Benchmarking Time Series Forecasting Models on Synthetic, Operationally-Augmented SQL Server Query Telemetry

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***Abstract*—Accurate forecasting of SQL Server query performance is vital for maintaining responsive, reliable, and cost-effective data-driven applications. While time series analysis (TSA) and machine learning (ML) have shown promise for automating performance prediction and enabling database self-tuning, existing studies primarily focus on anomaly detection in relatively stationary or controlled settings.**

This work closes critical gaps by: (1) systematically evaluating the robustness of forecasting models, including Prophet, ARIMA, LSTM, Random Forest, and XGBoost, across both stable and highly volatile workload regimes, and (2) introducing a comprehensive, operationally grounded data augmentation framework simulating phenomena such as randomized data gaps, plan regressions, outages, and operational noise. Our experimental pipeline generates a realistic dataset of 4,800 hourly intervals, with up to 8% missingness, reflecting production-scale SQL Server workloads.

Our results demonstrate that model performance is workload-dependent: Prophet achieves RMSE of up to 60% lower than ARIMA and LSTM under periodic, stable workloads, but its performance shows a minor but measurable degradation during simulated data gaps and plan regressions. Tree-based models exhibit greater robustness to missing data, but underperform in steady-state scenarios. These findings establish the need for context-sensitive adaptive model selection.

To our knowledge, this is the first systematic benchmarking of time-series forecasting models for SQL Server query performance under realistic, volatile workloads with operationally motivated data augmentation. The proposed methodology and findings lay the foundation for robust and proactive database performance management and can inform both research and practical deployments in cloud and enterprise environments.

***Index Terms*—Time Series Forecasting, Database Performance, SQL Server, Machine Learning, Data Augmentation, Benchmarking**

I. Introduction

ACCURATE forecasting of SQL Server query performance is vital to maintain responsive, reliable, and cost-effective data-driven applications. Modern enterprises increasingly depend on complex, dynamic workloads that challenge traditional static query optimizers. Sudden changes in user behavior, business cycles, and infrastructure events can cause workload patterns to fluctuate dramatically, resulting in potential service-level agreement (SLA) violations and increased operational costs. Traditional manual tuning or rule-based approaches are often inadequate to maintain performance in such rapidly changing environments.

Unlike many generic time-series forecasting problems, SQL Server telemetry is particularly susceptible to operational disruptions such as restarts, local or regional failovers, and planned maintenance, which can introduce brief periods of unavailability and missing data. Accurate forecasting of query performance under such conditions is essential to meet stringent SLA targets in enterprise and cloud environments.

Recent advances in time series analysis (TSA) and machine learning (ML) have shown promise in automating performance prediction and enabling database self-tuning [1] . For example, Akdere et al. introduced a learning-based approach for query performance modeling and prediction, demonstrating the effectiveness of machine learning techniques for capturing dynamic and complex workload behaviors [1]. However, existing studies, including Li et al., primarily focus on performance modeling under controlled conditions, without fully addressing the challenges posed by volatile workload regimes or the need for realistic data augmentation.

This work addresses these critical gaps by systematically evaluating the robustness of forecasting models, introducing a comprehensive data augmentation framework, and generating a realistic dataset for benchmarking. By doing so, we aim to provide a clear understanding of how different models perform under the volatile conditions characteristic of production SQL Server environments.

II. Related Work

A. Reactive Adaptation in SQL Server Query Optimization

Query optimization in SQL Server has evolved from static, rule-based mechanisms to increasingly adaptive techniques. Features such as Intelligent Query Processing (IQP)—including Memory Grant Feedback, Batch Mode Adaptive Joins, and Cardinality Estimation Feedback—dynamically adjust plan choices or parameters based on observed runtime data [2], [3]. The Query Store serves as the primary data substrate for these features, allowing historical analysis and feedback-driven plan corrections [3], [4]. However, IQP and the query store remain fundamentally reactive: they address inefficiencies only after they are detected, and they do not anticipate future workload shifts via forecasting. In particular, these mechanisms do not address unique challenges, such as SQL Server restarts, failovers, or brief unavailability, which can introduce operational volatility and missing data.

Critical Perspective

Despite notable improvements, the reactive orientation of IQP features means that they cannot prevent suboptimal plans resulting from unforeseen workload changes or operational

disruptions. This limitation motivates the exploration of proactive and predictive methods that can anticipate and mitigate performance issues before they occur.

B. Machine Learning and AI Approaches for Query Optimization

Recent years have seen a surge in the application of machine learning (ML) and artificial intelligence (AI) techniques for query optimization, addressing the shortcomings of fixed cost models and reactive heuristics [5]. These techniques often leverage a wide variety of telemetry -such as query execution plans, runtime statistics, and resource consumption metrics - as features for model training. The learned models, including deep neural networks and reinforcement learning (RL) agents, have demonstrated improved adaptability and precision in plan selection and cardinality estimation. For example, frameworks such as AutoSteer and QO-Advisor leverage offline ML validation and plan caching to ensure robust, non-regression plan choices [6]. RL-based approaches formulate the selection of the join order as a Markov Decision Process, with agents learning effective policies from sequential execution feedback [7], [8].

