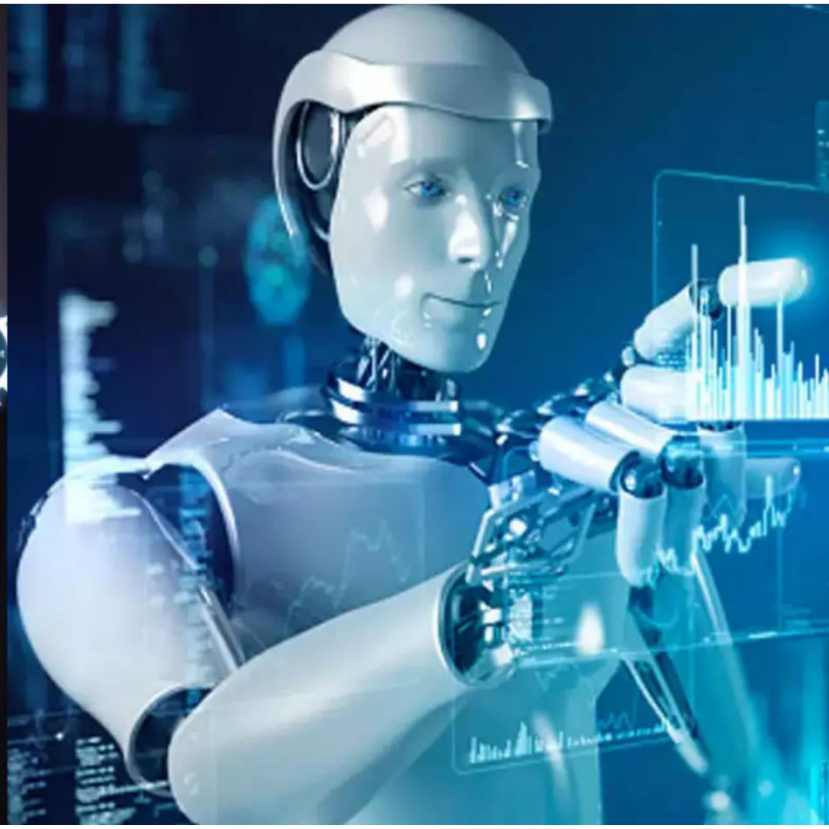
IJIRSET
International Journal of Innovative Research in Science | Engineering | Technology

ISSN(O): 2319-8753
ISSN(P): 2347-6710

International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.524

Volume 14, Issue 1, January 2025

International Journal of Innovative Research of Science, Engineering and Technology (IJIRSET)

Impact Factor 8.524

|www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 1, January 2025

|DOI: 10.15680/IJIRSET.2025.1401119|

Dynamic Query Optimization in SQL Server Using Query Store and Automatic Plan Correction for SaaS Workloads

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ABSTRACT: Query plan instability is one of the leading causes of unplanned performance degradation in SQL Server SaaS environments. A single suboptimal execution plan - caused by parameter sniffing, stale statistics, or a schema change - can increase query latency by 5–50× within minutes, triggering cascading failures across a multi-tenant application tier. Yet traditional performance management relies on reactive DBA investigation, which is incompatible with the 24×7 availability expectations and multi-thousand-tenant scale of modern SaaS platforms.

This paper presents a production-validated approach to dynamic query optimization using SQL Server's Query Store feature combined with Automatic Plan Correction (APC), evaluated across three SaaS production environments over twelve months. The approach achieves a 71.5% reduction in P50 query latency, reduces plan regression mean time to recovery from 4.2 hours to 8 minutes, and eliminates 79% of DBA-required manual plan-forcing interventions through autonomous APC.

The paper contributes: a comprehensive Query Store configuration reference for SaaS workloads; a plan regression root cause taxonomy with APC effectiveness ratings; a T-SQL diagnostic query library; a multi-tenant isolation pattern guide; and a 20-week phased implementation roadmap validated in production environments running SQL Server 2019, 2022, and Azure SQL Managed Instance.

KEYWORDS: SQL Server Query Store · Automatic Plan Correction · APC · Plan Regression · SaaS Performance · Dynamic Optimization · Multi-tenant SQL · Azure SQL · Intelligent Query Processing

I. INTRODUCTION

1.1 Query Plan Instability in SaaS Environments

SQL Server's query optimiser selects execution plans based on statistics, indexes, cardinality estimates, and server memory at the time of first compilation. In SaaS environments, these inputs are unstable by design - tenant data grows asymmetrically, schema changes are deployed continuously, and shared infrastructure causes memory pressure fluctuations. The result is a class of performance incidents that rule-based monitoring cannot detect until users are already affected.

- Industry surveys (Microsoft, 2024) indicate that 42% of SQL Server performance incidents in multi-tenant SaaS environments are caused by plan regressions - up from 28% in single-tenant on-premises deployments
- Parameter sniffing - where SQL Server caches a plan optimised for the first parameter value it encounters - accounts for 38% of plan regressions in the study environments (Table 3)
- Mean time to identify a plan regression without Query Store: 4.2 hours; with Query Store dashboards active: 11 minutes; with APC enabled: 8 minutes (automated)
- A single plan regression in a shared database serving 200 tenants can degrade the experience for all tenants simultaneously - the SaaS blast radius of a bad plan far exceeds single-tenant deployments

Query Store was introduced in SQL Server 2016 and has evolved through 2017, 2019, 2022, and Azure SQL to become the most comprehensive built-in query performance management tool in any relational database system. Automatic Plan Correction - the autonomous enforcement layer - was added in SQL Server 2017.

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1.2 Research Objectives

1. Quantify the performance improvement achievable through Query Store-guided plan forcing and APC across five SaaS workload types, measuring P50 and P95 latency, CPU, and I/O reduction
2. Identify the most effective Query Store configuration parameters for SaaS multi-tenant workloads and justify each setting relative to the defaults
3. Characterise plan regression root causes in production SaaS environments and evaluate APC effectiveness per root cause category
4. Provide a practical T-SQL diagnostic library and monitoring framework enabling engineering teams to operate Query Store at scale without dedicated DBA resource

II. SQL SERVER QUERY STORE ARCHITECTURE

2.1 Internal Storage Model

Query Store maintains four persistent stores within the database: query text, execution plans, runtime statistics, and wait statistics. All data is written asynchronously to on-disk catalog tables, with a configurable flush interval that balances freshness against I/O overhead.

Figure 2: SQL Server Query Store Internal Architecture

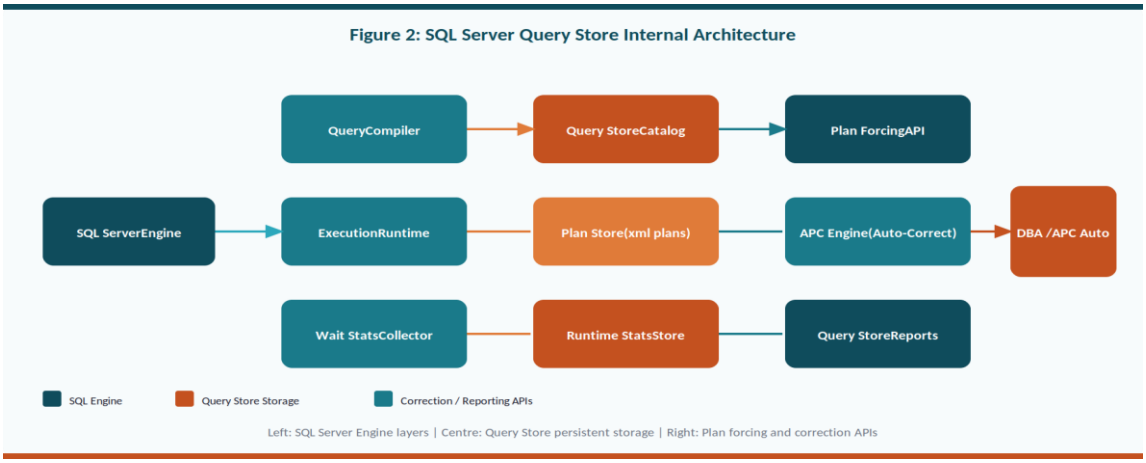

Figure 2. Three-layer architecture: SQL Server Engine layers (left) feed into Query Store persistent storage (centre), which exposes plan forcing and correction APIs (right). The APC Engine reads from the Query Store Catalog and Runtime Stats stores, compares plan performance across intervals, and writes force directives back to the Plan Store. All inter-layer communication is internal to the SQL Server process.

