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Original Article

Forecasting Software Delivery Bottlenecks Using Time-Series AI Models

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Abstract: *In an era of fast-paced software development and deployment, continuous integration and continuous delivery (CI/CD) have become foundational to modern DevOps practices. Despite the efficiencies these pipelines offer, unforeseen bottlenecks such as increased build queue times, test failures, and resource exhaustion continue to impact delivery timelines and degrade system performance. Traditional monitoring tools and rule-based alerts are reactive, offering little help in preemptively identifying pipeline stress points.*

This paper investigates the application of time-series artificial intelligence (AI) models to forecast software delivery bottlenecks before they occur. We explore and compare the efficacy of three models ARIMA, Long Short-Term Memory (LSTM) networks, and Facebook Prophet by applying them to CI/CD telemetry data, including build duration, test pass rate, queue times, and system resource utilization. These models are evaluated on their ability to predict future pipeline delays with high accuracy and low error rates.

Our findings reveal that LSTM and Prophet models outperform ARIMA in both accuracy and adaptability, particularly in capturing non-linear trends and sudden pipeline anomalies. With the capability to forecast delivery issues up to 24 hours in advance, these models present a significant opportunity for DevOps teams to mitigate risks, balance workloads, and improve overall software release velocity.

The proposed methodology paves the way for a predictive DevOps culture where delivery teams transition from reactive firefighting to proactive performance management. We conclude with practical recommendations for integrating these models into existing DevOps toolchains and highlight future directions in real-time automation, adaptive scheduling, and reinforcement learning integration.

Keywords: *Software Delivery Bottlenecks, Time-Series Forecasting, Artificial Intelligence, Devops, CI/CD Pipelines, Build Duration Prediction, Queue Time Forecasting, ARIMA, LSTM, Facebook Prophet, Predictive Analytics, Deployment Success Rate, Anomaly Detection, System Resource Utilization, Pipeline Performance Prediction, Infrastructure Scaling, Software Delivery Optimization.*

I. INTRODUCTION

In today's digital economy, the ability to deliver high-quality software rapidly and reliably is a key competitive differentiator. Organizations are increasingly adopting DevOps practices and Continuous Integration/Continuous Delivery (CI/CD) pipelines to streamline software development and deployment. These pipelines orchestrate a sequence of automated steps from code integration and testing to deployment aimed at accelerating time-to-market and improving system reliability. However, even with mature DevOps implementations, software delivery bottlenecks remain a persistent challenge.

A bottleneck in a CI/CD pipeline refers to any stage where the throughput is significantly reduced, causing delays in the overall software delivery process. Common causes include overloaded build servers, long test execution times, failed deployments, and infrastructure resource constraints. These issues not only delay product releases but also impact developer productivity and customer satisfaction. Identifying bottlenecks after they occur is reactive and often results in manual interventions, increased downtime, and lost development cycles.

To address this, there is a growing interest in forecasting delivery bottlenecks using intelligent, data-driven approaches. The idea is to move from reactive monitoring to proactive pipeline management by anticipating when and where delays are likely to occur allowing teams to take preventive actions such as allocating resources, rescheduling builds, or modifying pipeline configurations.

This paper explores the application of time-series AI models to predict future pipeline bottlenecks based on historical telemetry data. Time-series models are well-suited to this task because they capture temporal patterns, trends, and seasonality that are common in software delivery workflows. We investigate three forecasting techniques ARIMA (a classical statistical model), LSTM

(a deep learning model capable of learning temporal dependencies), and Prophet (a model developed by Facebook for business time-series forecasting).

The core contributions of this paper are:

- A data pipeline architecture for ingesting and transforming CI/CD telemetry data into a time-series format suitable for modeling.
- A comparative analysis of ARIMA, LSTM, and Prophet models in predicting pipeline performance metrics such as build queue times,test durations, and deployment success rates.
- A practical evaluation using real-world DevOps datasets from Jenkins and GitLab CI systems, demonstrating the forecasting accuracy and limitations of each approach.
- Recommendations for integrating time-series forecasting into DevOps toolchains to support intelligent pipeline orchestration and automated incident prevention.

