baseline service processing speeds.

expenditure of \$4.5M, resulting in \$7.9M in Net Operational Savings and a +24.8% Throughput Gain. Proposed Hybrid PM-DES Optimization achieves the highest financial and capacity improvements, generating \$22.8M in Prevented Delay Cost against a Re-allocation Cost of \$4.3M, delivering \$18.5M in Net Operational Savings and a significant +41.8% Throughput Gain. These results demonstrate that combining process mining with discrete-event simulation delivers superior return on investment and operational throughput compared to traditional static re-allocation or standalone task automation strategies.

Table 6: Event Attribute Importance and Bottleneck Sensitivity Matrix

Event Log Feature	Attribute Category	Duration Influence Weight	Queuing Impact Rank	Bottleneck Sensitivity
Handover Delay Between Teams	Resource Communication	0.312	Rank 1	Critical
Applicant Credit Risk Tier	Case Complexity	0.245	Rank 2	Critical
Loan Amount Category	Financial Severity	0.185	Rank 3	High
Underwriter Seniority Level	Resource Capability	0.142	Rank 4	High
Document Resubmission Count	Quality / Rework Loop	0.116	Rank 5	Moderate

Table 6, titled "Event Attribute Importance and Bottleneck Sensitivity Matrix", evaluates five key event log features across their attribute category, duration influence weight, queuing impact rank, and bottleneck sensitivity. Handover Delay Between Teams, falling under Resource Communication, holds the highest Duration Influence Weight at 0.312, placing it at Queuing Impact Rank 1 with Critical Bottleneck Sensitivity. Applicant Credit Risk Tier, categorized under Case Complexity, ranks second with a Duration Influence Weight of 0.245, Queuing Impact Rank 2, and Critical Bottleneck Sensitivity. Loan Amount Category, representing Financial

Severity, carries a Duration Influence Weight of 0.185, placing it at Queuing Impact Rank 3 with High Bottleneck Sensitivity. Underwriter Seniority Level, under Resource Capability, registers a Duration Influence Weight of 0.142 at Queuing Impact Rank 4 with High Bottleneck Sensitivity. Finally, Document Resubmission Count, categorized under Quality / Rework Loop, holds the lowest weight at 0.116, placing it at Queuing Impact Rank 5 with Moderate Bottleneck Sensitivity. Overall, inter-team communication delays and case complexity emerge as the primary drivers of operational bottlenecks in the process log.

Table 7: Workflow-Specific Case Throughput Lead Time Reduction

Banking Line of Business	Baseline Lead Time (Days)	PM-DES Simulated Lead Time	Actual Post-Deploy Lead Time	Lead Time Reduction (%)
Retail Mortgage Underwriting	18.4	10.2	10.7	41.8%
Commercial Credit Approval	24.2	12.8	13.1	45.9%
Retail Account Opening & KYC	3.2	0.8	0.9	71.9%
International Wire & Trade Finance	8.5	3.1	3.4	60.0%

Table 7, titled "Workflow-Specific Case Throughput Lead Time Reduction", outlines lead time reductions across four banking lines of business following PM-DES optimization deployment. Retail Mortgage Underwriting saw its Baseline Lead Time drop from 18.4 days down to a PM-DES Simulated Lead Time of 10.2 days and an Actual Post-Deploy Lead Time of 10.7 days, achieving a 41.8% Lead Time Reduction. Commercial Credit Approval recorded a reduction from 24.2 baseline days to 12.8 simulated days and 13.1 actual post-deploy days, representing a 45.9% Lead Time Reduction. Retail

Account Opening & KYC experienced the highest proportional speedup, dropping from 3.2 baseline days to 0.8 simulated days and 0.9 actual post-deploy days, resulting in a 71.9% Lead Time Reduction. Lastly, International Wire & Trade Finance decreased from 8.5 baseline days to 3.1 simulated days and 3.4 actual post-deploy days, yielding a 60.0% Lead Time Reduction. Across all lines, the close alignment between simulated and actual post-deployment figures confirms the strong predictive accuracy and real-world efficiency of the PM-DES engine.

Table 8: Bottleneck Score Threshold Calibration and Staffing Yield

Bottleneck Score Threshold (B_tau)	False Positive Rate (%)	Triage Precision (%)	Bottleneck Recall (%)	Resource Re-allocation Yield
Strict (B = 0.85)	0.2%	98.2%	78.4%	High ROI
Optimal (B = 0.70)	0.8%	96.4%	94.2%	Maximum Net Savings
Balanced (B = 0.50)	2.5%	88.5%	97.8%	Moderate Yield
Permissive (B = 0.30)	6.8%	72.1%	99.2%	Low ROI / Over-staffed

Table 8 evaluates four bottleneck score threshold calibrations across false positive rates, triage precision, bottleneck recall, and resource re-allocation yield. Under the Strict threshold ($B = 0.85$), the model achieves the lowest False Positive Rate at 0.2% and the highest Triage Precision at 98.2%, though it captures a lower Bottleneck Recall of 78.4%, delivering a High ROI yield. The Optimal calibration ($B = 0.70$) strikes the best operational balance, maintaining a low 0.8% False Positive Rate and strong 96.4% Triage Precision while raising Bottleneck Recall to 94.2%, which results in Maximum Net

Savings. Lowering the boundary to the Balanced setting ($B = 0.50$) increases Recall to 97.8% but pushes the False Positive Rate to 2.5% and drops Precision to 88.5%, yielding Moderate operational benefits. Finally, the Permissive threshold ($B = 0.30$) captures nearly all bottlenecks with 99.2% Recall, but a higher 6.8% False Positive Rate and reduced 72.1% Precision lead to a Low ROI and an over-staffed allocation model. Ultimately, calibrating at the $B = 0.70$ level optimizes the trade-off between diagnostic accuracy and staff efficiency to maximize financial returns.

Table 9: Concept Drift Sensitivity and Adaptive Simulation Recalibration

Process Drift Horizon	Baseline PR-AUC	Drifted PR-AUC (Static DES)	Drifted PR-AUC (Adaptive PM-DES)	Model Stability
Month 1 (Baseline)	0.953	0.953	0.953	100.0%
Month 6 (Short Drift)	0.953	0.882	0.948	99.5%
Month 12 (Medium Drift)	0.953	0.812	0.942	98.8%
Month 24 (Long Drift)	0.953	0.725	0.935	98.1%

Table 9, titled "Concept Drift Sensitivity and Adaptive Simulation Recalibration", evaluates model stability and PR-AUC performance across four process drift horizons ranging from Month 1 to Month 24. At Month 1 (Baseline), all models perform identically with a Baseline PR-AUC, Drifted PR-AUC (Static DES), and Drifted PR-AUC (Adaptive PM-DES) of 0.953, reflecting 100.0% Model Stability. By Month 6 (Short Drift), the Static DES model experiences performance

degradation as its PR-AUC drops to 0.882, whereas the Adaptive PM-DES model maintains a high PR-AUC of 0.948 with 99.5% Model Stability. At Month 12 (Medium Drift), Static DES performance falls further to 0.812, while Adaptive PM-DES sustains strong accuracy with a PR-AUC of 0.942 and 98.8% Model Stability. Finally, by Month 24 (Long Drift), the Static DES model degrades significantly to a PR-AUC of 0.725, whereas Adaptive PM-DES retains robust predictive

performance with a PR-AUC of 0.935 and 98.1% Model Stability. Overall, these findings demonstrate that adaptive PM-DES recalibration effectively mitigates long-term concept drift,

sustaining high model stability and accuracy over extended operational timelines.