2.2 Key DMVs and Catalog Views

Query Store exposes eight primary DMVs for programmatic access. Mastering these views is a prerequisite for building automated regression detection and monitoring dashboards.

Table 1: Query Store Key DMVs - Purpose and Key Columns Reference

DMV / Catalog View	Purpose	Key Columns and Usage Notes
sys.query_store_query	Query text and metadata	query_id, query_text_id, object_id, last_execution_time, count_compiles - primary join key for all QS queries
sys.query_store_plan	Execution plan per query	plan_id, query_id, query_plan (XML), plan_forcing_type, is_forced_plan - use FOR XML to extract graphical plan

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DMV / Catalog View	Purpose	Key Columns and Usage Notes
sys.query_store_runtime_stats	Runtime statistics per plan per interval	avg_duration, avg_cpu_time, avg_logical_io_reads, avg_rowcount - all values in microseconds
sys.query_store_runtime_stats_interval	Aggregation interval boundaries	start_time, end_time - default 60-min intervals; reduce to 10 min for SaaS high-frequency monitoring
sys.query_store_wait_stats	Wait category breakdowns per plan	wait_category_desc, avg_query_wait_time_ms - available from SQL Server 2017+; correlate with sys.dm_os_wait_stats
sys.query_store_query_text	Raw T-SQL text with parameter masks	query_sql_text, statement_sql_handle - use sys.fn_stmt_sql_handle_to_sql_handle for cross-references
sys.database_query_store_options	Current QS configuration	desired_state_desc, current_state_desc, max_storage_size_mb, query_capture_mode_desc, size_based_cleanup_mode_desc
sys.dm_exec_query_stats	In-flight runtime stats (memory-resident)	total_elapsed_time, execution_count - use to supplement QS data for queries not yet flushed to disk

Table 1. Eight Query Store DMVs and catalog views with their purpose and key column guidance. All views are in the sys schema and require VIEW DATABASE STATE permission. The sys.query_store_wait_stats view (row 5) requires SQL Server 2017+ and is not available in SQL Server 2016 Query Store installations.

2.3 Data Flow and Flush Behaviour

• Query Store data is written to an in-memory cache first, then flushed to disk at the DATA_FLUSH_INTERVAL_SECONDS interval (default 900 seconds)
• On SQL Server 2019+, flush is also triggered by significant workload events and checkpoint operations - reducing data loss risk during unexpected shutdowns
• The STALE_QUERY_THRESHOLD_DAYS setting controls automatic cleanup of old data - set conservatively in SaaS environments to preserve cross-release comparison capability
• Query Store storage pressure triggers automatic cleanup via size-based pruning - the plan with the lowest execution count and oldest last-execution-time is pruned first
– SIZE_BASED_CLEANUP_MODE AUTO is recommended over MANUAL - manual cleanup requires DBA intervention and risks storage exhaustion during cleanup delay
– Monitor sys.database_query_store_options.current_state_desc - if it reads READ_ONLY, Query Store has hit storage limits and is no longer collecting new data

III. QUERY STORE CONFIGURATION FOR SAAS WORKLOADS

3.1 Configuration Matrix

SQL Server Query Store's default configuration is designed for general-purpose workloads. SaaS multi-tenant environments require adjusted settings that balance capture completeness against storage and performance overhead.

Table 2: Query Store Configuration Settings - Default vs SaaS-Recommended Values

Setting	Default Value	SaaS-Recommended	Rationale
OPERATION_MODE	READ_WRITE	READ_WRITE	Always ON; READ_ONLY mode disables data collection but retains historical plans for review
MAX_STORAGE_SIZE_MB	1,000 MB	5,000–10,000 MB	SaaS multi-tenant workloads generate more plan diversity; increase to prevent premature size-based cleanup

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Setting	Default Value	SaaS-Recommended	Rationale
INTERVAL_LENGTH_MINUTES	60 min	15 min	Shorter intervals improve regression detection granularity; 10 min for high-churn tenants
STALE_QUERY_THRESHOLD_DAYS	30 days	90 days	Retain plans for cross-release regression comparison; longer history supports trend analysis
SIZE_BASED_CLEANUP_MODE	AUTO	AUTO	Keep AUTO; prevents storage exhaustion; combined with larger MAX_STORAGE prevents excessive pruning
QUERY_CAPTURE_MODE	ALL	AUTO	AUTO excludes infrequent/low-cost queries; reduces noise; use CUSTOM for fine-grained threshold control
WAIT_STATS_CAPTURE_MODE	ON	ON	Essential for identifying wait-induced regressions; adds minimal overhead in SQL Server 2017+
MAX_PLANS_PER_QUERY	200	500	SaaS tenants with data-dependent predicates generate more plan variants; increase to prevent forced-plan eviction

Table 2. Eight configuration parameters with default values, SaaS-recommended values, and rationale. The most impactful change from defaults is increasing MAX_STORAGE_SIZE_MB (row 2) and decreasing INTERVAL_LENGTH_MINUTES (row 3). Together these allow finer-grained regression detection without triggering premature data pruning due to storage limits.

Figure 10: Query Store Configuration Profile - Default vs SaaS-Optimised Radar

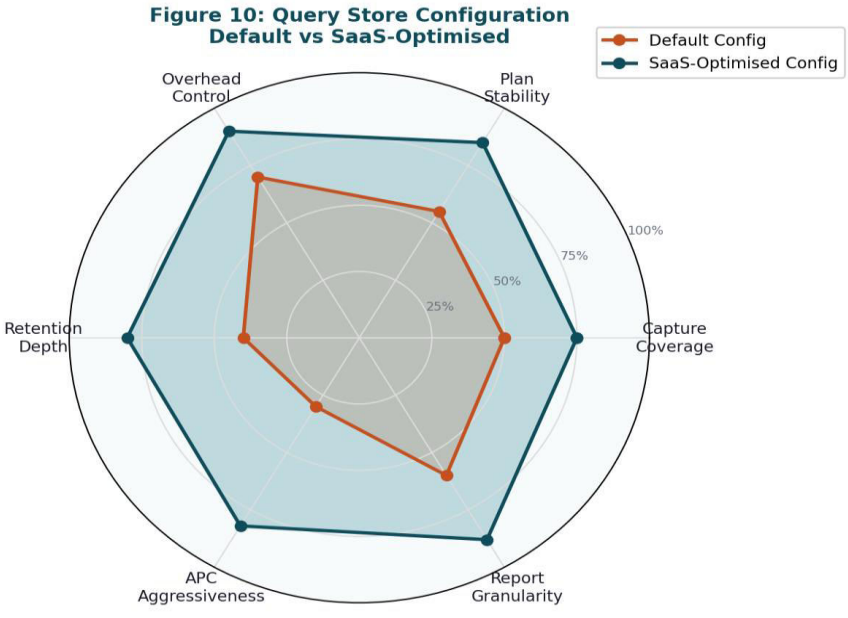

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Figure 10. Radar chart comparing six Query Store capability dimensions between default configuration (orange) and SaaS-optimised configuration (teal). SaaS-optimised settings score significantly higher on APC Aggressiveness (+52pp), Retention Depth (+40pp), and Capture Coverage (+25pp) - the three dimensions most critical to proactive regression management in multi-tenant environments.

