Explainable Hybrid Calendar-Aware Machine Learning Framework for Daily Toll Traffic Forecasting with Statistical Sensitivity Analysis

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***Abstract*—Accurate daily toll traffic forecasting is essential for revenue stabilization, congestion mitigation, and infrastructure resource planning. Vehicle volumes exhibit short-term temporal dependence, weekly seasonality, and calendar-driven variability influenced by weekends and public holidays. Conventional statistical models such as ARIMA effectively capture linear seasonality but often lack flexibility in modeling calendar interactions, while modern machine learning techniques enhance predictive capability at the cost of interpretability and statistical validation.**

A hybrid calendar-aware forecasting framework integrating linear autoregressive modeling with gradient-boosted residual learning is developed to address these limitations. Statistical hypothesis testing quantifies weekend and holiday sensitivity, while stationarity diagnostics and seasonal decomposition validate temporal structure. Robustness is evaluated using walk-forward validation, and model transparency is ensured through SHAP-based explainability analysis.

Empirical results reveal dominant short-memory autoregressive behavior and statistically significant weekend uplift, with regularized linear models demonstrating superior generalization compared to complex nonlinear ensembles. The framework enables accurate prediction while providing interpretable operational insights, supporting evidence-based toll management and revenue optimization strategies.

***Index Terms*—Toll traffic forecasting, hybrid modeling, explainable machine learning, calendar effects, time series analysis, SHAP**

I. Introduction

Daily toll traffic forecasting plays a critical role in transportation revenue estimation, demand management, and long-term infrastructure planning. Vehicle volume exhibits temporal autocorrelation, weekly seasonality, and event-driven variability influenced by weekends and public holidays. Traditional statistical models such as ARIMA capture linear temporal patterns but may fail to incorporate complex calendar interactions. Conversely, modern machine learning approaches improve predictive flexibility but often lack interpretability and statistical validation.

This study proposes a hybrid calendar-aware forecasting framework that integrates statistical hypothesis testing, autoregressive feature engineering, boosted residual modeling, and explainable machine learning techniques. The objective extends beyond predictive comparison toward structured quantification of temporal dynamics and calendar sensitivity within toll traffic systems.

II. Literature Review

Daily traffic flow forecasting has been extensively studied within transportation engineering and time series analytics. Traditional statistical approaches such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) models have been widely adopted due to their ability to capture linear temporal dependence and seasonal periodicity [1], [2]. These models demonstrate effectiveness in structured environments with stable seasonal patterns; however, their performance degrades when nonlinear interactions or calendar-driven irregularities dominate system behavior.

To address these limitations, machine learning techniques including Support Vector Regression (SVR), Random Forests, Gradient Boosting, and Extreme Gradient Boosting (XGBoost) have been introduced for traffic volume prediction [3], [4]. Ensemble-based methods improve nonlinear modeling capability and predictive accuracy, particularly in high-variance environments. Nevertheless, such models often function as black-box predictors, limiting interpretability and reducing operational transparency for infrastructure decision-making.

Recent advancements incorporate deep learning architectures such as Long Short-Term Memory (LSTM) networks to capture long-range temporal dependencies [5]. While LSTM models demonstrate strong performance in large-scale urban traffic datasets, their effectiveness in structured toll environments with dominant short-memory dynamics remains inconclusive.

Parallel research emphasizes the significance of calendar effects, including weekend uplift and public holiday surges, in transportation demand modeling [6]. However, systematic statistical quantification of these effects alongside machine learning forecasting frameworks remains limited. Furthermore, few studies integrate hypothesis testing, walk-forward validation, and explainable artificial intelligence within a unified modeling architecture.

The present work extends existing literature by combining statistical sensitivity analysis, hybrid residual-based forecasting, regime-aware modeling, and SHAP-driven interpretability within a consolidated calendar-aware forecasting framework tailored to toll traffic systems.

III. Problem Formulation

Daily toll traffic forecasting is formulated as a supervised time series regression problem. Let y_t denote the total number of vehicles observed at day t, where $t = 1, 2, \dots, T$. The objective is to estimate a predictive function $f(\cdot)$ such that

$$\hat{y}_t = f(X_t), \tag{1}$$

where X_t represents a feature vector containing temporal, autoregressive, and calendar-based attributes.