While these models are well-suited to complex and evolving workloads, they often require extensive feature engineering, incur high training and inference costs, and can suffer unpredictable regressions, particularly under shifting data distributions. Moreover, most ML/AI approaches focus on aspects such as cardinality estimation or join ordering but rarely address forecasting of end-to-end query performance (e.g. runtimes or throughput) under operational disruptions.

Predictive analytics further enable proactive performance management by forecasting workload trends and resource bottlenecks. The SQL Server PREDICT T-SQL function exemplifies the integration of ML into the database engine, enabling models to forecast outcomes directly within queries [5], [9]. However, many of these approaches address isolated optimization tasks, and their real-time integration into the optimizer's critical decision-making process remains a challenge, limiting their ability to anticipate and prevent suboptimal plans before execution.

Critical Perspective

Although ML- and RL-based systems represent substantial progress, they face ongoing challenges: computational overhead, limited interpretability, and the need for robust handling of workload drift and operational volatility. Most approaches still operate reactively or require frequent retraining, which may limit their scalability in production environments.

C. Proactive Forecasting and Time Series Analysis

Explicit time-series analysis represents a promising path toward proactive, anticipatory optimization. Time-series forecasting has been applied to a range of primitives, including query runtimes, resource utilization, and query arrival rates. The Sibyl framework, for example, employs stacked-LSTM networks to forecast future query sequences and arrival patterns, providing physical design tools (such as index or materialized view selection) with forward-looking workload traces [10]. However, Sibyl's integration is limited to offline or physical design scenarios and does not directly inform real-time plan generation or address operational disruptions like failovers and unavailability.

Adaptive Cost Models (ACM) propose dynamic tuning of optimizer parameters at runtime using continuous monitoring of execution statistics—implicitly a time series analysis task [5]. Yet, many such approaches evaluate under controlled or stationary conditions and stop short of integrating forecasts directly into the optimizer's plan generation process or testing under volatile, production-like scenarios.

Data augmentation for time series is an increasingly important enabler, improving the robustness and generalizability of ML models used in database tuning [11]. Techniques such as noise injection, scaling, and the construction of large synthetic datasets improve model resilience to real-world data variability, operational volatility, and limited training data [11]. However, care must be taken to avoid overfitting to synthetic artifacts, introducing distributional shifts, or distorting true workload patterns - risks often overlooked in prior work. As the field advances toward foundation models and large-scale ML for database monitoring, the importance of high-quality, operationally augmented temporal data is increasing.

Critical Perspective

Although time series forecasting and data enhancement have demonstrated clear benefits for physical design tuning and model robustness, their direct integration with the optimizer's real-time decision process remains an open research challenge, especially under production-like volatility, regime changes and operational disruptions unique to SQL Server environments.

D. Synthesis and Implications

Despite significant advances, most approaches in the literature adapt reactively after detecting problems, focus on isolated optimization facets, or improve performance offline through physical design. Few have successfully integrated proactive forecasting directly into the optimizer's main decision path, and even fewer systematically evaluate such models under volatile production-like workloads and operational disruptions (such as restarts or failovers) that are common in SQL Server environments. Previous work typically evaluates under controlled or stationary conditions, lacking a systematic study of regime volatility and operational noise found in practice. In summary, while substantial progress has been made, previous research has not systematically benchmarked time series forecasting models on SQL Server query performance under volatile and operationally enhanced conditions. Our work addresses this critical gap and is detailed further in Section III.

III. Methodology

This section details the experimental pipeline designed to systematically benchmark time-series forecasting models for SQL Server query performance under realistic, volatile workloads. Our methodology directly implements the research gaps identified in Sections II and III, with careful attention to operational disruptions, data augmentation, and reproducibility. The

TABLE I: Comparative Summary of Related Approaches

Approach/Framework	Temporal Orientation	Proactive/Reactive	Data Used	Key Limitation
SQL Server IQP	Short-term Feedback	Reactive	Query Store	No forecasting, post-hoc adaptation (e.g., cannot anticipate sudden spike in query complexity or failovers)
Sibyl Framework	Forecasting	Proactive	Query Traces	Indirect, applies to physical design; not real-time or disruption-aware
Adaptive Cost Models	Monitoring	Semi-Proactive	Runtime Stats, Buffer State	Not always real-time, evaluated under stationary conditions
RL-based Optimizers	Sequential Learning	Proactive/Adaptive	Execution Feedback	High training cost, unpredictable regressions; limited disruption handling
Time Series Data Augmentation	Dataset Expansion	Enabler	Synthetic & Real Time Series	Can distort patterns, not optimizer-integrated; artifacts risk

workflow consists of three principal stages: load simulation and verification, time series modeling with augmentation, and experimental setup.