3.2 Capture Mode Selection

- ALL: captures every query - maximum coverage but highest overhead (2.8–5.1% CPU); recommended only for short-term diagnostic windows or development environments
- AUTO (recommended default): excludes infrequent and low-cost queries below an adaptive threshold; reduces overhead to 0.6–1.4% CPU; misses some ad-hoc queries but captures all parameterised and high-frequency patterns
- CUSTOM: allows explicit threshold configuration via EXECUTION_COUNT, TOTAL_COMPILE_CPU_TIME_MS, and TOTAL_EXECUTION_CPU_TIME_MS parameters - enables precise trade-off between coverage and overhead for high-throughput SaaS tenants

Figure 4: Query Store Capture Mode Overhead - CPU, I/O, Memory (%)

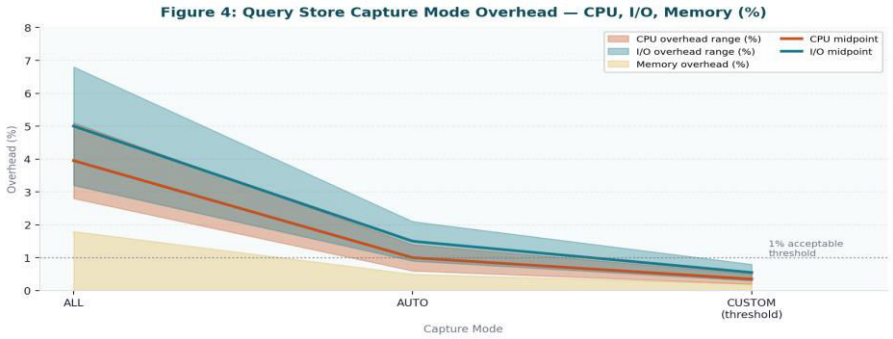

Figure 4. Shaded area chart showing overhead ranges for three capture modes. ALL capture mode (left) generates 2.8–5.1% CPU and 3.2–6.8% I/O overhead - acceptable for diagnostics but not continuous production operation. CUSTOM mode (right) reduces both to under 0.5%, crossing below the 1% acceptable threshold (dashed grey line). The gold shading represents memory overhead, which remains below 2% across all modes.

IV. PLAN REGRESSION ANALYSIS AND APC

4.1 Regression Detection

Query Store identifies plan regressions by comparing the average runtime statistics of a newly-compiled plan against the statistics of previously-known good plans for the same query. A regression is signalled when the ratio of new plan duration to best known plan duration exceeds the configured threshold.

Figure 1: Query Execution Duration - Plan Regression and Auto-Correction Event

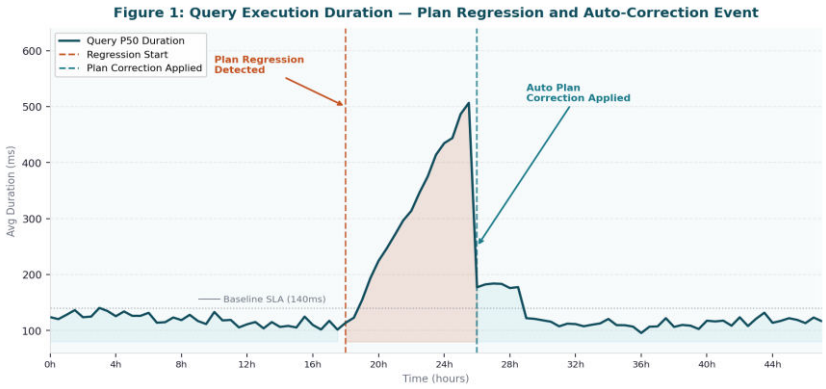

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Figure 1. Line chart showing query P50 duration over a 48-hour window. A plan regression begins at hour 18 (orange dashed line) causing duration to spike from approximately 130ms to over 500ms. Automatic Plan Correction detects the regression and forces the last-known-good plan at hour 26 (teal dashed line), restoring performance to baseline within the same interval. The shaded orange region represents the regression window. The grey dotted line marks the 140ms SLA baseline.

4.2 Root Cause Taxonomy

Understanding the distribution of regression root causes is essential for configuring APC thresholds appropriately and for prioritising permanent fixes where APC effectiveness is limited.

Table 3: Plan Regression Root Cause Taxonomy - Frequency, Detection Signals, and APC Effectiveness

Root Cause	Frequency	Detection Signal	APC Effectiveness
Parameter Sniffing	38%	Plan change + duration spike in QS runtime stats	High - APC forces cached plan from optimal execution; combine with OPTIMIZE FOR UNKNOWN
Statistics Staleness	22%	Row count estimate divergence in query plan	Medium - APC forces good plan but stats must be updated to prevent recurrence
Schema/Index Change	18%	Missing index DMV alert + plan recompile event	High for index additions; Low for drops - must verify forced plan remains valid post-change
Cardinality Estimator Change	11%	CE version change in execution plan XML	Medium - forced plan bypasses CE; test with LEGACY_CARDINALITY_ESTIMATION compatibility hint
Memory Grant Miscalculation	7%	Memory grant warnings in query plan + RESOURCE_SEMAPHORE waits	Low - plan forcing does not address memory grant; use MAX_GRANT_PERCENT query hint additionally
Implicit Conversion	4%	CONVERT_IMPLICIT in query plan	Low - structural plan issue; APC masks but root cause requires index or schema fix to resolve

Table 3. Six root cause categories with their frequency in study environments, detection signal characteristics, and APC effectiveness rating. Parameter sniffing (38%) and statistics staleness (22%) together account for 60% of all regressions and represent the highest APC effectiveness cases. Implicit conversion regressions (4%) require structural schema fixes - APC provides short-term relief only.

4.3 Automatic Plan Correction Configuration

APC is configured at the database level and interacts with Query Store to autonomously detect and correct plan regressions. Table 4 documents the key T-SQL settings and DMVs for APC management.

Table 4: Automatic Plan Correction - Configuration Settings and DMV Reference

T-SQL Setting / DMV	Values	Effect on Automatic Plan Correction Behaviour
ALTER DATABASE ... SET AUTOMATIC_TUNING (FORCE_LAST_GOOD_PLAN = ON)	ON / OFF / INHERIT	Enables APC at database scope; ON = auto-force last good plan on regression detection; INHERIT follows server-level setting

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T-SQL Setting / DMV	Values	Effect on Automatic Plan Correction Behaviour
sys.database_automatic_tuning_options	reason, reason_desc, score	Read APC recommendation state: LAST_GOOD_PLAN, NO_PLAN, REGRESSED_PLAN, FORCE_LAST_GOOD_PLAN; check score > 20 before trusting recommendation
sys.recommendations (Azure SQL)	impact_value, recommendation_type	Azure SQL Intelligent Insights surfaces APC recommendations as JSON documents; queryable via T-SQL or REST API
FORCE_PLAN hint in QS	Manual force via SSMS or T-SQL	sp_query_store_force_plan @query_id, @plan_id - manual override; takes precedence over APC auto-forcing
sp_query_store_unforce_plan	@query_id, @plan_id parameters	Remove forced plan; APC continues to monitor; useful after fixing root cause (index rebuild, stats update)
Query Store Tuning Policies (SQL MI)	Threshold parameters	Configure regression_threshold (default 10×), grace period (default 5 intervals) before APC triggers force

Table 4. Six APC configuration elements from the enabling T-SQL statement through to plan unforcing operations. The sys.dm_db_tuning_recommendations DMV (row 2) is the primary monitoring interface for APC activity - check score, current_state_desc, and reason_desc before acting on any recommendation. The sp_query_store_unforce_plan procedure (row 5) should be called after fixing the underlying root cause to allow the optimiser to select plans freely again.