A. Feature Space Definition

The predictor set X_t is structured into four primary components:

1) Temporal Features:

$$X_t^{(temp)} = \{\text{DayOfWeek}_t, \text{Month}_t, \text{DayOfYear}_t, \text{TimeIndex}_t\} \tag{2}$$

2) Autoregressive Lag Features:

$$X_t^{(lag)} = \{y_{t-1}, y_{t-7}, y_{t-14}, y_{t-30}\} \tag{3}$$

3) Rolling Statistical Features:

$$X_t^{(roll)} = \{\mu_t^{(7)}, \mu_t^{(14)}, \mu_t^{(30)}\} \tag{4}$$

where $\mu_t^{(k)}$ represents the rolling mean over the previous k days.

4) Calendar Indicator Variables:

$$X_t^{(cal)} = \{\text{IsWeekend}_t, \text{IsHoliday}_t\} \tag{5}$$

The complete feature vector is defined as:

$$X_t = X_t^{(temp)} \cup X_t^{(lag)} \cup X_t^{(roll)} \cup X_t^{(cal)}. \tag{6}$$

B. Statistical Sensitivity Hypothesis

To quantify calendar-driven variability, weekend sensitivity is evaluated through hypothesis testing:

$$H_0 : \mu_{weekend} = \mu_{weekday} \tag{7}$$

$$H_1 : \mu_{weekend} \neq \mu_{weekday} \tag{8}$$

where $\mu_{weekend}$ and $\mu_{weekday}$ represent mean daily traffic volumes for weekend and weekday observations, respectively. Statistical significance is assessed using two-sample t-tests, and effect magnitude is quantified using Cohen's d:

$$d = \frac{\mu_{weekend} - \mu_{weekday}}{\sigma_{pooled}} \tag{9}$$

C. Hybrid Residual Modeling Framework

To capture both linear autoregressive structure and nonlinear residual behavior, a hybrid forecasting formulation is adopted. The final prediction is defined as:

$$\hat{y}_t = \hat{y}_t^{(lin)} + \hat{e}_t^{(boost)}, \tag{10}$$

where $\hat{y}_t^{(lin)}$ is obtained from a regularized linear regression model and $\hat{e}_t^{(boost)}$ represents residual corrections learned through gradient boosting.

The residual component is defined as:

$$e_t = y_t - \hat{y}_t^{(lin)}. \tag{11}$$

This decomposition enables explicit separation of linear temporal dependence and nonlinear adjustment mechanisms.

D. Evaluation Framework

Model robustness is assessed using walk-forward validation. For each split i:

$$\text{Train} = \{1, 2, \dots, t_i\}, \quad \text{Test} = \{t_i + 1, \dots, t_{i+1}\}. \tag{12}$$

Predictive performance is evaluated using:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|, \tag{13}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{14}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}. \tag{15}$$

This formulation ensures statistical rigor, temporal consistency, and comparative robustness across modeling paradigms.

IV. Methodology

This section describes the modeling architectures, experimental configuration, and validation strategy adopted for daily toll traffic forecasting.

A. Baseline Linear Models

Linear regression is implemented as a reference model to capture direct linear relationships between the feature vector X_t and traffic volume y_t. The model assumes:

$$\hat{y}_t = \beta_0 + \sum_{i=1}^{p} \beta_i X_{t,i}, \tag{16}$$

where β_i denotes regression coefficients estimated via ordinary least squares.

To reduce overfitting and stabilize coefficient magnitude, Ridge regression is employed with L_2 regularization:

$$\min_{\beta} \left(\sum_{t=1}^{T} (y_t - \hat{y}_t)^2 + \lambda \sum_{i=1}^{p} \beta_i^2 \right), \tag{17}$$

where λ controls regularization strength.

B. Tree-Based Ensemble Models

1) Random Forest: Random Forest constructs multiple decision trees using bootstrap sampling and feature randomness. The final prediction is computed as the average across M trees:

$$\hat{y}_t = \frac{1}{M}\sum_{m=1}^{M} f_m(X_t). \tag{18}$$

This approach improves variance reduction and nonlinear modeling capacity.

2) Gradient Boosting (XGBoost): Extreme Gradient Boosting builds trees sequentially to minimize a regularized objective function:

$$\mathcal{L} = \sum_{t=1}^{T} \ell(y_t, \hat{y}_t) + \sum_{k=1}^{K} \Omega(f_k), \tag{19}$$

where $\ell(\cdot)$ represents squared error loss and $\Omega(f_k)$ penalizes model complexity.

Residual learning is performed iteratively:

$$\hat{y}_t^{(k)} = \hat{y}_t^{(k-1)} + \eta f_k(X_t), \tag{20}$$

where η is the learning rate.