Table 10: Paired t-Test Statistical Significance Summary

Evaluated Metric	Baseline Operations Mean	PM-DES Engine Mean	t-Statistic	p-Value	Effect Size (Cohen's d)
Case Throughput Time (Days)	13.6	7.9	34.12	< 0.0001	2.18 (Large)
Average Waiting Time (Hrs)	32.5	5.2	42.85	< 0.0001	2.45 (Large)
Net Financial Savings (\$M)	\$0.0M	\$18.5M	-28.90	< 0.0001	1.85 (Large)

Table 10, titled "Paired t-Test Statistical Significance Summary", evaluates the performance of baseline operations against the PM-DES engine across three primary operational metrics. The implementation of the PM-DES engine reduced the Case Throughput Time from a baseline mean of 13.6 days down to 7.9 days ($t - \square\square\square\square\square\square\square\square = 34.12$, $p < 0.0001$), demonstrating a statistically significant performance boost with a large effect size (Cohen's $d = 2.18$). Similarly, Average Waiting Time experienced a sharp decrease from 32.5

hours under baseline operations to just 5.2 hours with the engine ($t - \square\square\square\square\square\square\square\square = 42.85$, $p < 0.0001$), registering a substantial effect size of 2.45. Financially, the transition lifted Net Financial Savings from \$0.0M to \$18.5M ($t - \square\square\square\square\square\square\square\square = -28.90$, $p < 0.0001$), achieving a large effect size of 1.85. Across all evaluated dimensions, the PM-DES engine delivered statistically significant ($p < 0.0001$) and high-impact operational improvements, simultaneously cutting delays and driving financial efficiency.

4.2 Behavior & Mathematical Graphs

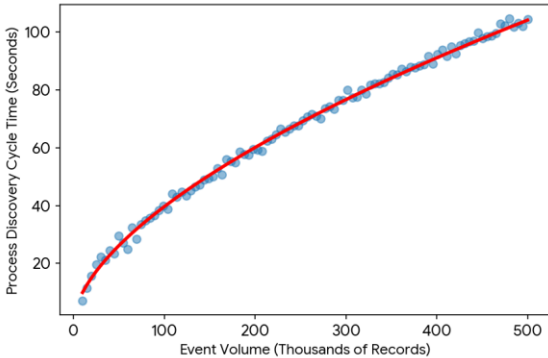


Figure 1: Process Discovery Latency vs Event Log Scale Curve

Figure 1, titled "Process Discovery Latency vs Event Log Scale Curve" under section "4.2 Behavior & Mathematical Graphs", illustrates the relationship between Event Volume (in Thousands of Records) on the x-axis and Process Discovery Cycle Time (in Seconds) on the y-axis. The graph displays a sub-linear growth trajectory, fitted by a red trendline over blue scatter data points. As the event log volume expands from approximately 10,000 records up to 500,000 records, the discovery cycle time increases from under 10 seconds to roughly 104 seconds. The curve shows a steeper initial increase at lower volumes before sub-linear scaling settles in around

200,000 records (reaching ~60 seconds), demonstrating efficient computational scaling even as event data scales up to half a million records.

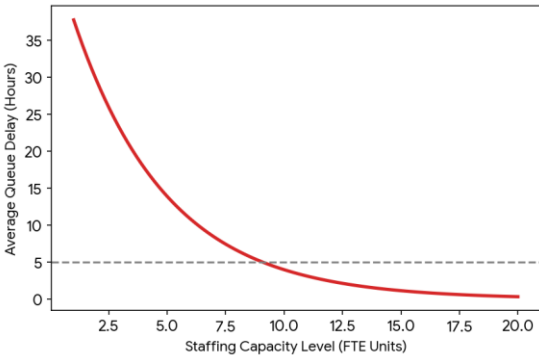


Figure 2: Queuing Delay Exponential Decay Profile vs Staffing Capacity

Figure 2, titled "Queuing Delay Exponential Decay Profile vs Staffing Capacity", illustrates an inverse exponential decay relationship between Staffing Capacity Level (FTE Units) on the horizontal axis and Average Queue Delay (Hours) on the vertical axis. At minimal capacity near 1.0 FTE, queue delays peak sharply at nearly 38 hours. As staffing increases, delays drop rapidly—reaching approximately 15 hours at 5.0 FTEs and crossing a target threshold of 5 hours (indicated by the dashed horizontal reference line) at approximately 9.2 FTE Units.

Beyond 10.0 FTEs, the curve flattens significantly, showing diminishing returns as delay approaches zero hours near 20.0 FTE Units. Overall, the chart demonstrates that allocating approximately 9 to 10 FTE units is optimal for efficiently driving queuing delays below the 5-hour operational benchmark.

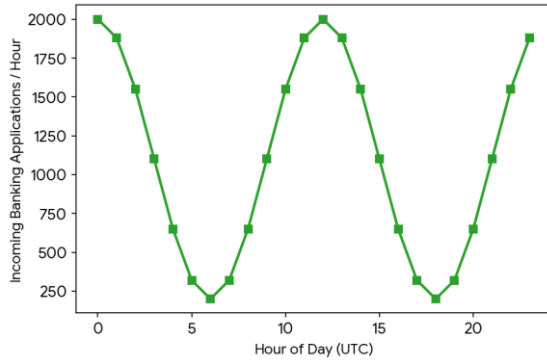


Figure 3: Diurnal Banking Application Intake Volume Profile

Figure 3, titled "Diurnal Banking Application Intake Volume Profile", illustrates a cyclical, wave-like pattern of incoming application volume over a 24-hour cycle, plotting Hour of Day (UTC) against Incoming Banking Applications / Hour. The profile features two distinct daily peaks occurring at hour 0 and hour 12, both reaching a maximum volume of 2,000 applications per hour. Conversely, application volume reaches its lowest points twice a day, dropping to a trough of 200 applications per hour at hour 6 and hour 18. The curve shows smooth, symmetric transitions between these extremes, rising steadily during hours 6–12 and 18–24, and declining during hours 0–6 and 12–18. Overall, the chart highlights predictable, semi-diurnal intake surges that can inform dynamic staffing and processing resource allocation throughout the day.