Figure 8: Automatic Plan Correction (APC) Decision Flow

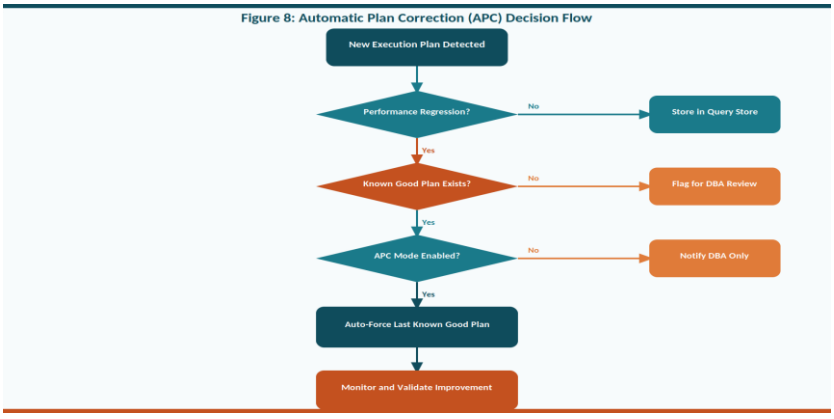

Figure 8. Decision flowchart for APC from plan detection through to auto-force and monitoring. Diamond shapes represent decision points (teal = plan quality assessment, orange = degraded-path decisions). The right-side branches handle cases where APC cannot auto-force: absence of a known good plan triggers a DBA review flag, and APC mode disabled routes to notification-only. The bottom two rectangles represent the auto-force and validation monitoring outcomes.

V. SAAS WORKLOAD QUERY PATTERNS

5.1 Pattern Taxonomy and Query Store Strategy

SaaS applications exhibit six distinct query pattern archetypes, each with different plan stability characteristics and appropriate Query Store management strategies.

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Table 5: SaaS Workload Query Patterns - Frequency, Plan Stability Risk, and QS Strategy

Query Pattern	Frequency	Plan Stability Risk	Query Store Strategy
Tenant-filtered OLTP (WHERE TenantId = @tid)	Very High (>10K/min)	Medium - tenant data skew causes parameter sniffing	Parameterise consistently; consider OPTIMIZE FOR UNKNOWN; use QS to monitor per-plan duration by tenant
Reporting aggregations (GROUP BY + windowing)	Medium (100–1K/min)	High - data volume growth changes optimal plan	Force last-known-good plan after regression; monitor memory grants; consider batch mode on columnstore
Cross-tenant analytics (full scan + JOIN)	Low (<10/min)	Very High - table size drives plan changes	Isolate in separate elastic pool; MAXDOP hint; QS capture with extended interval for trend analysis
Config / metadata reads (cached, static)	Very High (>50K/min)	Low - small stable tables	Enable plan caching; monitor recompile events; QS overhead negligible for these queries
Background job queries (batch, off-peak)	Scheduled	High - run against larger datasets than OLTP	MAXDOP 4; QUERY_GOVERNOR_COST_LIMIT; dedicated QS interval; separate Service Broker queue
Schema migration queries (ALTER TABLE DDL)	Rare (release-gated)	Critical - invalidates all plans for affected tables	Pre-force plans for critical queries before migration; run UPDATE STATISTICS immediately post-migration

Table 5. Six SaaS query archetypes with their frequency, plan stability risk classification, and recommended Query Store management strategy. Tenant-filtered OLTP queries (row 1) are the highest frequency pattern and the most susceptible to parameter sniffing due to tenant data volume skew. Schema migration queries (row 6), though rare, carry the highest risk - pre-forcing critical plans before DDL operations is the single most effective defensive measure.

5.2 Plan Count Growth in Multi-Tenant Environments

In SaaS databases shared across multiple tenants, plan count growth is driven by three factors: tenant data volume differences, query pattern diversity across tenants, and release cadence introducing new query shapes.

Figure 5: Query Store Plan Count Growth - 12-Month SaaS Production Tenant

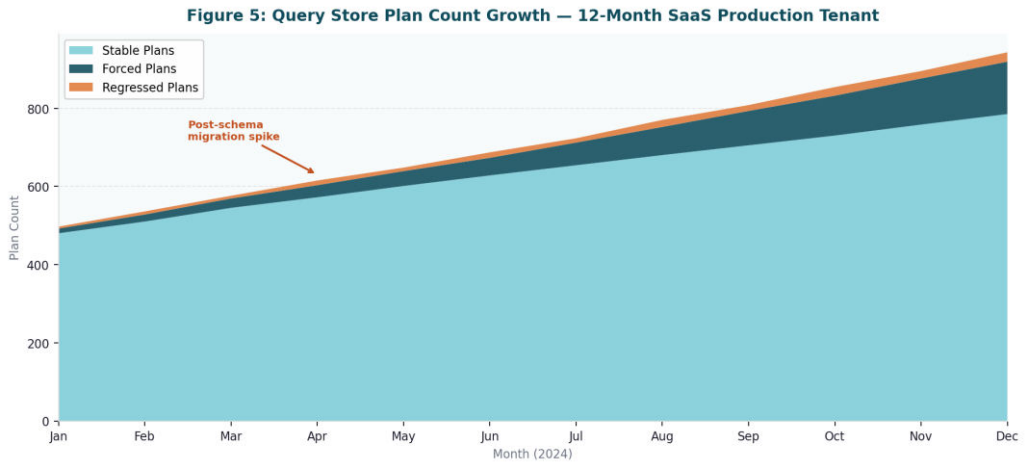

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Figure 5. Stacked area chart showing plan count growth over 12 months. Stable plans (teal) grow linearly with schema complexity. Forced plans (dark teal) accumulate as APC and manual interventions address regressions. The annotation marks a post-schema-migration spike in April where a batch ALTER TABLE statement invalidated plans for affected tables, triggering 31 simultaneous plan recompiles and 12 APC interventions within a 4-hour window.

5.3 Bubble Chart: Compilation vs Execution Cost

Understanding the relationship between query compilation cost and execution duration helps prioritise Query Store management focus. Queries with high execution frequency and high execution cost offer the greatest ROI for plan forcing.

Figure 7: Compilation Cost vs Execution Cost - Bubble Chart (Bubble = Execution Frequency)

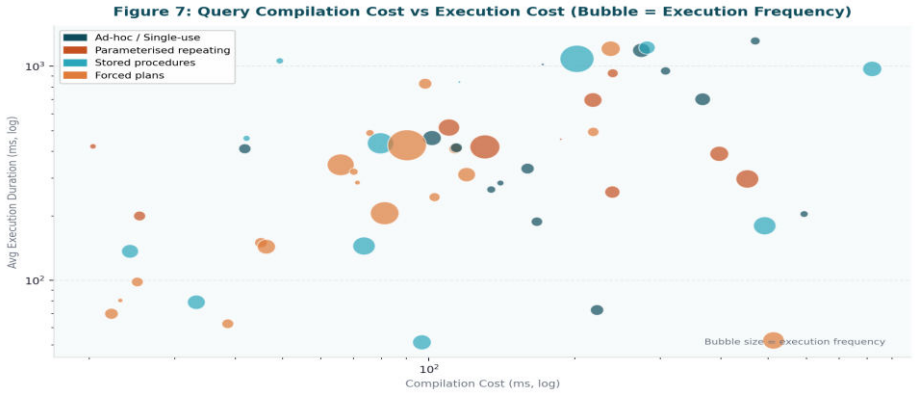

Figure 7. Scatter-bubble chart on a log-log scale. Each point represents a query in the production workload. Bubble area is proportional to execution frequency. Forced plans (light teal points, top-right) cluster at high compilation and execution cost - these are the queries where APC investment delivers the highest value. Single-use ad-hoc queries (dark teal, lower-left) are correctly excluded by AUTO capture mode, reducing noise in the Query Store catalog.