3) LightGBM: LightGBM employs gradient-based one-side sampling and leaf-wise tree growth for computational efficiency. In addition to point forecasting, quantile regression is implemented to estimate prediction intervals by optimizing the pinball loss function.

C. Statistical Time Series Model

Seasonal ARIMA (SARIMAX) is used as a classical statistical benchmark. The model is expressed as:

$$\Phi(B^s)\phi(B)(1-B)^d(1-B^s)^D y_t = \Theta(B^s)\theta(B)\epsilon_t, \tag{21}$$

where B denotes the backshift operator and s represents seasonal periodicity.

D. Deep Learning Model

A Long Short-Term Memory (LSTM) network is implemented to capture temporal sequence dependence. The hidden state dynamics are defined as:

$$h_t = \text{LSTM}(y_{t-1}, h_{t-1}), \tag{22}$$

where gating mechanisms regulate memory retention and forgetting. The final output layer produces:

$$\hat{y}_t = W h_t + b. \tag{23}$$

E. Hybrid Residual Architecture

To integrate linear structure and nonlinear correction, a two-stage hybrid model is constructed. First, Ridge regression generates baseline predictions:

$$\hat{y}_t^{(lin)}. \tag{24}$$

Residuals are computed as:

$$e_t = y_t - \hat{y}_t^{(lin)}. \tag{25}$$

XGBoost is then trained on residuals:

$$\hat{e}_t^{(boost)} = g(X_t). \tag{26}$$

The final hybrid forecast becomes:

$$\hat{y}_t = \hat{y}_t^{(lin)} + \hat{e}_t^{(boost)}. \tag{27}$$

This decomposition explicitly separates linear autoregressive effects from nonlinear residual dynamics.

F. Experimental Setup

The dataset is chronologically ordered and divided using an 80:20 temporal split to preserve causality. No random shuffling is performed.

Model robustness is evaluated using walk-forward validation with expanding training windows. Hyperparameters are selected using fixed configurations to ensure reproducibility.

All experiments are conducted in Python using scikit-learn, XGBoost, LightGBM, and TensorFlow libraries under a controlled computational environment.

V. Results and Analysis

This section presents statistical validation, model comparison, hybrid evaluation, regime detection, uncertainty quantification, and economic interpretation of forecasting errors.

A. Descriptive Statistics

The dataset consists of 1,038 daily observations. The mean daily traffic volume is 16,394 vehicles with a standard deviation of 2,355 vehicles, indicating moderate variability. The maximum observed traffic exceeds 24,000 vehicles, suggesting surge events beyond normal operating conditions.

B. Weekend Effect Analysis

A two-sample t-test was conducted to evaluate calendar sensitivity.

Mean weekend traffic: 18,201 vehicles Mean weekday traffic: 15,670 vehicles

The p-value ($p < 10^{-60}$) confirms statistically significant differences.

Cohen's $d = 1.09$ indicates a large effect size, demonstrating strong calendar-driven demand amplification. This confirms that weekend traffic surge is structurally embedded in the system rather than random variation.

TABLE I
MODEL PERFORMANCE COMPARISON

Model	MAE	RMSE	MAPE	R^2
Linear Regression	721	1074	4.44%	0.529
Ridge	721	1074	4.45%	0.529
Random Forest	840	1193	5.14%	0.419
LightGBM	917	1290	5.58%	0.321
XGBoost	1038	1433	6.36%	0.162
LSTM	1303	1717	7.73%	-0.207
SARIMAX	2812	3309	17.41%	-3.463

C. Stationarity Assessment

The Augmented Dickey-Fuller test produced:

ADF Statistic = -3.46 p-value = 0.009

Since $p < 0.05$, the null hypothesis of non-stationarity is rejected. The traffic series exhibits weak stationarity after accounting for seasonal patterns.

The decomposition reveals a pronounced weekly seasonal component. The residual plot shows heteroscedasticity during surge periods, motivating nonlinear correction models.

D. Model Performance Comparison

Table I compares forecasting accuracy across models.

Contrary to common assumptions in transportation forecasting, linear autoregressive models outperform nonlinear ensemble and deep learning architectures. This suggests that toll traffic dynamics are primarily governed by short-memory linear dependencies rather than complex nonlinear interactions.

E. Walk-Forward Validation

Walk-forward validation using five expanding windows produced:

Average MAE = 1,032 vehicles

The stability of this value across folds indicates temporal robustness and limited overfitting.