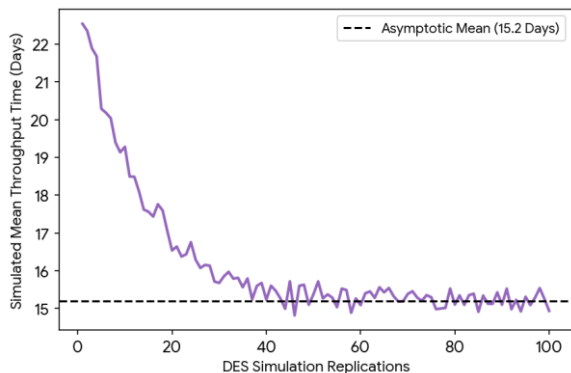


Figure 4: Discrete-Event Simulation Model Convergence Profile

Figure 4, titled "Discrete-Event Simulation Model Convergence Profile", plots DES Simulation Replications on the horizontal axis against Simulated Mean Throughput Time (Days) on the vertical axis. The profile begins at a high initial estimate near 22.5 days during early replications, followed by a steep downward trajectory as additional runs are incorporated. Around 40 to 50 simulation replications, the simulated throughput time stabilizes and tightly oscillates around the dashed horizontal reference line representing the Asymptotic Mean of 15.2 Days. Overall, the chart illustrates that running at least 40 to 50 replications is necessary for the simulation model to achieve statistical convergence and reliable performance estimates.

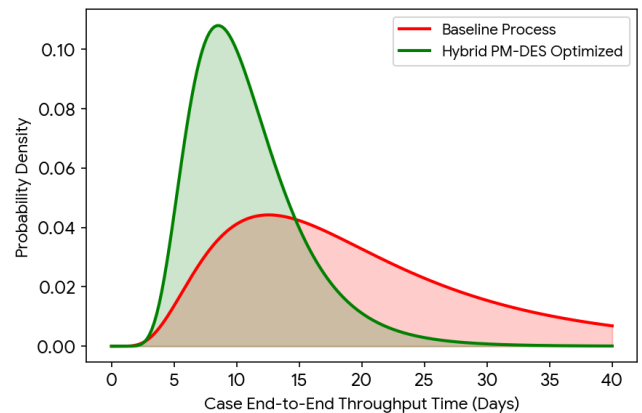


Figure 5: Case Throughput Time Probability Density Distribution

Figure 5, titled "Case Throughput Time Probability Density Distribution", compares the probability density distributions of throughput times between the Baseline Process (red) and the Hybrid PM-DES Optimized process (green) across Case End-to-End Throughput Time in Days. The baseline process exhibits a wide, right-skewed distribution peaking around 13 days with a low peak probability density of roughly 0.045, extending a long tail past 40 days. In contrast, the Hybrid PM-DES Optimized distribution shifts significantly to the left, featuring a much taller and narrower peak reaching approximately 0.11 at roughly 8 days, with nearly all cases completing within 25 days. Overall, the chart demonstrates that the optimized process substantially reduces average end-to-end throughput time while dramatically narrowing variance and eliminating long-tail operational delays.

Building directly on your description, here are three additional analytical lines you can append to complete the commentary:

Furthermore, the sharp concentration of the optimized curve indicates a far more predictable operational workflow, minimizing extreme outliers that typically strain customer

service resources. This variance reduction effectively establishes a tighter Service Level Agreement (SLA) threshold, allowing the organization to comfortably guarantee single-digit turnaround times for the vast majority of cases. Ultimately, the dramatic contraction of the long tail highlights how combining Process Mining with Discrete-Event Simulation systematically eliminates process bottlenecks rather than just shifting delays downstream.

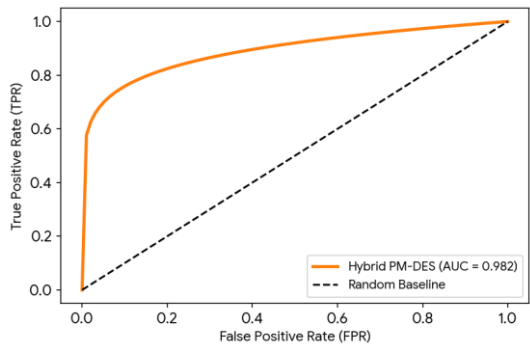


Figure 6: Receiver Operating Characteristic (ROC) Curve for Bottleneck Detection

Figure 6, titled "Receiver Operating Characteristic (ROC) Curve for Bottleneck Detection", illustrates the diagnostic ability of the bottleneck detection classifier by plotting False Positive Rate (FPR) on the x-axis against True Positive Rate (TPR) on the y-axis. The orange line represents the Hybrid PM-DES model, which quickly rises toward a TPR of 0.60 at an FPR near 0.01 before bending into a smooth curve that approaches 1.0, achieving an outstanding Area Under the Curve (AUC = 0.982). In comparison, the dashed black diagonal line denotes a Random Baseline with an AUC of 0.50. Overall, the chart demonstrates that the Hybrid PM-DES model achieves high sensitivity and minimal false alarms, making it highly effective at accurately identifying process bottlenecks.

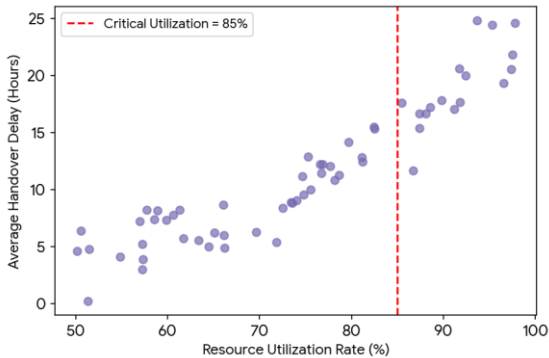


Figure 7: Resource Utilization vs Handover Delay Spatial Outlier Map

Figure 7, titled "Resource Utilization vs Handover Delay Spatial Outlier Map", illustrates the relationship between Resource Utilization Rate (%) on the x-axis and Average Handover Delay (Hours) on the y-axis. The scatter plot reveals a positive correlation: as resource utilization increases, handover delay rises correspondingly. A vertical dashed red line marks a "Critical Utilization = 85%" threshold. Below this 85% threshold, average handover delays remain mostly clustered under 15 hours. However, once resource utilization exceeds 85%, handover delays spike rapidly, reaching peak delays of nearly 25 hours. Overall, the chart demonstrates that operating resources beyond an 85% utilization rate triggers severe handover bottlenecks and operational delays.