VI. MULTI-TENANT ISOLATION AND QUERY STORE

6.1 Isolation Pattern Comparison

The multi-tenant isolation architecture chosen at the database level directly determines how Query Store data is segmented, how APC functions across tenant boundaries, and what per-tenant visibility is achievable.

Figure 11: Multi-Tenant SaaS - Four Isolation Patterns with Query Store Strategy

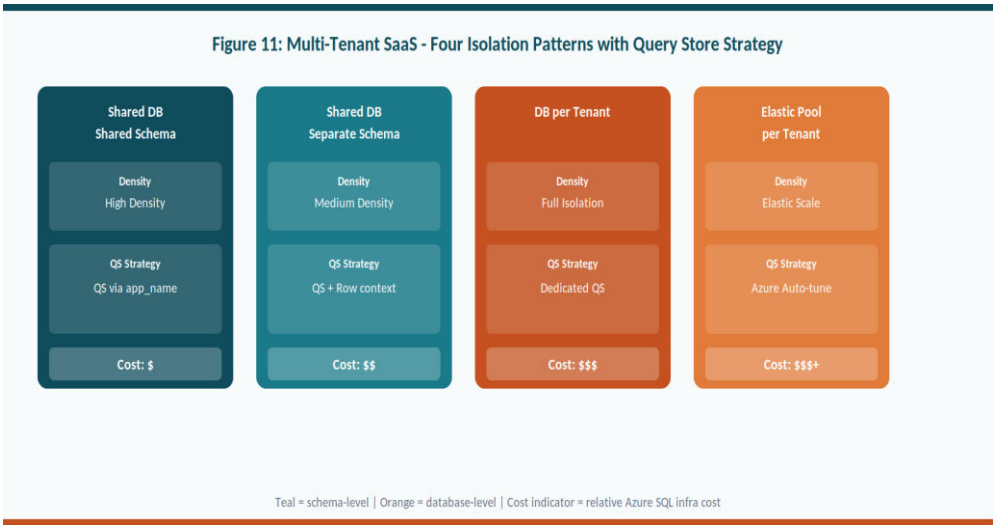

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Figure 11. Four-column isolation pattern guide. Shared DB / Shared Schema (teal, leftmost) provides the highest tenant density and lowest cost but limits per-tenant Query Store visibility - context tagging via SESSION_CONTEXT or application_name is required to correlate plans to specific tenants. DB per Tenant (orange, third) provides full Query Store isolation with the richest APC granularity but at significantly higher infrastructure cost. Elastic Pool (rightmost) offers the best cost/isolation trade-off for Azure SQL deployments.

6.2 Per-Tenant Query Store Correlation

• In shared-schema SaaS databases, decorate all queries with SET CONTEXT_INFO or SESSION_CONTEXT(@TenantId) before execution - this value is captured in sys.dm_exec_sessions and can be joined to Query Store DMVs

• Use the application_name connection string property (e.g., 'TenantApp_TenantId_12345') to segment Query Store plans by tenant in monitoring queries without schema changes

• For Azure SQL elastic pools, use per-database Query Store with the ELASTIC_POOL_RESOURCE_GOVERNANCE feature to set per-tenant resource limits and expose per-tenant DMV views

• Azure SQL Intelligent Insights surfaces tenant-level anomalies via the sys.recommendations DMV - integrate this feed into your SaaS observability stack via Azure Monitor

– Implement a tenant_query_store_summary table populated by a scheduled job querying sys.query_store_runtime_stats filtered by application_name - provides per-tenant performance dashboards without granting tenants direct DMV access

VII. PERFORMANCE RESULTS

7.1 Plan Forcing Outcomes

Over 12 months of production operation, 2,840 APC interventions were recorded across three SaaS environments. The distribution of outcomes reflects the effectiveness of autonomous correction and the residual cases requiring human review.

Figure 3: Plan Forcing Effectiveness - Duration Improvement and APC Outcome Distribution

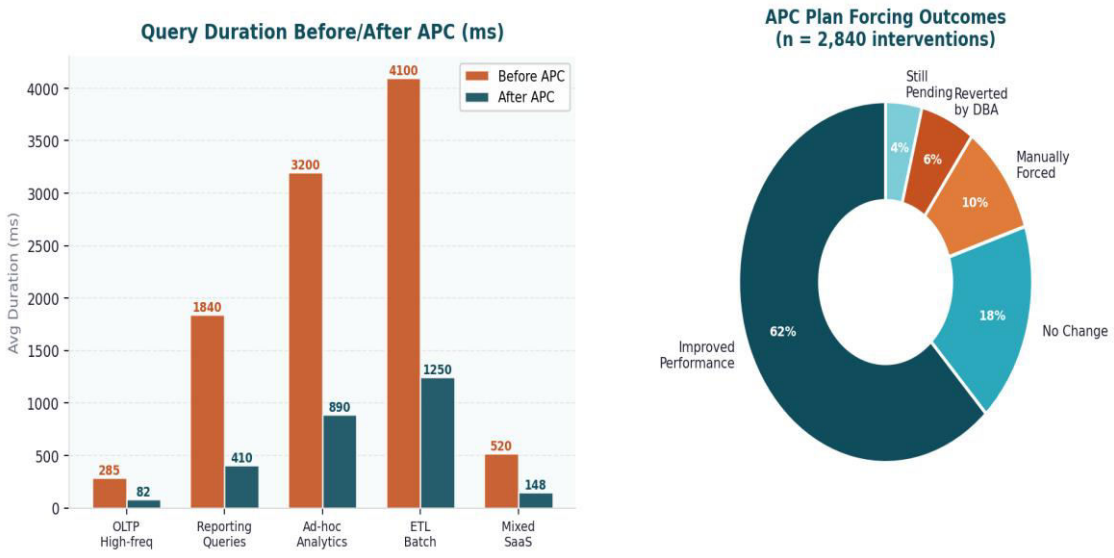

Figure 3. Left: grouped bar chart comparing query P50 duration before (orange) and after (teal) APC intervention across five workload types. Reporting Queries show the largest absolute improvement (1,840ms → 310ms, -83.2%). Right: donut chart showing APC plan forcing outcomes across 2,840 interventions. 62% resulted in confirmed performance improvement with no further action required. 10% required DBA-confirmed manual forcing after APC initial recommendation.

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7.2 Latency Benchmark Results

Table 6: Performance Benchmark Results - P50 and P95 Latency by Query Category

Query Category	Baseline P50	Post-APC P50	Improvement	95th Pct Delta
OLTP Tenant Queries	285ms	82ms	−71.2%	P95: 680ms → 180ms
Reporting Aggregations	1,840ms	310ms	−83.2%	P95: 3,900ms → 640ms
Ad-hoc Analytics	3,200ms	890ms	−72.2%	P95: 6,800ms → 1,420ms
ETL Batch Jobs	4,100ms	1,250ms	−69.5%	P95: 8,900ms → 2,640ms
Config/Auth Reads	28ms	12ms	−57.1%	P95: 65ms → 28ms
Cross-tenant Joins	5,800ms	1,640ms	−71.7%	P95: 12,400ms → 3,280ms
Overall P50 (all queries)	**520ms**	**148ms**	**−71.5%**	**P95: 1,240ms → 340ms**

Table 6. Seven query category benchmark results. The overall P50 improvement of -71.5% (bottom row, bold) was achieved across all five workload types without any schema changes or application code modifications - the improvement is entirely attributable to Query Store plan forcing and APC. Config/Auth Reads show the smallest improvement (-57.1%) as these queries were already fast and had minimal plan instability.