By forecasting software delivery bottlenecks in advance, organizations can reduce downtime, optimize resource utilization, and foster a more resilient DevOps culture. This research marks a step toward the realization of **AIOps** (Artificial Intelligence for IT Operations) in software engineering, where AI models augment human decision-making across the development lifecycle.

II. BACKGROUND AND RELATED WORK

DevOps is a cultural and technical movement aimed at unifying software development (Dev) and IT operations (Ops) for faster and more reliable software delivery. At the heart of DevOps lies the CI/CD (Continuous Integration and Continuous Delivery) pipeline, which automates the stages of code integration, testing, deployment, and monitoring.

However, as pipelines grow more complex with microservices, distributed architectures, and frequent code commits, the likelihood of bottlenecks periods of slowed or halted progress increases. Common sources include test case bloat, slow build processes, hardware limitations, and misconfigured deployment scripts.

A. Related Work:

- Xuet al. (2020) used clustering methods for detecting performance anomalies in CI/CD environments.
- Kumar and Shah (2022) applied ARIMA to model CI delays but lacked real-time retraining mechanisms.
- K Zhang et al. (2023) leveraged LSTM for performance forecasting in cloud infrastructure, highlighting the superiority of deep learning in capturing non-linear trends.

Despite these advancements, few studies directly address forecasting delivery bottlenecks in CI/CD pipelines using time-series AI models. This paper fills that gap with a practical, comparative approach using ARIMA, LSTM, and Prophet.

III. PROBLEM STATEMENT

Modern CI/CD pipelines handle thousands of builds, tests, and deployments daily. However, identifying when and where bottlenecks will occur is still a challenge. The reactive nature of current systems often results in:

- Missed deployment deadlines
- Developer frustration due to queue time delays
- Unoptimized resource allocation

A. This research poses the following problem statement:

Can we leverage time-series AI models to predict future software delivery bottlenecks based on historical pipeline telemetry data?

We define bottlenecks in measurable terms such as:

- Excessive build_queue_time (> X minutes)
- Test phase duration exceeding SLA
- High variance in deployment_success_rateThe goal is to predict these anomalies in advance, ideally 4–24 hours before they occur.

IV. DATA COLLECTION AND FEATURE ENGINEERING

A. Data Sources

Data was gathered over a continuous period of six months from enterprise-scale CI/CD systems, primarily Jenkins and GitLab CI pipelines, which were integrated into the development infrastructure of a mid-sized software organization. The datasets captured a variety of time-stamped metrics and logs critical for identifying software delivery bottlenecks.

The key attributes collected include:

a) Build_Duration

The total time taken from the initiation of the CI build process to its successful completion or failure.

b) Queue_Time

The time a build job spent in the queue before being picked up by an executor, often indicative of infrastructure. saturation.

c) Test_Pass_Rate

The proportion of successfully passed test cases in each build relative to the total number of tests executed.

d) Cpu_Usage And Memory_Usage

System telemetry metrics collected from the underlying build nodes, representing resource utilization during CI execution.

e) Deployment_Success

A binary indicator (1 = deployment succeeded, 0 = failed), useful as the ground truth for supervised learning tasks.

Additional logs and metadata such as commit timestamps, codebase branch, and build trigger type (manual vs. automated) were also captured to support contextual analysis.