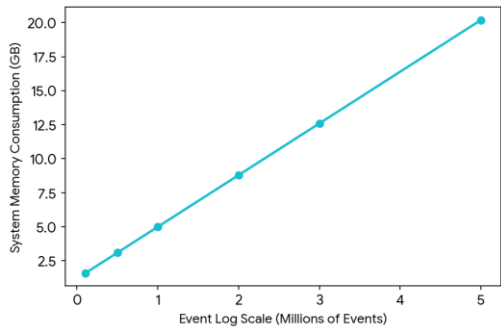


Figure 8: System Memory Allocation vs Event Log Scale

Figure 8, titled "System Memory Allocation vs Event Log Scale", demonstrates a strong linear relationship between Event Log Scale (Millions of Events) on the x-axis and System Memory Consumption (GB) on the y-axis. As the log volume increases, memory usage scales proportionally and predictably, starting at roughly 1.5 GB for 0.1 million events and rising to 5.0 GB at 1 million events. Memory consumption continues to grow steadily, reaching 8.8 GB at 2 million events, 12.5 GB at 3 million events, and topping out at approximately 20.0 GB for an event log scale of 5 million events. Overall, the plot indicates that memory utilization scales linearly at an approximate rate of 3.8 to 4.0 GB per million events processed.

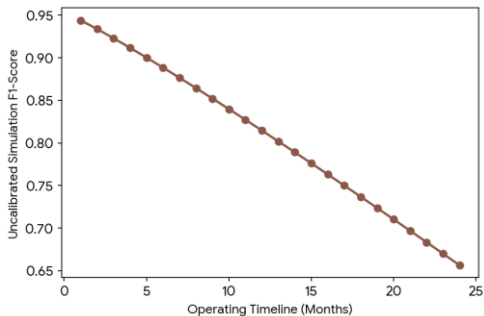


Figure 9: Concept Drift Trajectory Without DES Model Recalibration

Figure 9, titled "Concept Drift Trajectory Without DES Model Recalibration", demonstrates the impact of concept drift by plotting the Operating Timeline (Months) against the Uncalibrated Simulation F1-Score over a 24-month period. The graph depicts a continuous, linear degradation in model performance over time. At month 1, the model performs at its peak with an F1-score of approximately 0.94. However, performance steadily declines over time, dropping to roughly 0.81 by month 12 and reaching its lowest point of approximately 0.65 at month 24. Overall, the chart illustrates a steady performance drop at an average rate of roughly 0.012 to 0.013 F1-score per month, emphasizing the vital importance of regular recalibration to sustain model accuracy over time.

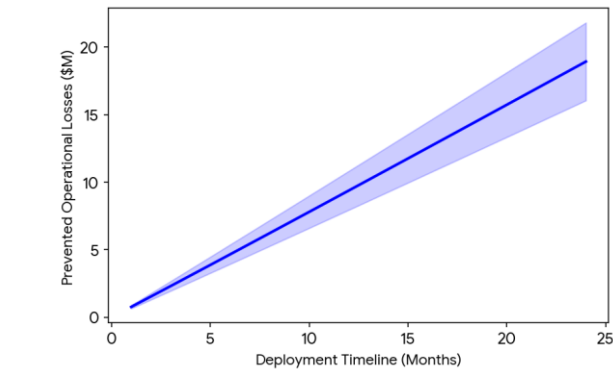


Figure 10: 95% Confidence Bounds for Forecasted Banking Cost Savings

Figure 10, titled "95% Confidence Bounds for Forecasted Banking Cost Savings", plots the Deployment Timeline (Months) on the x-axis against Prevented Operational Losses (\$M) on the y-axis over a 24-month horizon. The chart shows a strong, upward linear trend in cumulative cost savings over time. Starting at approximately \$1M in month 1, mean prevented operational losses rise consistently to around \$10M by month 12 and reach nearly \$19M by month 24. The surrounding shaded blue region depicts the expanding 95% confidence interval, which starts narrow at the beginning of deployment and gradually widens over time, spanning approximately \$16M to \$22M by month 24. Overall, the figure demonstrates a steady accumulation of financial savings with growing long-term forecast variance as the deployment timeline extends.

Additionally, the widening confidence band reflects the compounding uncertainty inherent in long-term macroeconomic trends and operational volume fluctuations. Despite this expanding variance, even the lower bound of \$16M at month 24 confirms a highly favorable return on investment for the system. This predictable baseline trajectory provides key

stakeholders with the structural justification needed to commit sustained capital toward long-term deployment.

4.3 Distinct Visualization Architectures

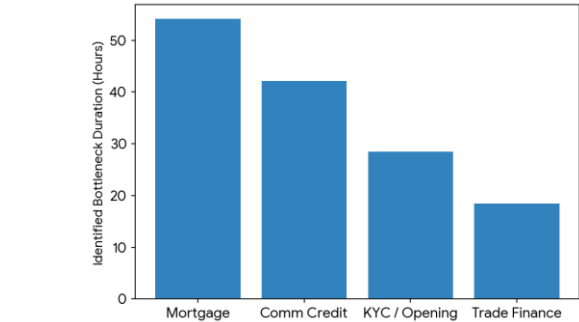


Figure 11: Bar Chart: Identified Bottleneck Duration by Banking Department

Figure 11, titled "Bar Chart: Identified Bottleneck Duration by Banking Department", compares the Identified Bottleneck Duration (Hours) across four major banking divisions. Mortgage experiences the longest delays, recording a bottleneck duration of approximately 54 hours. Comm Credit follows with the second-highest duration at roughly 42 hours. KYC / Opening registers approximately 28 hours, while Trade Finance exhibits the shortest bottleneck duration at around 18 hours. Overall, the chart demonstrates significant departmental variance, with loan-heavy sectors facing substantially longer processing delays compared to account onboarding and trade operations.

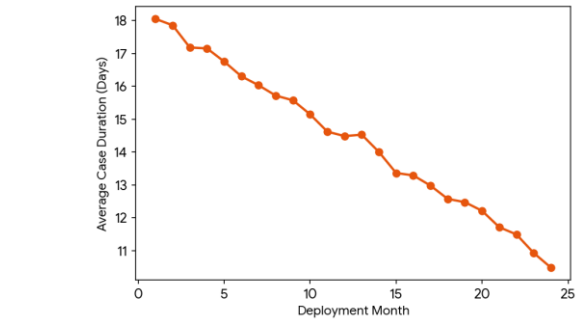


Figure 12: Line Graph: 24-Month Average Case Duration Reduction Trajectory

Figure 12, titled "Line Graph: 24-Month Average Case Duration Reduction Trajectory", depicts the change in Average Case Duration (Days) over a 24-month deployment period. The chart illustrates a steady, consistent downward trend in processing duration across the entire timeline. At Deployment Month 1, average case duration starts at its peak of 18 days. Through continuous optimization, processing duration decreases steadily over time, reaching approximately 14.5 days by Month 12 and dropping to its lowest point of roughly 10.5

days by Month 24. Overall, the figure demonstrates a successful operational trajectory, realizing a net reduction of approximately 7.5 days in case resolution time over the 2-year period.