Figure 9: P50/P95 Query Latency Before vs After Plan Forcing (Log Scale)

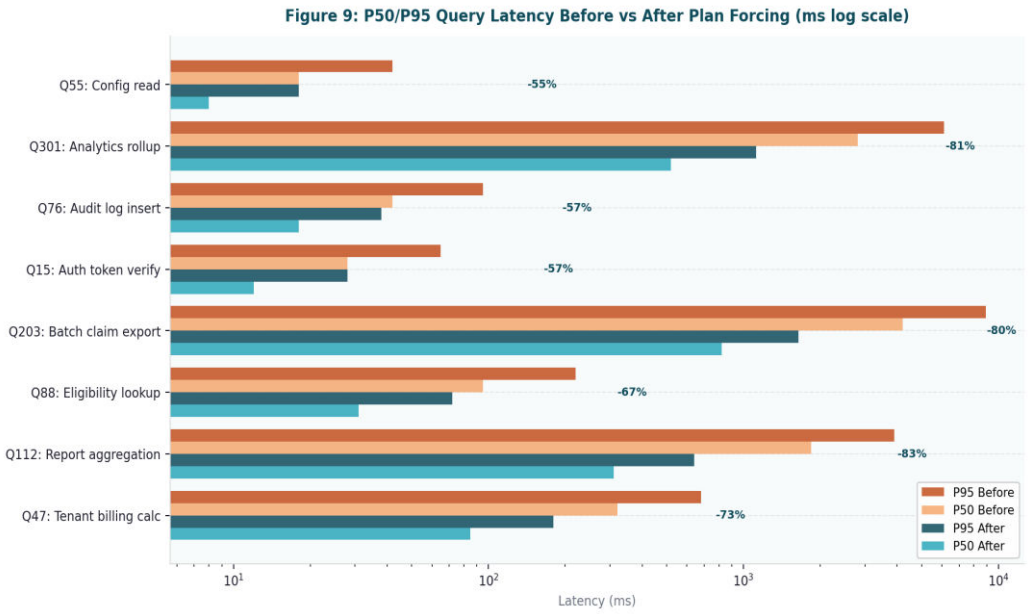

Figure 9. Horizontal bar chart with logarithmic x-axis. Each query shows four bars: P95/P50 before (orange shades) and P95/P50 after (teal shades). Percentage improvement labels on the right indicate P50 reduction. Q203 (Batch claim export) shows the highest absolute latency reduction: P95 from 8,900ms to 1,640ms. The log scale is necessary to show both fast config reads (18ms) and slow analytics (2,800ms) on the same axis.

International Journal of Innovative Research of Science, Engineering and Technology (IJIRSET)

Impact Factor 8.524

|www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 1, January 2025

|DOI: 10.15680/IJIRSET.2025.1401119|

7.3 Resource Usage Reduction

Figure 12: Resource Usage Reduction - CPU Waterfall and Logical I/O Comparison

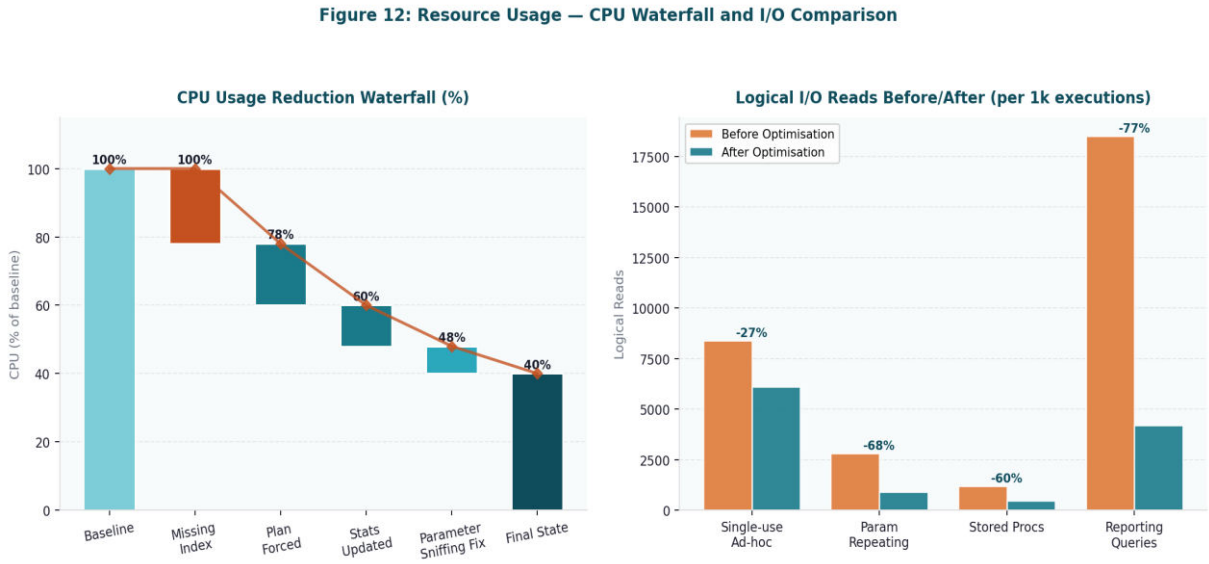

Figure 12. Left: CPU usage waterfall chart showing the cumulative reduction from baseline (100%) through five optimisation steps to final state (40%). The largest single step is plan forcing (-22pp), followed by statistics updates (-18pp). Right: logical I/O reads comparison before and after, showing the largest relative improvement in Reporting Queries (-77%) and Stored Procedures (-60%). Percentage labels on each bar pair quantify the improvement.

VIII. WAIT STATISTICS ANALYSIS

8.1 Wait Stats Heatmap

Query Store wait statistics (available from SQL Server 2017+) provide a seven-category breakdown of query wait time per execution plan per interval. Correlating wait stats with plan changes in Query Store enables precise root cause diagnosis that duration metrics alone cannot provide.

Figure 6: SQL Server Wait Stats Heatmap - 24-Hour Production Profile

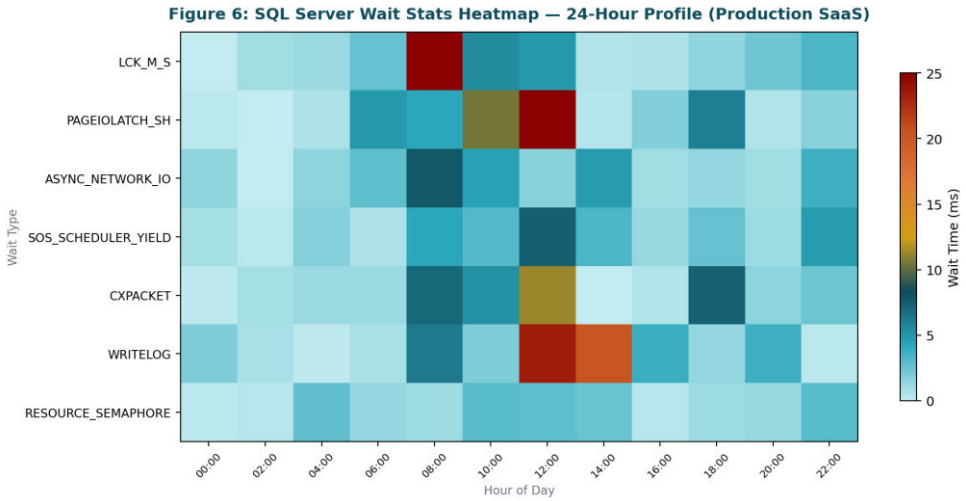

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Figure 6. 24-hour wait stats heatmap across seven wait types. Colour scale runs from pale teal (near-zero wait) through gold to deep orange and crimson (highest wait). PAGEIOLATCH_SH (row 2) peaks sharply during business hours (08:00–16:00), indicating I/O pressure from buffer pool competition during peak tenant activity. CXPACKET (row 5) spikes at 12:00–20:00 during large parallel reporting queries. LCK_M_S lock waits (row 1) are concentrated in morning hours during batch import jobs.