B. Feature Engineering

Accurate forecasting of delivery bottlenecks hinges on constructing features that preserve temporal structure while enriching the signal quality. The following techniques were used to engineer features suitable for time-series modeling:

a) Lag Features

Created by shifting key metrics (e.g., build_duration, queue_time) back by 1 to 5 timesteps (t-1 to t-5). These features help the model understand autoregressive patterns and recent historical dependencies.

b) Rolling Statistics

Computed moving averages, medians, and standard deviations across sliding windows (5, 10, and 20 builds) for metrics such as test_pass_rate and cpu_usage. These capture temporal trends, anomalies, and variability.

c) Time-Based Features

Extracted cyclical temporal features such as hour of the day, day of the week, and weekend flag. These help the model learn periodic patterns in delivery performance (e.g., longer build times during peak hours).

d) Event Indicators

Binary flags were added to denote *release windows*, *code freeze periods*, and *scheduled maintenance events*. These categorical features capture external events that often correlate with system slowdowns or build failures.

e) Derived Ratios

Features such as build_efficiency_ratio = build_duration / queue_time and resource_intensity = (cpu_usage + memory_usage) / build_duration were computed to encapsulate system behavior beyond raw metrics.

f) Categorical Encoding

Commit branch (e.g., master, dev, feature/*) and trigger type were one-hot encoded to help differentiate contextual build characteristics

C. Handling Missing Values

Missing data points were handled using interpolation techniques. Linear interpolation was applied to regularly spaced numeric metrics, while *spline interpolation* was reserved for data with non-linear temporal trends. Outlier detection was performed using Z-score analysis, and anomalies were imputed using backward or forward filling based on the feature type and temporal proximity.

V. TIME-SERIES FORECASTING MODELS

In order to predict potential bottlenecks in software delivery pipelines, we evaluated a range of time-series forecasting models, each selected for their ability to address specific patterns and challenges inherent in CI/CD operational data. The forecasting target was typically *build duration* or *queue time*, framed as a regression problem over a time window.

A. ARIMA (AutoRegressive Integrated Moving Average)

ARIMA is a statistical model traditionally used in univariate time-series forecasting. It combines three components:

- AutoRegression (AR) : Predicts future values based on past values.
- Integration (I) : Applies differencing to make the series stationary.

- Moving Average (MA) : Models the error of the prediction as a linear combination of past forecast errors.

a) Model Justification

ARIMA is well-suited for stationary series where the underlying patterns follow linear trends with minimal volatility. In the context of CI/CD, it provided a baseline for modeling relatively stable environments, such as predictable test cycles or low-change queues.

b) Limitations

- Assumes linearity and stationarity, which are often violated in real-world DevOps telemetry.
- Requires careful manual parameter tuning (p, d, q).
- Struggles with capturing complex dependencies such as periodic load spikes or cascading failures.

B. LSTM (Long Short-Term Memory)

LSTM networks, a special type of Recurrent Neural Network (RNN), are explicitly designed to learn and retain long-term dependencies in sequential data. LSTM cells use gated mechanisms to manage memory and mitigate vanishing gradients, which makes them highly effective for learning nonlinear temporal patterns.

a) Why LSTM for CI/CD Data

- Capable of modeling nonlinear relationships between build metadata, system telemetry, and delivery outcomes.
- Adapts well to irregular build schedules, variable team workloads, and periodic stress events (e.g., sprint ends or release cycles).
- Can learn time-lagged effects, such as delayed resource contention or compounded failures.

b) Model Configuration

i) Input Shape

batch_size, time_steps, num_features) – e.g., 32x10x7 for a batch of 32 samples, each with 10 time steps and 7 engineered features.

ii) Layers

Stacked LSTM layers followed by Dense layers.

iii) Optimizer:

Adam (adaptive learning rate optimization).

iv) Loss Function

Mean Squared Error (MSE), selected for its sensitivity to large deviations in build durations.

v) Regularization

Dropout layers (rate = 0.2 to 0.4) to reduce overfitting, especially when training on limited historical data.

c) Training Considerations

- Used sliding window sampling to generate training sequences.
- Min-max normalization applied to ensure stable convergence.
- Early stopping and checkpointing employed to avoid overfitting and reduce training time.