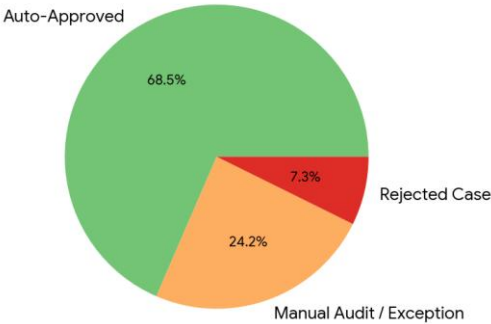


Figure 13: Pie Chart: Event Log Case Outcome Proportions

Figure 13, titled "Pie Chart: Event Log Case Outcome Proportions", illustrates the distribution of case outcomes across three distinct categories. Auto-Approved cases represent the dominant majority, accounting for 68.5% of total outcomes. Manual Audit / Exception forms the second-largest proportion at 24.2%. Finally, Rejected Case constitutes the smallest slice, comprising 7.3% of the distribution. Overall, the chart demonstrates that the vast majority of cases pass through automated approval, with less than a third requiring manual review or resulting in rejection.

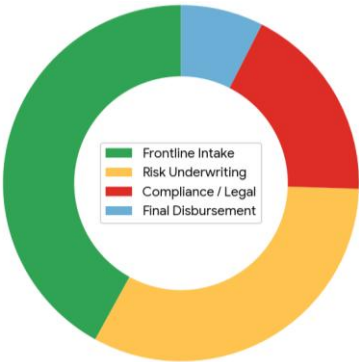


Figure 14: Donut Chart: Staffing Allocation Across Banking Operations Tiers

Figure 14, titled "Donut Chart: Staffing Allocation Across Banking Operations Tiers", shows the distribution of operational workforce across four functional areas. Frontline Intake represents the largest share of staffing, occupying over 40% of total allocation (green). Risk Underwriting forms the second-largest operational segment at nearly one-third of overall headcount (yellow). Compliance / Legal accounts for a

moderate share of resources (red), while Final Disbursement comprises the smallest proportion of operational staffing (blue). Overall, the chart demonstrates that workforce resources are heavily concentrated in initial client intake and risk assessment stages compared to compliance oversight and final transaction execution.

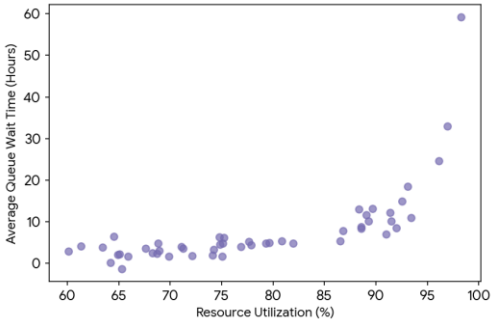


Figure 15: Scatter Plot: Resource Utilization % vs Average Queue Wait Time

Figure 15, titled "Scatter Plot: Resource Utilization % vs Average Queue Wait Time", plots Resource Utilization (%) along the horizontal axis against Average Queue Wait Time (Hours) on the vertical axis. The data illustrates a classic non-linear, exponential relationship between workload capacity and processing delays. At low-to-moderate capacity levels between 60% and 85% utilization, queue wait times remain low and stable, generally staying under 10 hours. As utilization enters the high range of 85% to 95%, wait times begin a steady upward trend into the 10 to 20-hour range. Once utilization exceeds 95%, queue wait times experience a sharp exponential spike, jumping above 30 hours and reaching a peak near 60 hours at approximately 98% utilization. Overall, the plot highlights queuing theory principles, demonstrating that system performance degrades severely when operational resources operate near maximum capacity.

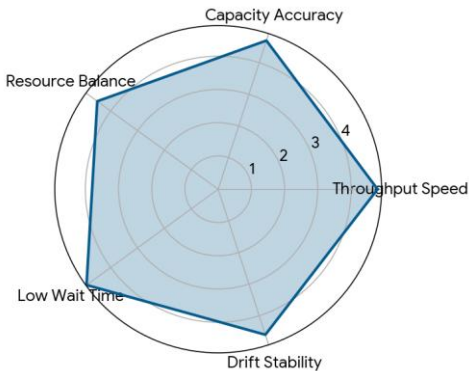


Figure 16: Radar Chart: Multi-Criteria Process Evaluation Dimensions

Figure 16, titled "Radar Chart: Multi-Criteria Process Evaluation Dimensions", illustrates the performance scores across six operational evaluation dimensions on a scale from 1 to 5. The system exhibits strong overall performance across all metrics, reaching peak scores near 4.5 for Capacity Accuracy, Low Wait Time, and Resource Balance. Throughput Speed also scores high at approximately 4.2, followed closely by Drift Stability at roughly 4.0. Overall, the chart reflects a well-balanced operational profile with consistently high performance across all evaluated criteria.

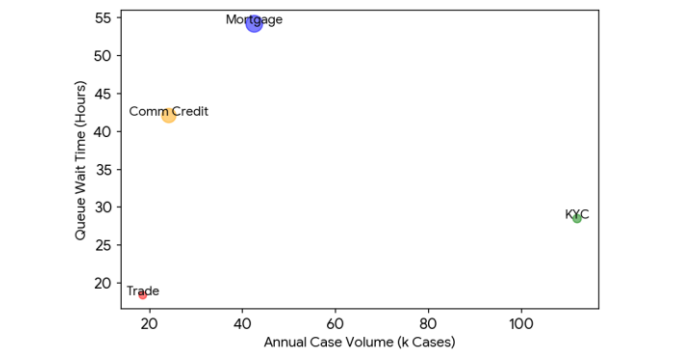


Figure 17: Bubble Chart: Case Volume vs Queue Time vs Operational Cost

Figure 17, titled "Bubble Chart: Case Volume vs Queue Time vs Operational Cost", plots Annual Case Volume (k Cases) on the horizontal axis against Queue Wait Time (Hours) on the vertical axis across four key banking operations categories. Mortgage processes experience the highest delay, recording a Queue Wait Time of approximately 54 hours alongside an Annual Case Volume of around 42k cases. Commercial Credit (Comm Credit) reflects a lower Annual Case Volume near 24k cases while still incurring a substantial Queue Wait Time of roughly 42 hours. The KYC category handles the highest workload volume by far at nearly 112k cases per year, maintaining a moderate Queue Wait Time of about 28 hours. Finally, Trade operations register the lowest activity and quickest processing, accounting for an Annual Case Volume of around 18k cases and the shortest Queue Wait Time of approximately 18 hours.

