Project Proposal: Adaptive Traffic Management with Human-in-the-Loop Reinforcement Learning
Target Conference: NeurIPS/ICML (Focus: ML for Real-World Systems, Time Series, RL, Human-AI Interaction)

1. Proposed Title

FACTS: Feedback-Aware Closed-Loop Traffic Stabilization via Hybrid Time Series Forecasting and Anomaly-Aware Reinforcement Learning

2. Problem Statement & Novelty

Research Gap:
Current traffic forecasting and anomaly detection models operate in isolation, assuming static human behavior. Real-world systems, however, involve feedback loops: predictions (e.g., congestion alerts) alter driver behavior, invalidating initial forecasts. This creates a moving target that existing methods (ARIMA, LSTM, etc.) fail to address.
Novelty:

- First unified framework combining anomaly detection, forecasting, and human feedback modeling in traffic systems.
- Closed-loop RL: Agent dynamically adapts to human responses (e.g., rerouting) by simulating feedback via hybrid real-synthetic data.
- Reward shaping based on traffic stability metrics (e.g., entropy reduction in flow variance).

3. Methodology

Pipeline Overview

I. **Data Preprocessing & Anomaly Detection**
   A. Dataset: PeMS (California highways) for traffic flow/speed; NYC Taxi for route-choice patterns.
   B. Anomaly Detection: Use SOTA models (e.g., USAD, TranAD) to flag sudden drops in speed/flow (accidents) or surges (events).

II. **Hybrid Simulation Environment**
   A. SUMO Integration: Initialize simulations with PeMS data, calibrated using NYC Taxi route preferences.
   B. Feedback Modeling: Simulate driver responses to RL actions (e.g., 30% reroute on Waze alerts, stochastic delays in reaction time).

III. **RL Agent Design**

A. State Space: Time series features (flow, speed) + anomaly flags + simulated driver adherence rates.
B. Action Space: Adjust traffic light cycles, send reroute suggestions, activate dynamic lane reversals.
C. Reward Function:

$$R = \underbrace{\alpha \cdot TravelTimeReduction}_{ForecastingGoal} + \underbrace{\beta \cdot AnomalySeverityReduction}_{DetectionGoal} - \underbrace{\gamma \cdot FlowEntropy}_{StabilityPenalty}$$

D.

IV. Forecasting-Driven Adaptation

A. Train a Temporal Fusion Transformer (TFT) to predict traffic states 15–30 mins ahead.
B. Use forecasts to preemptively trigger RL actions (e.g., preempt congestion by rerouting before anomalies escalate).

4. Key Innovations

1. Human Feedback as a Learnable Variable
   - Model driver compliance rates as a latent variable updated via RL interactions (e.g., Bayesian belief updates).
2. Anomaly-Aware Reward Shaping
   - Prioritize actions that resolve anomalies without creating secondary bottlenecks (e.g., penalize over-concentration on detours).
3. Hybrid Data Augmentation
   - Combine PeMS/NYC Taxi with SUMO-simulated feedback loops to generate diverse training scenarios (e.g., accidents + rerouting cascades).

5. Expected Contributions

1. Theoretical: Formalize human-in-the-loop dynamics in time series as a Partially Observable Markov Decision Process (POMDP), where driver responses introduce stochastic state transitions.
2. Technical: Release FACTS, an open-source framework integrating anomaly detection (PyTorch), forecasting (Darts), and RL (Stable Baselines3) with SUMO.
3. Empirical: Demonstrate 20–30% improvement in traffic stability (reduced flow entropy) over baselines (GNNs, pure RL) on PeMS and synthetic accident scenarios.

6. Evaluation Plan

- Baselines: Compare against (1) Isolation-based SOTA (e.g., DeepAR for forecasting, LSTM-AE for anomalies), (2) RL-only (DQN, PPO).
- Metrics:
    - Forecasting: MAE, RMSE for traffic volume/speed.
    - Anomaly Detection: F1-score (event-based).
    - System Stability: Flow entropy, secondary anomaly rate.
- Ablation Studies: Test contributions of feedback modeling, hybrid data, and reward terms.

8. Broader Impact

- **Scalability: Framework generalizes to smart cities (e.g., Singapore, Dubai) with real-time traffic APIs.**
- **Ethics: Reduce congestion-related emissions; Simulate equity (e.g., avoid rerouting bias to low-income areas).**

9. Conclusion

FACTS bridges a critical gap in adaptive traffic systems by unifying anomaly detection, forecasting, and human feedback loops via RL. By leveraging hybrid data and simulation, it offers a path toward self-stabilizing traffic networks, making it highly publishable in ML/transportation venues.

Why A Conference?

- NeurIPS/ICML: Strong fit for ML + real-world systems tracks.
- Novelty: First to model traffic feedback loops as a POMDP with hybrid data.
- Impact: Tackles UNDP Sustainability Goals (SDG 11: Sustainable Cities).