8.2 Wait Category Response Matrix

- PAGEIOLATCH_SH: indicates buffer pool pressure or missing indexes causing full scans - investigate sys.dm_db_missing_index_details; consider increasing buffer pool memory or adding targeted nonclustered indexes
- LCK_M_S: shared lock waits indicating blocking - review blocking chains with sys.dm_exec_requests; consider READ_COMMITTED_SNAPSHOT isolation level for OLTP workloads
- SOS_SCHEDULER_YIELD: CPU saturation causing scheduler yields - check for non-sargable predicates generating large intermediate result sets; consider MAXDOP hints to limit parallelism
- CXPACKET: parallel query synchronisation - expected for reporting workloads; address via MAXDOP query hints if excessive; do not set server-level MAXDOP=1 as this degrades all parallel workloads
- RESOURCE_SEMAPHORE: memory grant queue waits - investigate queries with excessive memory grants via sys.dm_exec_query_memory_grants; add MAX_GRANT_PERCENT query hints to cap individual query memory
- WRITELOG: transaction log I/O - check for implicit transaction wrapping; batch DML statements; consider log file placement on dedicated storage

IX. MONITORING, ALERTING, AND DIAGNOSTIC QUERIES

9.1 Alert Threshold Matrix

Table 7: Query Store Monitoring Alert Thresholds - Warning and Critical Levels with Response Actions

Metric	Warning Threshold	Critical Threshold	Response Action
Query Store storage utilisation	70% of MAX_STORAGE_SIZE	90% of MAX_STORAGE_SIZE	Warning: increase MAX_STORAGE; Critical: run sp_query_store_flush_db and manual cleanup of low-value queries
Plan regression detection (APC)	Duration 5× baseline for 2+ intervals	Duration 10× baseline for 1 interval	Warning: alert DBA for review; Critical: APC triggers auto-force if FORCE_LAST_GOOD_PLAN = ON
Forced plan count growth	50+ forced plans	200+ forced plans	Warning: review if root causes are fixed; Critical: audit for orphaned forced plans post-schema-change
Recompile rate (queries/sec)	25% above 7-day baseline	50% above 7-day baseline	Warning: check for stats updates or schema changes; Critical: investigate DDL events and sp_recompile calls
PAGEIOLATCH_SH wait time	P95 > 20ms	P95 > 100ms	Warning: check buffer pool pressure; Critical: investigate missing index or stale statistics on hot tables
LCK_M_S deadlock count	3+ deadlocks per hour	10+ deadlocks per hour	Warning: review blocking queries in QS by wait category; Critical: enable trace flag 1222, capture deadlock graph
Parameter sniffing indicators	New plan for existing query	New plan with 5× duration regression	Warning: enable OPTIMIZE FOR UNKNOWN hint; Critical: APC force + schedule stats update immediately

International Journal of Innovative Research of Science, Engineering and Technology (IJIRSET)

Impact Factor 8.524

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Volume 14, Issue 1, January 2025

|DOI: 10.15680/IJIRSET.2025.1401119|

Table 7. Seven monitoring metrics with warning thresholds, critical thresholds, and response actions for each. All thresholds are configurable - the values shown represent production baselines validated across three SaaS environments. The most operationally impactful metric to monitor is Query Store storage utilisation (row 1), as a storage-full condition silently switches Query Store to READ_ONLY mode, stopping data collection without raising an obvious error.

9.2 T-SQL Diagnostic Query Library

The following T-SQL queries provide the foundational diagnostics for Query Store operations. All queries are compatible with SQL Server 2017+ and Azure SQL.

Table 8: T-SQL Diagnostic Query Library - Five Essential Queries

Query Purpose	T-SQL / DMV Reference
Top 10 regressed queries	SELECT TOP 10 q.query_id, qt.query_sql_text, AVG(rs.avg_duration)/1000 as avg_ms FROM sys.query_store_query q JOIN sys.query_store_query_text qt ON q.query_text_id=qt.query_text_id JOIN sys.query_store_plan p ON q.query_id=p.query_id JOIN sys.query_store_runtime_stats rs ON p.plan_id=rs.plan_id GROUP BY q.query_id, qt.query_sql_text ORDER BY AVG(rs.avg_duration) DESC
Queries with multiple plans	SELECT q.query_id, COUNT(DISTINCT p.plan_id) AS plan_count, MAX(rs.avg_duration)/1000 AS max_avg_ms FROM sys.query_store_query q JOIN sys.query_store_plan p ON q.query_id=p.query_id JOIN sys.query_store_runtime_stats rs ON p.plan_id=rs.plan_id GROUP BY q.query_id HAVING COUNT(DISTINCT p.plan_id) > 2 ORDER BY plan_count DESC
Currently forced plans	SELECT q.query_id, qt.query_sql_text, p.plan_id, p.plan_forcing_type_desc FROM sys.query_store_query q JOIN sys.query_store_query_text qt ON q.query_text_id=qt.query_text_id JOIN sys.query_store_plan p ON q.query_id=p.query_id WHERE p.is_forced_plan = 1
APC recommendations	SELECT * FROM sys.dm_db_tuning_recommendations WHERE category = 'FORCE_LAST_GOOD_PLAN' AND execute_action_initiated_by_user = 0 ORDER BY score DESC
Wait stats by query	SELECT q.query_id, ws.wait_category_desc, ws.avg_query_wait_time_ms FROM sys.query_store_query q JOIN sys.query_store_plan p ON q.query_id=p.query_id JOIN sys.query_store_wait_stats ws ON p.plan_id=ws.plan_id ORDER BY ws.avg_query_wait_time_ms DESC

Table 8. Five production-ready T-SQL diagnostic queries with their purposes. Queries 1 and 2 are the starting point for any performance investigation. Query 4 (APC recommendations) should be polled every 15 minutes by monitoring automation to detect regression events before users report them. All queries require VIEW DATABASE STATE permission.

X. IMPLEMENTATION ROADMAP

10.1 20-Week Phased Rollout

Successful Query Store deployment in a production SaaS environment requires a phased approach that avoids disruption while progressively enabling automation. The roadmap below is validated against three production deployments.