d) Prophet

Prophet is an additive time-series forecasting model developed by Facebook that decomposes time series into trend, seasonality, and holiday effects:

- Trend: Piecewise linear or logistic growth curve.
- Seasonality: Weekly, daily, or yearly patterns modeled using Fourier series.
- Holidays/Events: Custom events (e.g., release freeze or sprint-end days) explicitly encoded.

e) Model Strengths

- High interpretability and ease of tuning, making it appealing to DevOps teams without deep ML expertise.
- Automatically detects change-points in trend and adjusts forecasts accordingly.
- Handles missing data and outliers robustly without pre-processing.

f) Use Case Fit

Prophet was particularly effective for identifying recurring patterns such as end-of-week delivery slowdowns or productivity dips after holiday periods. While not as flexible as LSTM in modeling nonlinear dependencies, its modular approach proved valuable in environments requiring explainable forecasts.

g) Hyperparameters Used

- changepoint_prior_scale = 0.05 for flexible trend detection.
- seasonality_mode = 'additive' for environments with low interaction effects.
- Included custom regressors for system load and event indicators.

h) Model Selection Summary:

Each model contributed uniquely to the forecasting pipeline:

- ARIMA served as a simple, fast baseline.
- LSTM offered superior accuracy in high-noise, high-complexity settings.
- Prophet balanced interpretability with predictive performance, making it ideal for operational dashboards.

Subsequent sections detail the evaluation metrics, performance comparisons, and model deployment architecture used for real-time bottleneck prediction in software delivery workflows.

VI. IMPLEMENTATION

To validate the effectiveness of the proposed forecasting models, we developed an end-to-end time-series forecasting pipeline using Python. Each model ARIMA, LSTM, and Prophet was implemented using mature, production-grade libraries within the Python ecosystem.

A. Tools and Frameworks

a) ARIMA

Implemented using the statsmodels library, which provides a robust framework for classical statistical modeling and time-series analysis.

b) LSTM

Developed using TensorFlow 2.x and Keras, which support flexible neural network architectures and GPU acceleration.

c) *Prophet*:

Implemented using the prophet library (formerly fbprophet), known for its simplicity, modularity, and ease of incorporating domain-specific seasonality.

B. Workflow Pipeline

The forecasting pipeline was structured as follows:

a) Data Preprocessing

- Applied outlier filtering using interquartile range (IQR) and Z-score techniques.
- Interpolated missing values using linear and spline methods depending on the metric's variability.
- Normalized continuous features using Min-Max scaling (for LSTM) and standardization (for ARIMA).
- Encoded categorical variables (e.g., trigger type, branch) via one-hot encoding

b) Feature Engineering

- Incorporated lag features, rolling statistics, and time-based features as described in Section 4.2.
- Constructed event flags for known release cycles and high-risk deployment windows.

c) Dataset Splitting

- Applied a chronological train/validation/test split using a 70/15/15 ratio to preserve temporal order.
- For LSTM and ARIMA, additional care was taken to avoid data leakage due to time-dependent sequences.

d) Rolling Window Cross-Validation

- Implemented rolling (walk-forward) validation to simulate real-world production forecasting.
- Models were retrained on expanding windows, with performance measured on a sliding test set.
- For LSTM, early stopping and learning rate schedulers were used to improve generalization.

e) Forecast Generation

- Each model was tasked with predicting *build_duration* and *queue_time* over a 24-hour rolling forecast horizon, updated at regular intervals.
- LSTM generated multi-step forecasts using a sequence-to-sequence architecture, while Prophet and ARIMA produced daily-level point forecasts.

f) Visualization & Error Analysis

- Forecasts and confidence intervals were visualized using matplotlib, seaborn, and plotly.

- Residual diagnostics were performed to detect autocorrelation and forecast bias.
- Feature importance (for Prophet) and attention weight visualization (for LSTM, using integrated gradients) were used to enhance interpretability.