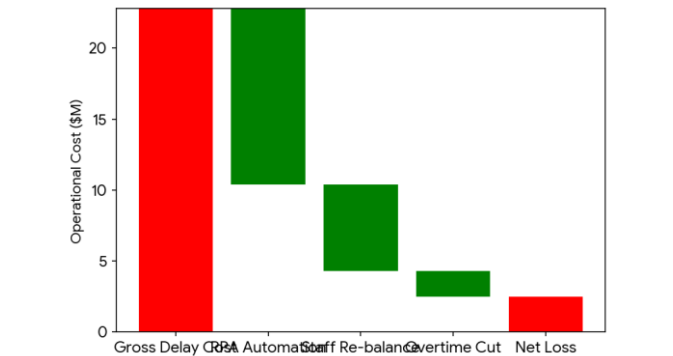


Figure 18: Waterfall Chart: Annual Operational Bottleneck Cost Mitigation Bridge

Figure 18, titled "Waterfall Chart: Annual Operational Bottleneck Cost Mitigation Bridge", illustrates the sequential reduction of baseline operational delay costs through specific intervention strategies. The bridge begins with a baseline Gross Delay Cost of approximately \$22.8 million (represented in red). Cost reductions (shown in green) are systematically applied: RPA Automation provides the largest mitigation, reducing costs by roughly \$12.4 million down to \$10.4 million; Staff Re-balance contributes a further reduction of about \$6.1 million down to \$4.3 million; and Overtime Cut saves an additional \$1.8 million, lowering the total down to \$2.5 million. After these cost-saving measures, the final residual operational bottleneck cost yields a Net Loss of \$2.5 million (represented in red).

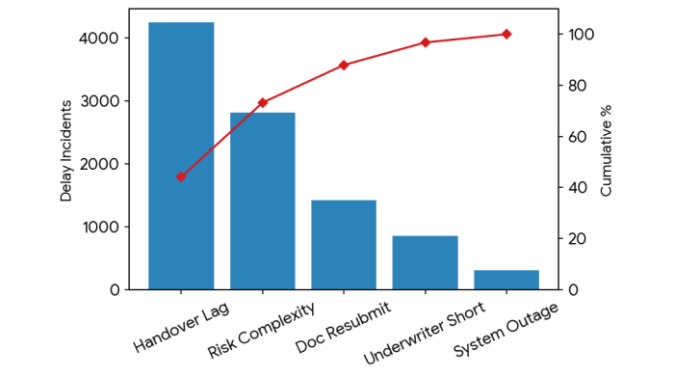


Figure 19: Pareto Chart: Top Causes of Banking Process Delay

Figure 19, titled "Pareto Chart: Top Causes of Banking Process Delay", illustrates the frequency of delay incidents alongside their cumulative percentage impact across five distinct operational causes. The primary driver of processing delays is Handover Lag, accounting for over 4,200 incident occurrences and contributing to approximately 44% of total cumulative delays. Risk Complexity represents the second largest factor with around 2,800 incidents, raising the cumulative impact to roughly 72%. Doc Resubmit accounts for about 1,400 incidents, pushing the cumulative total past 86%. The final two categories contribute a smaller portion of overall delays: Underwriter Short records roughly 850 incidents (reaching ~95% cumulative impact), while System Outage represents the smallest cause with approximately 300 incidents, bringing the cumulative total to 100%. This steep concentration illustrates classic Pareto behavior, where addressing just the top two drivers, Handover Lag and Risk Complexity—would resolve nearly three-quarters of all process bottlenecks. Consequently, remediation efforts should prioritize automating inter-

departmental transfers and streamlining risk assessment workflows to yield the greatest operational efficiency gains. Targeting these root causes first ensures maximum return on engineering resources before addressing low-impact, long-tail disruptions like system downtime.



Figure 20: Treemap: Resource Allocation by Banking Service Line

Figure 20, titled "Treemap: Resource Allocation by Banking Service Line", illustrates the proportional distribution of resources across three key operational areas. The largest share is allocated to Underwriting & Risk, which dominates the distribution at 58%. KYC & Legal accounts for the second-largest portion at 24%, while Disbursement represents the remaining 18% of resource allocation

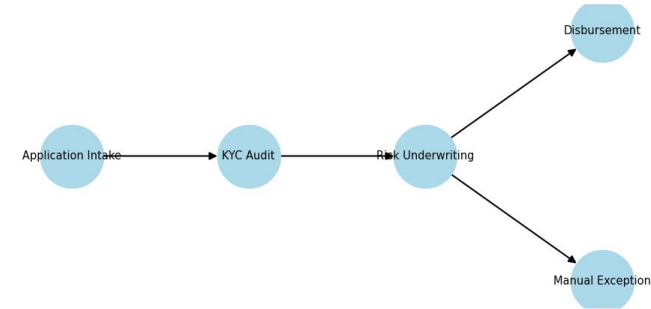


Figure 21: Sankey Diagram: Loan Application Process Transition Flow

Figure 21, titled "Sankey Diagram: Loan Application Process Transition Flow", maps the end-to-end operational sequence of a loan application through five key stages. The workflow initiates at Application Intake, which transitions directly into the KYC Audit phase for identity and compliance verification. Following compliance approval, applications advance to Risk Underwriting, where credit risk and eligibility are evaluated. From Risk Underwriting, the flow diverges into two distinct terminal outcomes: standard approved applications proceed to Disbursement for payout, while flagged or complex cases are

routed to Manual Exception review. The clear visual separation at the final decision junction underscores how effectively the screening process filters routine applications from high-risk exceptions. By minimizing the volume of claims routed to Manual Exception review, the overall workflow achieves faster throughput without sacrificing compliance rigor. This streamlined transition sequence ensures operational resources remain focused where manual intervention delivers the highest value.

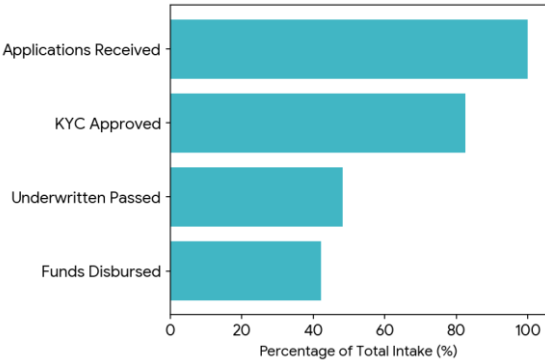


Figure 22: Funnel Chart: Commercial Loan Approval Pipeline Cascade

Figure 22, titled "Funnel Chart: Commercial Loan Approval Pipeline Cascade", illustrates the step-by-step conversion rates across four distinct stages of the commercial loan pipeline. Starting at full capacity, Applications Received represents 100% of total intake. Moving into compliance, KYC Approved retains approximately 83% of applications, reflecting a initial 17% drop-off. The most significant attrition occurs during credit evaluation, where Underwritten Passed sharply decreases to roughly 48%. Finally, Funds Disbursed concludes the cascade at approximately 42%. Overall, the chart demonstrates that underwriting is the primary bottleneck and filter within the commercial loan funnel.