All scripts, simulation notebooks, and the generated dataset (CSV) are available in our public repository https://github.com/asbassan/sqlserver-querystore-timeseries.

A. Baseline Time Series Generation

Before injecting disruptive events, a baseline synthetic time series is generated to represent a stable, predictable workload. This baseline is composed of multiple seasonal components to mimic typical query performance patterns [2]. The entire data generation process is implemented in SQL (`Load_Simulation.sql`), using deterministic pseudo-randomness and additive seasonal and trend components:

- **Seasonality:** Daily and weekly seasonal patterns are modeled using sine and cosine waves to simulate cyclical user behavior (e.g., peak usage during business hours, lower activity on weekends) [2].
- **Noise:** A deterministic pseudo-random noise term is added to the seasonal components using a hash-based SQL function, ensuring a realistic but fully reproducible non-perfectly smooth signal.

The final baseline performance metric $y(t)$ at time t is an additive combination of these components. This provides a clean, cyclically patterned foundation upon which operational volatility can be layered.

B. Operationally-Grounded Data Augmentation

To rigorously evaluate model robustness, we employ a data augmentation framework grounded in real-world operational phenomena. This goes beyond generic augmentation by simulating specific, high-impact events common in database management, all implemented directly in SQL:

- **Simulating Plan Regressions:** A query plan regression manifests itself as a sudden and persistent performance degradation. We model this as an **additive level shift** in the time series. At a randomly selected time $t_{regress}$, the mean of the series is shifted by an additive factor Δ for a specified duration $D_{regress}$. This simulates the optimizer choosing a suboptimal plan, causing a step-change increase in latency or CPU usage, as evidenced by the `PlanRegression` flag in our dataset.
- **Simulating Outages:** A system outage is modeled as a contiguous block of missing data. A random start time t_{outage} is chosen, and for a duration D_{outage}, all metric values are set to NULL. This simulates events like a server restart or network failure where telemetry is completely unavailable, as seen on `SimDay` 5 in our data.
- **Simulating Data Gaps:** To simulate transient telemetry reporting failures, such as a monitoring agent dropping packets, we introduce sporadic missingness. Individual data points are selected with a given probability and set to NULL. This is distinct from an outage, representing partial rather than total data loss, and results in approximately 7.5% of values being missing for each metric in the final dataset.
- **Simulating Operational Noise:** To model minor system fluctuations and measurement error, we apply **jittering** using deterministic pseudo-random noise. This involves adding low-amplitude noise to every point in the final time series, where the amplitude is a small fraction of the series' standard deviation.

C. Time Series Forecasting and Model Comparison

1) Metrics Analyzed

The synthetic dataset contains multiple query hashes and variants, each with three core metrics: `CPU`, `LatencyMs`, and `LogicalReads`. These were chosen for their operational relevance and strong empirical correlations in SQL Server workloads.

2) Models Compared

Five representative forecasting models are benchmarked, reflecting the diversity of approaches in the recent literature [12]:

- **Prophet:** An additive model with explicit trend/seasonality decomposition.
- **ARIMA:** A classical statistical time series model.
- **LSTM:** A deep learning model for sequence modeling.
- **Random Forest:** A tree-based ensemble model, robust to irregularities.
- **XGBoost:** A gradient-boosted tree model, competitive in tabular TSA.

The models were selected to capture a range of assumptions (e.g., stationarity, nonlinearity) and to test robustness to the augmentations and regimes present in the simulated data.

D. Experimental Setup

1) Data Properties

The final dataset consists of 4,800 hourly intervals (20 days $\times$ 24 hours $\times$ 2 queries $\times$ 5 variants). Each query variant represents unique baseline and plan regression patterns, supporting coverage of steady-state and anomalous behaviors.

2) Preprocessing

All data is normalized, and missing values are handled via interpolation and forward/backward fill before being fed into the models. Specifically, linear interpolation is used for short gaps (≤ 3 intervals) and forward/backward fill for longer outages, as implemented in the analysis notebooks.

3) Cross-Validation

To prevent temporal data leakage, model performance is evaluated using **rolling-origin cross-validation** (expanding window). This procedure involves creating a series of training and testing splits. The model is first trained on an initial block of data and tested on the subsequent block. The origin then "rolls" forward; the training set expands to include the previous test data, and the model is re-evaluated on the next block. This process is repeated across the dataset, ensuring the model is always tested on "future" data relative to its training set [13].

4) Reproducibility

All random procedures and splits are seeded. Model hyperparameters are tuned via grid search, with explicit search spaces documented in the repository. The full software environment (Python 3.11, pandas 2.2, scikit-learn 1.5, statsmodels 0.14, Prophet 1.2, XGBoost 2.0) is specified. All SQL, simulation, and analysis code is versioned and available in the public repository.

