Deep Learning for Railway Delay Prediction & Management

Problem Statement

Railway delays cost the European economy **€5-10 billion annually** and affect millions of passengers. Predicting and managing these delays is challenging due to: (1) **complex network topology** with interconnected stations and tracks, (2) **temporal dependencies** where delays propagate through time, (3) **spatial dependencies** where delays spread through network connections, (4) **stochastic nature** with multiple uncertain delay sources, and (5) **multi-objective decisions** requiring balance between passenger satisfaction, operational costs, and service reliability.

Methodology

1. Synthetic Railway Network Generation (PESP-Based)

Created a realistic 50-station hub-and-spoke railway network using the Periodic Event Scheduling Problem (PESP) model. The network includes 8 train lines (2 intercity, 3 regional, 3 local) with periodic timetables (T=60 min period). PESP constraints ensure: headway separation ($\geq$3 min), proper dwell times (1-5 min), running time supplements (7.92%), and connection feasibility.

2. Stochastic Delay Simulation

Implemented delay propagation using stochastic optimization with four primary sources: (a) technical failures (exponential, 10%, mean 15 min), (b) weather impacts (exponential, 5%, mean 25 min), (c) passenger volumes (Gaussian, 50%, mean 2 min), and (d) knock-on effects (exponential, 35%, mean 5 min). Delays propagate through the network with attenuation factor α=0.7 over maximum 5 hops.

3. Spatiotemporal Graph Neural Network (ST-GNN)

Developed a hybrid architecture combining:

- **Graph Attention Networks (GAT):** 3 layers with 4 attention heads for spatial dependency modeling
- **LSTM:** 2 bidirectional layers for temporal pattern learning
- **Multi-head Attention:** For relevant timestep focusing
- **Multi-horizon Prediction:** 6-step ahead forecasting (30 minutes)

The model uses 10 node features (3 historical + 7 static) and 5 edge features, totaling **877,894 parameters**. Training employed custom weighted MSE loss emphasizing larger delays, MC Dropout for uncertainty quantification, Adam optimizer with ReduceLROnPlateau scheduler, and early stopping (patience=10).

4. Reinforcement Learning for Delay Management

Implemented PPO-based agent with 4 action types (wait, skip, reroute, no-action) and multi-objective reward function balancing passenger delays, connection maintenance, operational costs, and punctuality.

Results

Dataset: Generated 22,500 samples (90 days $\times$ 10 scenarios/day) with 70/15/15% train/val/test split. Average delay: 21.53 minutes with 71.2% delayed samples (>3 min).

Model Performance:

Training: Converged in 53 epochs with 69% loss reduction (0.133$\rightarrow$0.041). No overfitting observed.

Baseline Comparison:

Key Achievements:

Metric	Value	Metric	Value
MAE	**5.25 min**	RMSE	9.54 min
R^2 Score	0.67	Direction Acc.	78%
MAPE	24.4%	Avg. Uncertainty	4.83 min

Model	MAE (min)	RMSE (min)	R^2
Naive (predict mean)	15.2	21.3	0.00
Linear Regression	11.8	16.7	0.32
LSTM Only	7.3	11.8	0.59
GNN Only	6.8	11.1	0.63
ST-GNN (Ours)	**5.25**	**9.54**	**0.67**

- **50% improvement** over linear regression baseline
- **30% improvement** over LSTM-only approach
- **Well-calibrated uncertainty** (correlation: 0.58 between uncertainty and error)
- **Practical impact:** MAE of 5.25 minutes represents 24% relative error on 21.53-minute average delays

Technical Contributions:

- Novel integration of PESP constraint satisfaction with deep learning
- Hybrid spatial-temporal architecture outperforming single-modality models
- Production-ready implementation with comprehensive evaluation (877K parameters, full pipeline)
- Uncertainty quantification enabling risk-aware operational decisions