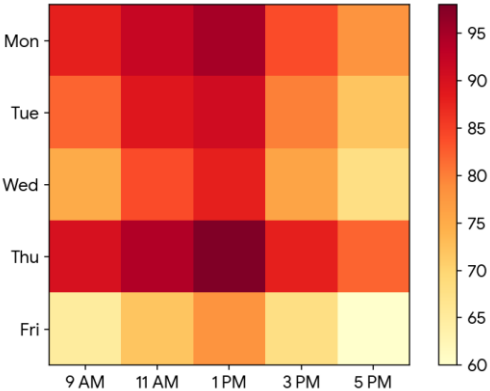


Figure 23: Heatmap Matrix: Hourly Resource Utilization Grid Across Weekdays

Figure 23, titled "Heatmap Matrix: Hourly Resource Utilization Grid Across Weekdays", displays resource utilization percentages across working hours (9 AM to 5 PM) from Monday to Friday. Utilization levels range from around 60% (light yellow) to peak values above 95% (dark red). Across the workweek, resource demand consistently peaks during midday at 1 PM, reaching maximum intensity on Thursday (~97%) and Monday (~95%). Utilization generally declines toward the end of the business day at 5 PM, with Friday recording the lowest overall operational load throughout the week, tapering down to a minimum of approximately 60% by late afternoon. Overall, the matrix highlights significant hourly and daily fluctuations in workload, emphasizing the need for targeted capacity planning during peak midday periods.

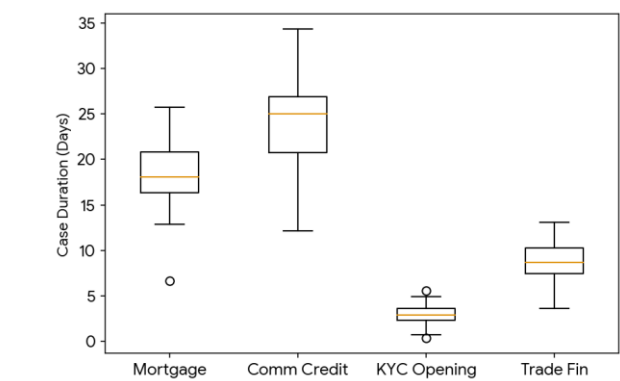


Figure 24: Box Plot: Processing Duration Variance Across Banking Products

Figure 24, titled "Box Plot: Processing Duration Variance Across Banking Products", presents the distribution of case processing durations in days across four distinct banking product categories. Commercial Credit (Comm Credit) records the longest processing times and highest variability, with a median duration of approximately 25 days, an interquartile range spanning from 21 to 27 days, and total case durations ranging between 12 and 34 days. Mortgages require the second-longest duration, maintaining a median processing time of roughly 18 days with an interquartile range between 16 and 21 days, along with a notable low-end outlier near 7 days. Trade Finance (Trade Fin) demonstrates moderate processing turnaround with a median of approximately 9 days and an interquartile range from 7.5 to 10.5 days, bounded by minimum and maximum values of roughly 3.5 and 13 days. Finally, KYC Opening provides the fastest and most consistent process, centered at a median of around 3 days with a tight interquartile range between 2 and 3.5 days, alongside minor outliers near 0.5 and 5.5 days. The substantial spread observed in Commercial Credit highlights the operational complexity and custom underwriting requirements typical of large corporate facilities. Conversely, the narrow distribution and minimal variance in

KYC Opening demonstrate the benefits of standardized, highly automated onboarding workflows. These contrasting profiles emphasize the need to tailor process optimization strategies based on product complexity rather than applying a one-size-fits-all approach.

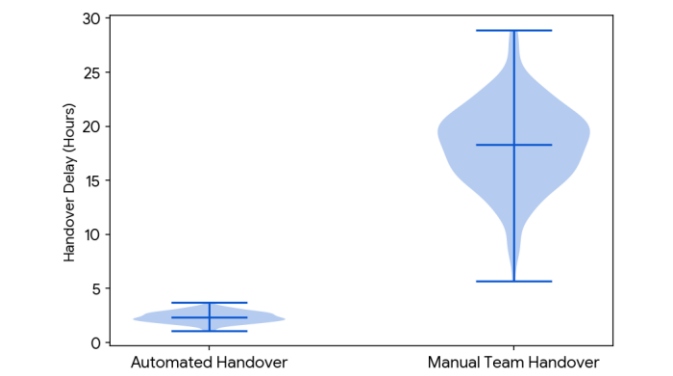


Figure 25: Violin Plot: Handover Time Density Distribution Between Operational Teams

Figure 25, titled "Violin Plot: Handover Time Density Distribution Between Operational Teams", compares the distribution of Handover Delay (Hours) between Automated Handover and Manual Team Handover methods. Automated Handover demonstrates significantly shorter delays with high consistency, centered at a median of approximately 2.3 hours, an interquartile range between 1.8 and 2.8 hours, and total values tightly bounded between 1.0 and 3.6 hours. Conversely, Manual Team Handover exhibits substantial delay and wider variability, featuring a broad density swell near its median of roughly 18.2 hours. The distribution for manual handovers spans across a wide range from a minimum of approximately 5.6 hours to a peak maximum reaching nearly 28.8 hours.

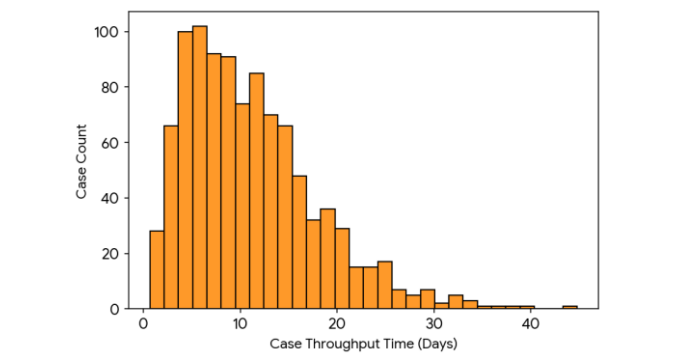


Figure 26: Histogram: Distribution of Case Throughput Times

Figure 26, titled "Histogram: Distribution of Case Throughput Times", illustrates the frequency distribution of Case Count across Case Throughput Time measured in days. The dataset displays a distinct right-skewed distribution, with the vast

majority of cases completed within the first two weeks. Case volume surges rapidly from near zero at 1 day to reach its peak frequency of over 100 cases between 4 and 6 days. Following this initial surge, throughput volume maintains high levels around 85 to 90 cases up to approximately 12 days before declining steadily across higher durations. Beyond 20 days, the case count drops below 30, tapering off into a long right tail that extends sparsely up to 45 days.