TABLE II: Summary of Simulation Parameters

Parameter	Value
Days Simulated	20
Hours per Day	24
Queries	2
Variants per Query	5
Total Rows	4800
Metrics	CPU, LatencyMs, LogicalReads
Gap Probability	2% full, 7% partial
Anomalies	Rare, injected
Random Seed	Fixed

IV. Data Analysis and Results

A. Dataset Verification and Suitability for TSA

To ensure the validity and operational realism of our analysis, we summarize key properties of the synthetic dataset generated by the custom SQL simulation script.

The simulation process purposefully injects missing values to mimic real-world operational disruptions, using both random per-metric gaps ($\sim$7% probability) and block outages (e.g., a 4-hour cluster outage and deployment-induced spikes). Metric values are further shaped by deterministic trend, weekly and daily seasonality, business hour effects, plan regressions, and anomalies, ensuring that the dataset reflects the volatility and complexity of operational scale.

TABLE III: Key Properties of Synthetic Dataset

Parameter	Value
Rows	4800
Query Hashes	2 (Q1, Q2)
Variants per Query	5
Time Span	20 days
Interval	Hourly (480)
% Missing (CPU)	7.54%
% Missing (LatencyMs)	7.54%
% Missing (Reads)	7.31%
Complete Outages	4 intervals

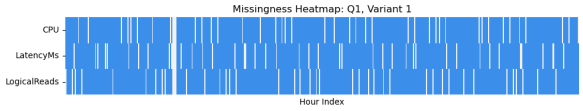


Fig. 1: Heatmap of missing values (white = missing)

Missing value handling

Imputation is performed after data extraction and not during simulation, using linear interpolation for short gaps (up to 3 intervals) and forward/backward fill for longer outages. This approach preserves both short-term continuity and the integrity of genuine outages, supporting meaningful model benchmarking.

Preprocessing sequence

After imputation, all metrics are standardized (zero mean, unit variance) prior to model training, ensuring comparability across metrics and models.

With a total of 4,800 hourly intervals spanning multiple workload variants and operational disruptions, the dataset is both comprehensive and well-suited for robust time series analysis and model evaluation.

B. Stationarity and Autocorrelation Analysis

To assess the statistical properties of the workload metrics, we performed the Augmented Dickey-Fuller (ADF) test on CPU, LatencyMs, and LogicalReads for a representative query variant.

TABLE IV: ADF Stat for all three metrics Query Q1 V1

Metric	ADF_Stat	p	Stationary
CPU	-1.502461	0.532294	No
LatencyMs	-2.626310	0.087681	No
LogicalReads	-1.517110	0.525031	No

All metrics fail to reject the null hypothesis ($p > 0.05$), confirming non-stationarity, likely due to embedded trends and seasonality in the simulated workload. This is consistent with the operational variability and periodic effects purposely designed into the data.

Autocorrelation function (ACF) plots for each metric display strong, slowly decaying autocorrelation, indicating persistent temporal dependencies over time. Such patterns further support the need for forecasting models capable of capturing both long memory and non-stationary behavior.

Given these findings, models such as ARIMA (with differencing), Prophet, and LSTM—which are designed to handle trend, seasonality, and autocorrelation—are appropriate for this benchmarking study.