C. Execution Environment

a) Compute Infrastructure:

- LSTM models were trained on an NVIDIA GPU-enabled environment (Tesla V100 with 16GB VRAM) using Google Colab Pro and AWS SageMaker notebooks.
- ARIMA and Prophet were executed on CPU-bound environments due to their lower compute requirements.

b) Runtime Optimization:

- TensorFlow's mixed-precision training and model checkpointing were enabled to reduce training time.
- Batch sizes and sequence lengths were tuned through grid search to optimize for convergence and accuracy.

D. Evaluation Targets

All models were evaluated on two key time-series:

- build_duration: Total elapsed time of CI builds, a direct measure of pipeline throughput.
- queue_time:Waiting time before job execution, indicative of infrastructure congestion or scheduling inefficiencies.Performance results, comparisons, and metrics are detailed in Section 7.

VII. EVALUATION METRICS

We used the following metrics:

- MAE (Mean Absolute Error) : Measures average magnitude of prediction errors.
- RMSE (Root Mean Squared Error) : Penalizes larger errors more than MAE.
- MAPE (Mean Absolute Percentage Error) : Normalized error rate as a percentage.

Model	MAE	RMSE	MAPE (%)
ARIMA	4.5	6.1	19.8
LSTM	2.1	3	10.4
Prophet	2.5	3.2	11.9

Table 1 : LSTM Outperforms ARIMA and Prophet Across All Metrics.

Results show that LSTM outperforms ARIMA and Prophet across all metrics.

VII. RESULTS AND DISCUSSION

The LSTM model was able to predict queue time spikes and test phase slowdowns with high accuracy. Prophet was a close second and had the advantage of being interpretable.

A. Key Findings

- Predictive horizon of up to 24 hours was effective for most bottleneck types.
- LSTM excelled in capturing sharp spikes, especially during release days.
- Prophet's seasonality detection helped anticipate weekend build backlogs.

B. Operational Impact

- Teams using LSTM forecasts reduced average queue delays by 28%.
- Engineers could proactively scale infrastructure or reroute jobs.

IX. CHALLENGES AND LIMITATIONS

- Data Quality : Missing or inconsistent telemetry data required significant preprocessing.
- Concept Drift : Pipelines evolve over time; models need retraining to remain accurate.
- Interpretability : LSTM is a black-box model, which may not be suitable for all teams.
- Infrastructure Overhead : Running predictive models in production pipelines introduces computational costs.

X. CONCLUSION AND FUTURE WORK

This study demonstrates the effectiveness of time-series AI models particularly LSTM and Prophet in forecasting CI/CD pipeline bottlenecks. These models enable DevOps teams to shift from reactive to proactive strategies, improving delivery reliability and velocity.

A. Future Work Includes

- Integrating forecasting directly into CI/CD tools (e.g., Jenkins plugins)
- Using Reinforcement Learning for adaptive pipeline control
- Scaling to multi-tenant, multi-cloud CI/CD systems
- Incorporating non-time-series signals (e.g., code change metrics, commit metadata)

The convergence of DevOps, AI, and Time-Series Modeling holds immense potential in achieving self-healing, intelligent delivery pipelines.

XI. REFERENCES

[1] Xu, R., Wang, J., & Liu, T. (2020). *Anomaly Detection in Continuous Deployment Pipelines using Machine Learning*. Journal of Systems and Software.

[2] Kumar, V., & Shah, P. (2022). *Predictive Modeling of Deployment Delays in DevOps Using ARIMA*. ACM DevOps Conf.

[3] Zhang, L., Kim, Y., & Chen, M. (2023). *Leveraging Deep Learning for CI/CD Observability in Cloud-Native Environments*. IEEE Trans. Cloud Computing.

[4] Taylor, S.J., & Letham, B. (2018). *Forecasting at Scale*. The American Statistician.

[5] Hochreiter, S., & Schmidhuber, J. (1997). *Long Short-Term Memory*. Neural Computation