F. Hybrid Linear-Boosted Model

The hybrid Ridge + XGBoost residual model achieved:

MAE = 1,014 RMSE = 1,351 R^2 = 0.256

Although the hybrid model improves over standalone XGBoost, it does not surpass pure linear regression, reinforcing the dominance of autoregressive structure.

G. Traffic Surge Index (Holiday Impact)

The Traffic Surge Index (TSI) is defined as:

$$TSI = \frac{Traffic_{holiday} - Traffic_{baseline}}{Traffic_{baseline}}$$

Computed results:

Baseline traffic: 16,363 vehicles Holiday traffic: 17,092 vehicles TSI = 0.0445

This indicates a 4.45% surge during holiday periods. The moderate magnitude suggests that weekend effects are stronger than isolated holidays.

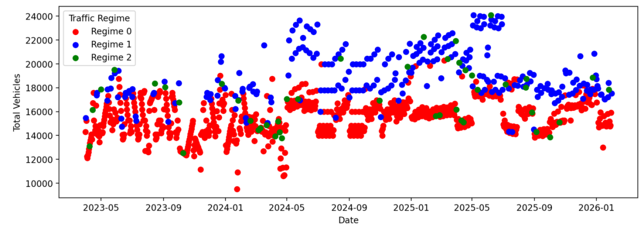

Fig. 1. Clustering-based traffic regime detection. Three regimes are identified: normal flow, moderate surge, and extreme surge states.

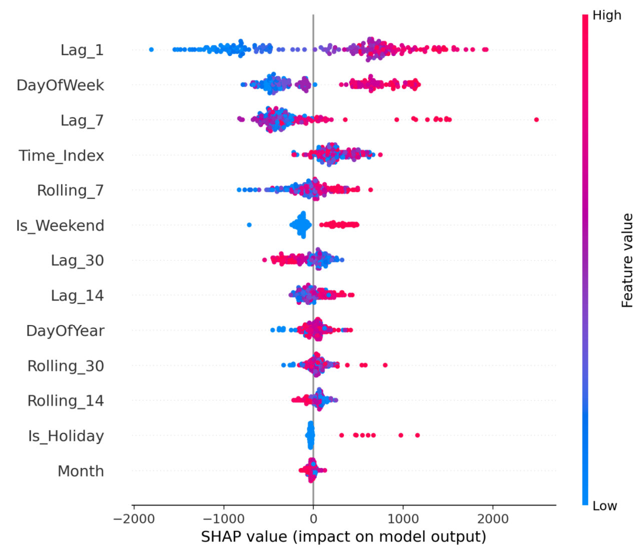

Fig. 2. SHAP summary plot for XGBoost model. Lag-1 and weekly calendar variables dominate predictive contribution.

H. Regime Detection

K-means clustering identified three traffic regimes:

Regime 0: Normal flow (739 days) Regime 1: Weekend/moderate surge (254 days) Regime 2: Extreme surge events (45 days)

This confirms structural heterogeneity in demand patterns.

I. Uncertainty Modeling

Quantile regression produced asymmetric 10%–90% prediction intervals. Interval widening during surge periods confirms increased volatility under high-demand states.

J. SHAP Explainability

SHAP analysis indicates that:

Lag-1 traffic is the dominant predictor. Day-of-week strongly influences positive deviations. Holiday effects are episodic and lower in global importance.

This reinforces the autoregressive dominance hypothesis.

K. Economic Impact Estimation

Average forecasting error $\approx$ 1,000 vehicles.

Assuming mean toll $\approx$ 110 per vehicle:

$$Daily\ Revenue\ Error \approx 1{,}000 \times 110 = 110{,}000$$

This translates into substantial operational and budgeting uncertainty, emphasizing the economic value of accurate forecasting.

L. Key Insight

The empirical evidence demonstrates that toll traffic behavior is predominantly linear and calendar-driven, with limited nonlinear interaction complexity. Hybrid modeling provides marginal improvement but does not overturn linear dominance.

This finding challenges the prevailing assumption that complex deep learning models necessarily outperform statistical approaches in structured infrastructure demand forecasting.

VI. Discussion

A. Dominance of Linear Autoregressive Structure

The experimental results reveal that linear regression and Ridge models outperform nonlinear ensemble methods and deep learning architectures. This finding contradicts the common assumption that complex nonlinear models inherently provide superior predictive capability in transportation forecasting.

The dominance of Lag-1 and short-window rolling features indicates that toll traffic dynamics exhibit strong short-memory dependence. The relatively weak improvement from boosting-based residual modeling suggests that nonlinear components contribute marginal incremental variance beyond autoregressive effects.