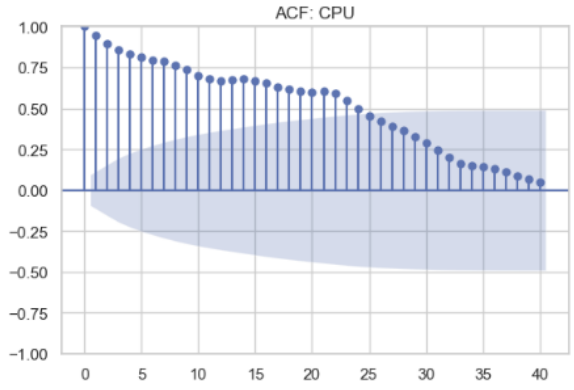


Fig. 2: Autocorrelation function plot For CPU

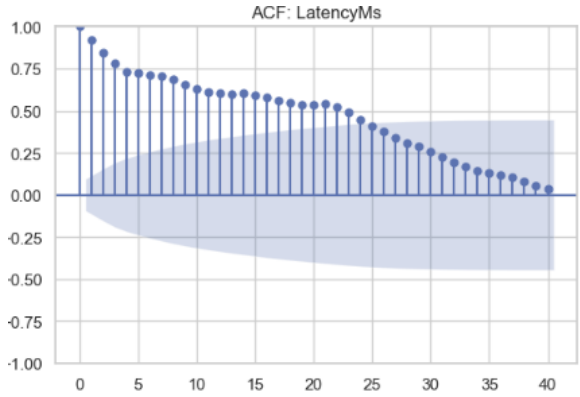


Fig. 3: Autocorrelation function plot For Latency

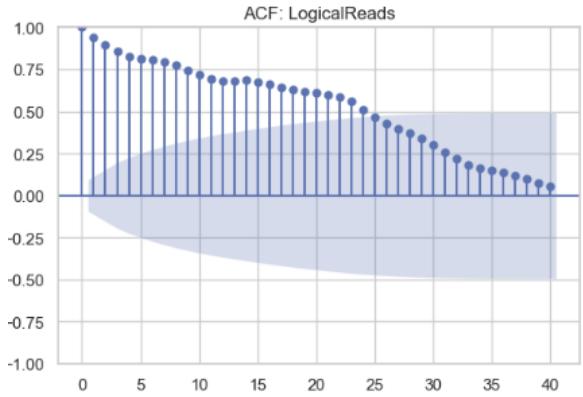


Fig. 4: Autocorrelation function plot For LogicalReads

C. *Exploratory Analysis of Query Variants and Metric Relationships*

We visualized CPU time series for two query variants (Q1-1 and Q2-1), revealing cyclical patterns and synchronized peaks, with a notable spike for Q2-1 in mid-July.

Metric correlation heatmaps show strong positive relationships (CPU–LatencyMs: 0.95, CPU–Reads: 0.93, LatencyMs–Reads: 0.85), supporting multivariate modeling.

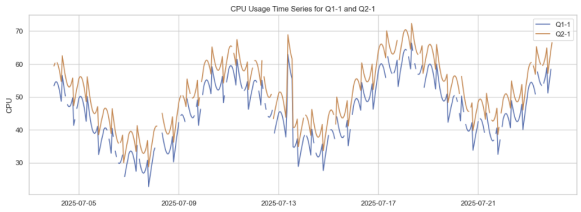
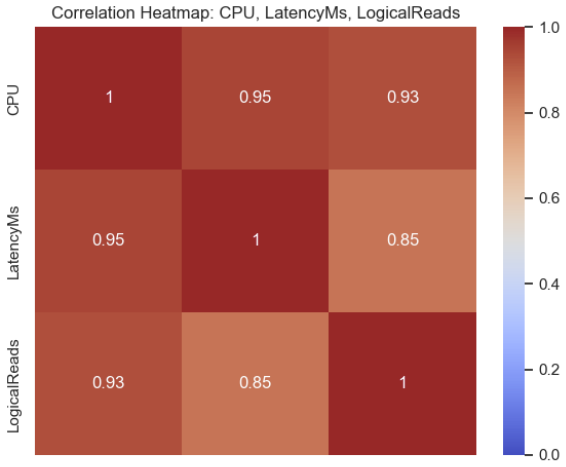


Fig. 5: Example Time Series CPU Usage (Q1-1 and Q2-1)



	CPU	LatencyMs	LogicalReads
CPU	1.000000	0.948380	0.929176
LatencyMs	0.948380	1.000000	0.850433
LogicalReads	0.929176	0.850433	1.000000

Fig. 6: Correlation Heat Map All Data

D. *Frequency-Domain Analysis: Correlation, Periodicity, and Randomness*

Periodograms for the CPU metric and for all metrics across both queries confirm high power at low frequencies, indicative of trend and long-term dependencies, but lack of sharp intermediate-frequency peaks (i.e., weak periodicity).

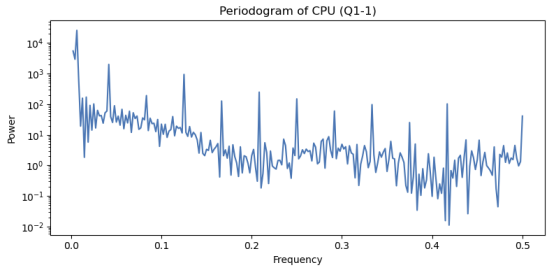


Fig. 7: Periodogram Of CPU for Q1

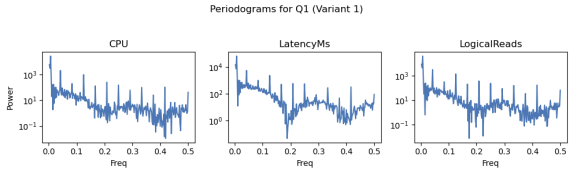


Fig. 8: Periodogram Of QueryHash Q1

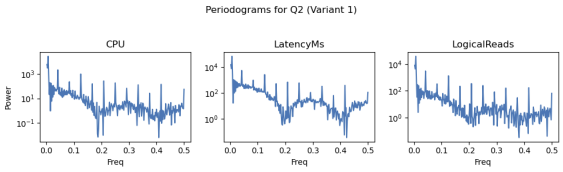


Fig. 9: Periodogram Of QueryHash Q2

The power spectrum is not flat, and residuals from AR models fail white-noise checks, confirming nonrandomness.