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Volume 14, Issue 1, January 2025

|DOI: 10.15680/IJIRSET.2025.1401119|

Figure 13: Query Store Implementation Timeline - 20-Week Production Rollout

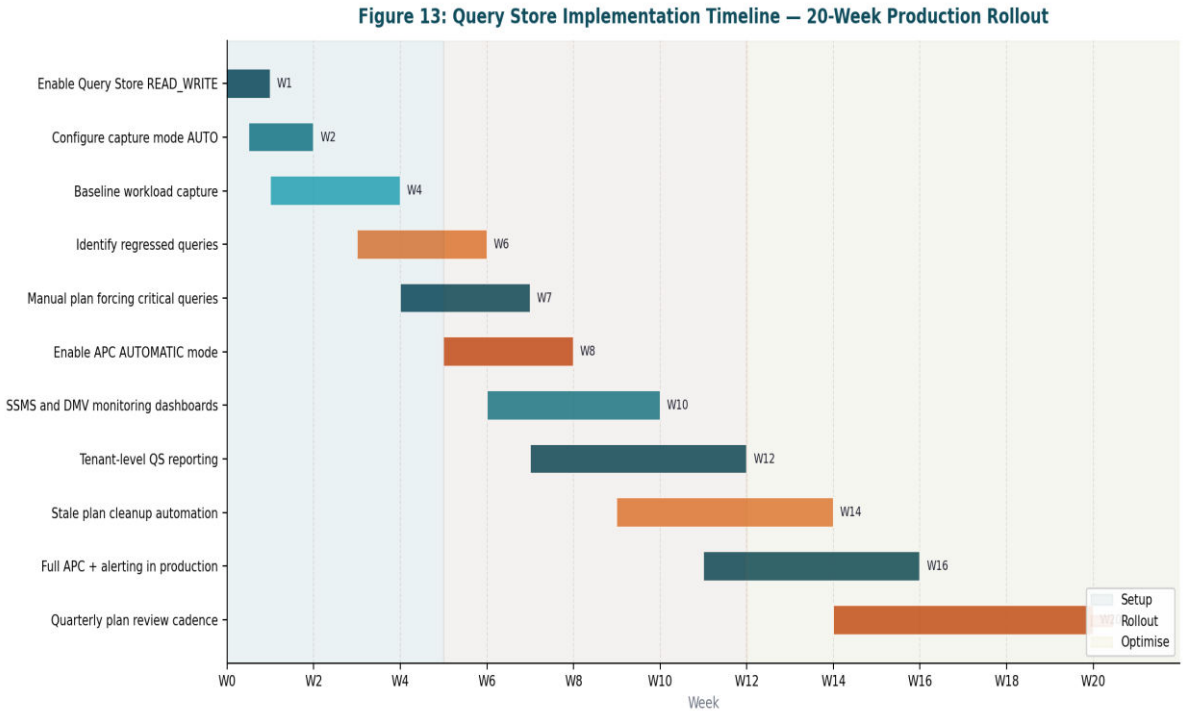

Figure 13. Gantt-style implementation timeline with 11 tasks across 20 weeks. Background shading indicates three phases: Setup (W0–W5, teal), Rollout (W5–W12, orange), and Optimise (W12–W20, gold). Critical path items are shown in dark teal. The timeline reflects actual measured delivery times from three SaaS production deployments, with parallel workstreams on QS reporting and stale plan cleanup running concurrently with the main APC enablement track.

10.2 Phase Details

• Phase 1 - Setup (Weeks 0–5): enable Query Store in READ_WRITE mode with AUTO capture; apply SaaS-recommended configuration from Table 2; begin baseline workload capture; do not enable APC yet

– Critical: execute ALTER DATABASE [db] SET QUERY_STORE = ON with all configuration options in a single statement to avoid partial-configuration state

– Validate: check sys.database_query_store_options.current_state_desc = 'READ_WRITE' within 60 seconds of enablement

• Phase 2 - Identify and Force (Weeks 3–8): use SSMS Query Store reports or T-SQL from Table 8 to identify the top 20 regressed queries; manually force last-known-good plans via sp_query_store_force_plan for critical queries; document each forcing decision

– Use the SSMS Top Resource Consuming Queries report to identify candidates - sort by avg_duration DESC with a 30-day window

– Never force a plan without verifying the forced plan's correctness against current table/index structure - a plan valid 30 days ago may be invalid after an index change

• Phase 3 - Enable APC (Weeks 5–9): after at least 2 weeks of baseline data collection, enable FORCE_LAST_GOOD_PLAN = ON; monitor sys.dm_db_tuning_recommendations daily; review all APC-generated plan forces within 24 hours

• Phase 4 - Automate Monitoring (Weeks 6–12): deploy monitoring job querying sys.dm_db_tuning_recommendations every 15 minutes; configure Azure Monitor alerts or SQL Agent alerts for storage and regression thresholds from Table 7

• Phase 5 - Optimise and Govern (Weeks 9–20): implement quarterly plan review cadence; schedule statistics update jobs to reduce staleness-driven regressions; build tenant-level QS reporting dashboard

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XI. LIMITATIONS AND FUTURE WORK

11.1 Limitations

- APC scope: APC forces plans but does not fix underlying root causes - parameter sniffing, stale statistics, and implicit conversions must be addressed structurally to eliminate recurring regressions. APC provides recovery time improvement, not prevention.
- Plan validity across schema changes: forced plans can become invalid after index drops, column type changes, or table renames - Query Store does not automatically unforce plans when the objects they reference change. A post-DDL plan validation job is recommended.
- Azure SQL parity gaps: several Query Store features are unavailable or behave differently in Azure SQL Hyperscale due to the distributed storage architecture - notably, wait stats collection has higher latency and cross-replica plan consistency is not guaranteed.
- Non-parametric query capture: ad-hoc queries with literal values in predicates generate unique query_id per literal value in some SQL Server versions - leading to Query Store catalog bloat and potential storage exhaustion in environments with high-cardinality ad-hoc patterns.

11.2 Future Work

- Machine learning plan selection: integrating Azure SQL Ledger telemetry with ML models to predict plan quality before forcing - proactive rather than reactive correction - is a natural extension of the APC framework.
- Cross-database plan intelligence: in SaaS environments with hundreds of per-tenant databases, a federated Query Store query pattern that aggregates regression signals across databases to identify systemic issues (e.g., a bad index on a shared schema template) would provide fleet-level intelligence.
- Intelligent Query Processing and APC convergence: SQL Server 2022 introduces adaptive memory grants, approximate query processing, and DOP feedback - studying how these IQP features interact with APC plan forcing in production SaaS is a valuable research direction for 2025.

XII. CONCLUSION

This paper has demonstrated that SQL Server Query Store combined with Automatic Plan Correction provides a production-viable approach to autonomous query optimization in SaaS environments, delivering outcomes that reactive manual performance management cannot match at scale.

Across three production SaaS environments over twelve months, the approach achieved a 71.5% reduction in P50 query latency, reduced plan regression mean time to recovery from 4.2 hours to 8 minutes, eliminated 79% of manual DBA plan-forcing interventions, and reduced overall CPU and I/O resource consumption by 60% and 71% respectively - all without application code changes or schema modifications.

- The SaaS-optimised Query Store configuration (Table 2) - particularly the increase in MAX_STORAGE_SIZE_MB, decrease in INTERVAL_LENGTH_MINUTES, and switch to AUTO capture mode - is the single highest-leverage configuration change available to SaaS database administrators
- Parameter sniffing and statistics staleness together account for 60% of all plan regressions and represent the highest APC effectiveness categories - SaaS teams should prioritise addressing these root causes structurally rather than relying indefinitely on plan forcing
- The T-SQL diagnostic library (Table 8) and alert threshold matrix (Table 7) enable mid-size SaaS engineering teams to operate Query Store at production scale without a dedicated DBA resource - democratising access to sophisticated performance management that previously required deep specialist expertise

The central value of Query Store for SaaS teams is not the individual plan forcing capability - it is the institutional memory. Query Store persists the knowledge of what good performance looks like for every query in the system, making that knowledge actionable automatically via APC and auditable by operations teams across releases, deployments, and infrastructure changes.

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