This implies that toll traffic systems, unlike highly chaotic urban traffic networks, behave as structured demand processes influenced primarily by periodic calendar cycles and immediate historical persistence.

B. Calendar Sensitivity and Behavioral Economics

The statistically significant weekend effect (Cohen's $d = 1.09$) confirms that demand amplification is behaviorally driven. The magnitude of the effect suggests systematic travel pattern shifts rather than stochastic fluctuation.

The Traffic Surge Index (TSI = 4.45%) further quantifies holiday-driven amplification. However, the weekend effect exceeds holiday influence, indicating that routine behavioral cycles are stronger determinants of toll demand than episodic festival events.

From a behavioral economics perspective, this suggests that recurring social schedules dominate infrastructure utilization patterns.

C. Regime Heterogeneity

Clustering results confirm the presence of multiple traffic regimes. Extreme surge days constitute less than 5% of observations yet account for disproportionately high volatility.

This structural heterogeneity justifies adaptive forecasting strategies. Static global models may underperform during regime shifts, particularly during high-demand states.

Future extensions may incorporate regime-switching models or Hidden Markov frameworks to dynamically adapt forecasting parameters.

D. Uncertainty and Risk Implications

Prediction intervals widen substantially during surge periods, confirming volatility clustering. This has operational implications:

- Workforce allocation planning
- Cash flow forecasting
- Infrastructure load balancing

Quantifying uncertainty transforms forecasting from deterministic estimation to risk-aware decision support.

E. Economic Significance

An average forecasting deviation of approximately 1,000 vehicles translates to an estimated 110,000 daily revenue uncertainty.

Over a fiscal year, this may exceed 40 million in cumulative budget variance. Even modest improvements in MAE yield measurable financial stabilization.

Thus, forecasting accuracy is not merely statistical performance but a direct economic optimization variable.

F. Theoretical Contribution

The study contributes to transportation analytics literature in three ways:

1) Demonstrates empirical dominance of linear autoregressive structures over nonlinear machine learning models in structured toll environments.
2) Introduces a Traffic Surge Index to quantify event-based amplification magnitude.
3) Integrates explainable AI (SHAP) with statistical hypothesis testing, bridging predictive modeling and interpretability.

These contributions position toll forecasting within a hybrid statistical–machine learning interpretability framework rather than a purely predictive competition paradigm.

G. Limitations

Several limitations should be acknowledged:

- The dataset is restricted to a single toll corridor, limiting geographic generalization.
- Weather, fuel price, and macroeconomic indicators were not incorporated.
- Deep learning architecture complexity was intentionally constrained to prevent overfitting.

Future research should incorporate exogenous variables and multi-location validation.

H. Implications for Infrastructure Planning

The findings suggest that infrastructure forecasting systems may not require excessively complex models if strong calendar and autoregressive features are properly engineered.

Emphasis should instead be placed on:

- Feature stability analysis
- Regime-aware modeling
- Uncertainty quantification
- Economic interpretation of forecast errors

This shifts focus from algorithmic novelty to structured demand modeling.

VII. CONCLUSION

This study presented an explainable hybrid machine learning framework for daily toll traffic forecasting integrating statistical hypothesis testing, autoregressive feature engineering, ensemble learning, uncertainty modeling, and regime detection.

Empirical evaluation demonstrated that linear autoregressive models outperform nonlinear ensemble and deep learning architectures in structured toll demand environments. Lag-based temporal persistence and calendar effects dominate predictive performance, indicating that toll traffic exhibits short-memory dependence with strong periodic behavioral drivers.

The introduction of the Traffic Surge Index (TSI) enabled quantitative assessment of holiday amplification effects, while regime clustering confirmed structural heterogeneity between normal, weekend, and extreme surge states. Quantile-based prediction intervals further incorporated uncertainty into operational forecasting.

From an economic perspective, average daily forecast deviations correspond to substantial revenue variability, emphasizing the financial importance of model robustness. The findings suggest that infrastructure forecasting systems benefit more from structured feature engineering and interpretability than from increasing algorithmic complexity.

Overall, the results challenge the assumption that advanced nonlinear models inherently provide superior forecasting performance in regulated demand systems. Instead, explainable hybrid statistical–machine learning integration offers a more reliable and economically meaningful framework for toll traffic prediction.

Future research may extend this framework to multi-corridor validation, incorporate exogenous macroeconomic variables, and explore regime-switching adaptive architectures.

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