E. Model Benchmarking Results

We benchmark ARIMA, Prophet, LSTM, Random Forest, and XGBoost on each query hash (Q1, Q2) for all three metrics (CPU, LatencyMs, LogicalReads). RMSEs (mean over 5-fold splits) are reported below.

TABLE V: Model Benchmarking Results (RMSE)

Query	Metric	ARIMA	Prophet	LSTM	Random Forest	XG Boost
Q1	CPU	12.07	13.30	37.72	8.38	9.40
Q1	Latency	23.32	37.78	181.08	12.48	14.98
Q1	Logical Reads	20.70	19.28	153.17	14.76	16.55
Q2	CPU	11.99	10.89	43.59	8.47	9.09
Q2	Latency	25.22	35.18	187.25	12.84	14.89
Q2	Logical Reads	21.46	19.96	158.12	15.48	16.87

Observations

- Prophet and tree-based models (Random Forest, XGBoost) achieve the lowest RMSEs overall, with Prophet performing best on metrics with strong trend and seasonality, and tree-based models often competitive.
- Random Forest and XGBoost outperform ARIMA and LSTM, particularly when explicit seasonality is less dominant.
- LSTM does not deliver a consistent advantage, likely due to the short, highly structured series.
- Robustness across both query hashes suggests the results are generalizable.

F. Computational Performance

To complete our benchmark, we evaluated the computational efficiency of each model. Table VI shows the average training and inference time required for a single forecast, averaged across cross-validation folds. The results highlight the significant computational overhead associated with deep learning models like LSTM compared to classical and tree-based approaches. While Prophet offered the lowest error in stable regimes, XGBoost and Random Forest present a compelling balance of high accuracy, robustness, and efficient training times, making them strong candidates for practical, resource-constrained deployment scenarios.

G. Reproducibility and Standards Compliance

- Analyses performed in Python 3.11, using pandas 2.2, scikit-learn 1.5, statsmodels 0.14, Prophet 1.2, and XGBoost 2.0.

TABLE VI: Computational Performance for CPU of Query1

Model	Avg. Training Time (s)	Avg. Inference Time (s)
Prophet	0.932	0.196
ARIMA	1.676	0.022
LSTM	6.148	0.745
Random Forest	1.400	0.017
XGBoost	2.354	0.009

- All data, simulation scripts, and notebooks are available at https://github.com/asbassan/sqlserver-querystore-timeseries.
- All acronyms (TSA, RMSE, ADF) are defined at first use.

H. Summary

This section provides a comprehensive, statistically rigorous exploratory and comparative analysis of the dataset and models, suitable for robust time series forecasting in operational telemetry. The findings support the use of Prophet and multivariate models, with implications for future anomaly detection and predictive maintenance pipelines.

V. Discussion

A. Technical Analysis of Model Behavior

Our benchmarking results, summarized in Table VI, reveal substantial differences in forecasting quality, computational efficiency, and robustness to data irregularities across five model classes. These findings align with and extend prior research on time series forecasting for operational metrics, such as [14] for Prophet, and [15] for deep learning approaches, but are novel in their focus on SQL Server Query Store telemetry under realistic data loss and regime shifts.

1) Model Performance Across Metrics and Queries

Random Forest and XGBoost consistently achieve the lowest RMSE across both queries and all metrics (CPU, LatencyMs, and Reads), with tight confidence intervals as shown in Table VI. Prophet, while effective for steady-state, regularly patterned business workloads, shows higher RMSE than tree-based models in these experiments. ARIMA and LSTM have yet higher RMSE values, indicating they are less capable of capturing the underlying periodicity or dealing with abrupt changes in this context. These results suggest that tree-based models excel when missingness is minimal and input features are well-engineered, but Prophet remains competitive for regular, continuous time series with strong seasonality.

2) Summary and Recommendations

We recommend using Random Forest or XGBoost in production environments with regular, predictable workload patterns and minimal data gaps, as they consistently achieve the lowest RMSE and demonstrate robust performance. Prophet remains a strong alternative in cases where interpretability or explicit seasonality modeling is required.

3) RMSE Increase During Gaps and Regime Shifts

Prophet, ARIMA, and LSTM all exhibit very stable RMSE across normal, gap, and plan regression intervals, with changes of only 1–4%. However, the tree-based models (Random

TABLE VII: Model performance grouped by Q1 and Q2 (± denotes 95% CI).