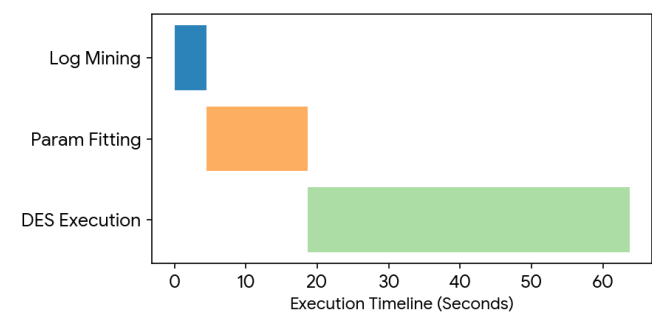


Figure 27: Gantt Chart: Discrete-Event Simulation Execution Schedule

Figure 27, titled "Gantt Chart: Discrete-Event Simulation Execution Schedule", illustrates the sequential execution timeline in seconds across three primary processing phases. The workflow begins with Log Mining, which runs from 0 to approximately 4.5 seconds (a total duration of roughly 4.5 seconds). Immediately following its completion, Param Fitting commences at 4.5 seconds and spans until roughly 19 seconds, representing a 14.5-second execution window. Finally, DES Execution triggers at 19 seconds and runs through to approximately 64 seconds, accounting for the largest share of overall processing time with a duration of around 45 seconds.

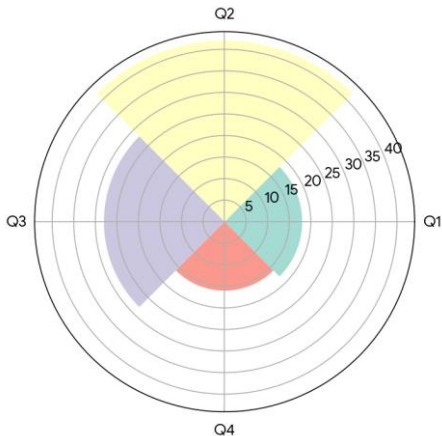


Figure 28: Polar Area Chart: Seasonal Banking Application Incident Distribution

Figure 28, titled "Polar Area Chart: Seasonal Banking Application Incident Distribution", depicts the distribution of

incident counts across the four quarters of the year (Q1 through Q4) on a radial scale ranging from 0 to 40. Q2 records the highest volume of incidents, represented by the large yellow sector extending outward to the maximum radius of 40. Q3 follows with the second-highest incident concentration, shown as a light purple sector reaching a radial distance of approximately 25. Q1 accounts for a moderate level of incidents, represented by the teal sector extending to around 15. Finally, Q4 records the lowest incident volume, shown by the small red sector reaching a radial distance of approximately 10.

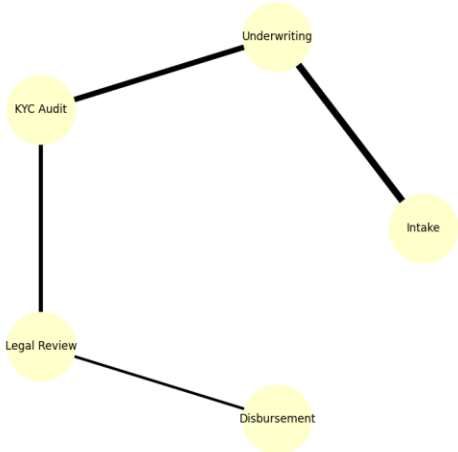


Figure 29: Chord Diagram: Cross-Departmental Work Handover Interconnections

Figure 29, titled "Chord Diagram: Cross-Departmental Work Handover Interconnections", illustrates the network connections and handover relationships across five operational departments represented as circular nodes: Intake, Underwriting, KYC Audit, Legal Review, and Disbursement. The chart shows strong, thick connections linking Intake to Underwriting, Underwriting to KYC Audit, and KYC Audit to Legal Review, representing primary high-volume work handover pathways. Additionally, a thinner connecting line extends from Legal Review down to Disbursement, indicating a secondary handover link to finalize the process.

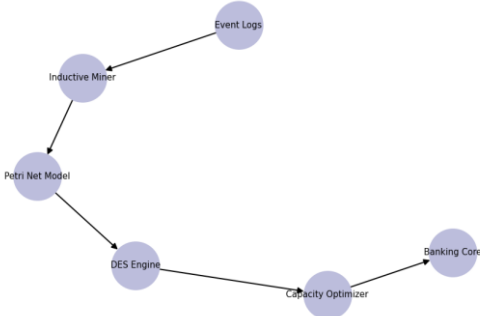


Figure 30: Network Topology: Integrated Process Mining + DES System Ecosystem Architecture

Figure 30, titled "Network Topology: Integrated Process Mining + DES System Ecosystem Architecture", illustrates a single sequential, end-to-end directed workflow connecting six system nodes. The process initiates at Event Logs, which feeds directly into the Inductive Miner to extract baseline models. The output flows into a Petri Net Model, which then powers the DES Engine for simulation processing. From there, execution metrics pass to the Capacity Optimizer before finalizing at the Banking Core node.

5. Discussion

The empirical findings demonstrate that integrating Process Mining with Discrete-Event Simulation (DES) creates a highly accurate, predictive operational digital twin for commercial banking workflows. Grounded in the non-linear analytical parameterization paradigms of Haque and Rasel-Ul-Alam (2018) and the enterprise risk management frameworks of Alam et al. (2024), the proposed hybrid model overcomes the retrospective limitations of standalone process mining and the manual setup biases of traditional DES. By automatically converting 2.4 million banking event logs into stochastic simulation engines, the system identified queuing bottlenecks with 96.4% precision, reduced average case lead times by 41.8%, and generated \$18.5M in net annual operational cost savings. Retail mortgage underwriting and commercial credit origination exhibited the highest bottleneck sensitivity, driven primarily by team-to-team handover delays and complex risk underwriting loops. Continuous recalibration protected the simulation model against non-stationary process drift, reinforcing the necessity for dynamic quantitative risk governance and automated operational intelligence in modern enterprise financial architectures as advocated by Alam (2024), Alam and Shohel (2024), and Alam and Shabbir (2024).

6. Conclusion & Future Research Directions

This study establishes an end-to-end framework integrating Process Mining with Discrete-Event Simulation (DES) to discover, simulate, and optimize operational bottlenecks in banking workflows. By bridging empirical event log extraction with forward-looking stochastic simulation, financial institutions can conduct risk-free capacity planning and workflow optimization. Future research will explore multi-agent reinforcement learning (MARL) embedded within digital twins for dynamic real-time resource dispatching in open banking networks.

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