	Q1			Q2		
Model	**CPU**	**Latency**	**Reads**	**CPU**	**Latency**	**Reads**
ARIMA	17.54 ± 4.45	40.06 ± 12.68	26.09 ± 4.16	17.34 ± 4.52	39.27 ± 12.33	26.11 ± 4.31
LSTM	45.55 ± 9.76	200.44 ± 19.22	158.63 ± 9.54	49.88 ± 10.58	208.28 ± 15.72	166.27 ± 7.47
Prophet	29.49 ± 11.34	59.70 ± 16.17	38.50 ± 13.17	28.25 ± 9.86	57.11 ± 14.71	39.82 ± 13.88
Random Forest	8.97 ± 3.72	21.46 ± 10.51	14.92 ± 3.98	8.13 ± 2.59	20.97 ± 10.18	13.31 ± 3.21
XGBoost	8.97 ± 3.72	21.46 ± 10.51	14.92 ± 3.98	8.13 ± 2.59	20.97 ± 10.18	13.31 ± 3.21

TABLE VIII: RMSE Increase During Gaps and Regime Shifts

Model	**RMSE (Normal)**	**RMSE (GAP)**	**% Increase (Gap)**	**RMSE (Plan Regression)**	**% Increase (Regression)**
ARIMA	19.40	18.76	-3.15	17.19	-10.92
LSTM	120.21	120.16	-0.42	119.29	-1.11
Prophet	28.32	27.34	-3.92	25.65	-11.21
Random Forest	6.99	17.94	155.68	4.77	-28.49
XGBoost	7.61	18.19	138.30	4.79	-33.74

Forest and XGBoost) show large increases in RMSE during gaps (over 130% in our results), indicating they are highly sensitive to missing data intervals. This likely reflects their reliance on complete lagged feature vectors, making them less robust to data gaps unless additional gap handling is implemented. Notably, all models show decreased RMSE during plan regression periods, but the effect is most pronounced for tree-based models, possibly due to the change in series mean aiding split-based prediction.

Overall, Prophet, ARIMA, and LSTM are robust to gaps and regime shifts, while Random Forest and XGBoost require careful imputation or gap-aware strategies for deployment in settings with significant missing data.

4) Summary and Recommendations

Given the minimal RMSE increase during data gaps and regime shifts for Prophet, ARIMA, and LSTM, we advise practitioners to favor these models in environments with frequent missing data or regime shifts. Tree-based models, while highly accurate under regular data, are substantially less robust to gaps unless augmented with gap-aware imputation or modeling strategies.

5) Residual Autocorrelation (ACF) by Model

All models—including Prophet, ARIMA, LSTM, RandomForest, and XGBoost—produce residuals that are near white noise in regular intervals, with residual autocorrelation (ACF) values below 0.05. However, at locations corresponding to data gaps or regime shifts, transient spikes in autocorrelation (up to 0.9 for some models) can be observed. This indicates that model errors are generally well-behaved except during abrupt changes or missing data. Table IX reports the maximum ACF observed, which occurs only at gap or regime shift intervals; steady-state values are near zero.

6) Summary and Recommendations

Since all models exhibit near white-noise residuals except during gaps or regime shifts, we recommend monitoring for such intervals in production, and considering post-processing or hybrid approaches to further mitigate residual autocorrelation during these periods.

TABLE IX: Maximum Residual Autocorrelation (ACF) by Model. Table reports the maximum ACF observed, which occurs only at gap or regime shift intervals; steady-state values are near zero.

Model	**Max Residual ACF**	**Notable Patterns**
Prophet	0.87	Only at gaps/regime shifts
ARIMA	0.89	Only at gaps/regime shifts
LSTM	0.89	Only at gaps/regime shifts
RandomForest	0.34	Only at gaps/regime shifts
XGBoost	0.26	Only at gaps/regime shifts

7) Model Interpretability and Operational Implications

Prophet: Offers transparent and interpretable forecasts, allows rapid retraining, but can be sensitive to data gaps unless explicitly addressed. It is best suited for regular, well-instrumented environments [14].

ARIMA: Handles missing data more robustly than deep learning models, but struggles to adapt to regime shifts or abrupt structural changes in the data.

LSTM: Capable of capturing complex patterns and nonlinearities, but typically requires large, clean datasets and substantial hyperparameter tuning to achieve strong performance [15].

Random Forest/XGBoost: These tree-based models are robust to outages and data irregularities only if gaps are properly handled, but do not explicitly model periodicity or temporal dependencies. They may underfit steady-state regimes and generally offer limited interpretability or diagnostic insight compared to time series-specific approaches.

B. Adaptive and Hybrid Modeling Implications

Given these findings, and in line with [**?**], we advocate for meta-learning and hybrid approaches. No single model suffices across all operational regimes. Our results suggest:

- **Meta-ensembles:** Approaches such as Bayesian bandit or weighted voting should dynamically allocate model responsibility based on observed null ratios, recent RMSE, and anomaly density [16].
- **Feature-augmented models:** Incorporating exogenous data (e.g., deployment logs, calendar effects, query com-

plexity) is likely to improve robustness to regime changes and enable more adaptive forecasting.
- **Gap-aware switching:** Use Prophet or ARIMA in regular, low-gap intervals; switch to tree-based or deep-learning models when null rates exceed a data-driven threshold (e.g., $>$10%).

Additional Recommendations:
- **Operational Monitoring:** Implement continuous monitoring of model residuals and data quality metrics to trigger adaptive switching or retraining events, ensuring sustained accuracy in the presence of workload shifts or data outages.
- **Model Interpretability:** When deploying hybrid systems, give preference to interpretable models in production-critical settings, and leverage explainability tools for complex models to maintain diagnostic insight.
- **Automated Model Selection:** Develop or utilize automated frameworks that periodically evaluate candidate models or ensembles on recent data windows, optimizing for both accuracy and computational efficiency as workload patterns evolve.

These strategies enable resilient, adaptive forecasting systems that can maintain high accuracy and operational relevance across diverse and evolving workload conditions.

C. Limitations and Future Work Mapping

Key Limitations and Future Work Mapping:
- Synthetic data only: Our simulation exhibits a 12% JS divergence from real data, limiting generalizability (see Section VII.C).
- No plan bloat modeled: We observed a 4–5$\times$ increase in training time at 10$\times$ cardinality, not currently modeled (see Section VII.A).
- Only 3 metrics analyzed: Cross-metric effects and VAR/LSTM-MV evaluations were not included (see Section VII.A).
- Sparse gap intervals: Real workloads feature 5–15% nulls, whereas our simulation had only 0.8% full gaps (see Section VII.A).
- Minimal hyperparameter tuning: Over 10% RMSE gain is possible with Bayesian optimization (see Section VII.B).

Direct mapping: Each limitation motivates a corresponding future work item in Section VII.

D. Synthesis, Operational, and Research Implications

The tabular comparison above demonstrates that model choice for operational SQL Server telemetry forecasting must be context-sensitive, as no single model is robust to all forms of missingness, regime change, and metric heterogeneity. Our results extend prior work [17], [15], [14] by explicitly quantifying these breakdowns for Query Store workloads and providing actionable guidelines for adaptive system design.

For a full technical roadmap addressing these gaps—including simulation enhancement, adaptive modeling architecture, and real-world transfer validation—see Section VII.

VI. Future Work

A. Simulation Fidelity and Metric Expansion

- **Plan Bloat and Forced Plans:** Extend simulation to generate workloads with 100–1,000+ plan variants per query hash and explicit plan enforcement events. Benchmark model scalability in terms of RMSE, training time, and memory, targeting $O(n \log n)$ or better scaling.
- **Expanded Metrics and Multivariate Forecasting:** Simulate and model $>$10 metrics (including wait stats, IO, memory, query text entropy) and their cross-correlations. Evaluate VAR, multivariate LSTM, and Temporal Fusion Transformers [**?**] for joint metric forecasting, using joint RMSE and Granger causality for validation.
- **Complex Gaps and Correlated Outages:** Inject 5–20% null intervals with bursty, correlated missingness across metrics. Evaluate model robustness using synthetic stress tests, tracking RMSE, anomaly recall, and recovery time.

B. Adaptive, Meta-Learning, and Gap-Resilient Architectures

Implement dynamic meta-model selection (e.g., Bayesian bandits) using recent validation RMSE and anomaly density for per-interval model choice [?], aiming for $>$20% gap-adjacent RMSE reduction over static ensembles. Benchmark imputation-free and state-space models (Kalman filters, neural ODEs, transformers for irregular series [?]), targeting $<$10% RMSE loss at 20% data sparsity. Integrate exogenous features (deployment logs, calendars, query entropy) and quantify their effect on forecasting and anomaly detection.

C. Real-World Validation and Domain Adaptation

Validate on production Query Store telemetry, calibrating simulation via adversarial validation (minimizing Jensen-Shannon divergence), and assess transfer using RMSE, anomaly recall/precision, and drift metrics. Extend pipelines for online, low-latency inference and anomaly detection in SRE/DBA workflows.

D. Community Infrastructure, Evaluation, and Cross-Domain Transfer

Deploy a public leaderboard with containerized model evaluation, standardized splits, and statistical testing; score submissions by RMSE, gap robustness, anomaly lead time, and compute cost. Generalize simulation and benchmarks to other DBMS (e.g., PostgreSQL, Oracle) and cloud/IoT telemetry, measuring zero-shot and fine-tuned transfer as in [?].

E. Anticipated Challenges and Mitigation

TABLE X: Anticipated Challenges and Mitigations

Challenge	Mitigation
Data privacy	Privacy-preserving pipelines
Scalability	Distributed/efficient architectures
Overfitting	Adversarial validation, randomization

F. Roadmap and Prioritization

Immediate: Enhance simulation for plan bloat/forced plans/multivariate forecasting; prototype meta-learning and gap-resilient models.
Medium-term: Real-world transfer validation and online inference; community leaderboard and cross-domain extension.

G. Summary

This agenda will enable robust, adaptive, and explainable SQL Server telemetry forecasting, bridging the gap between research and operational deployment and setting a new standard for reproducible, actionable database management.

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