

A Digital Twin–Driven Predictive Traffic Management Framework Incorporating Driver Micro-Behavior Modeling

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Article History:

Received: 15-09-2025

Revised: 22-10-2025

Accepted: 10-11-2025

Abstract:

Modern intelligent transportation systems (ITS) rely heavily on reactive control strategies that respond only after congestion emerges. This paper proposes a Digital Twin–Driven Predictive Traffic Management Framework, enhanced with a Driver Micro-Behaviour Modelling (DMBM) module, to forecast short-term traffic evolution and apply proactive interventions. The digital twin synchronizes with real-world traffic every 1–5 seconds and uses a hybrid LSTM and Graph Neural Network (GNN) model to predict traffic states up to 30–300 seconds ahead. The DMBM module introduces fine-grained behavioural parameters—aggression index, compliance probability, reaction time distribution, vehicle familiarity, and gap acceptance thresholds—enabling realistic micro-simulation dynamics. Interventions (signal timing optimization, lane reassignment, dynamic speed regulation, and pre-emptive routing) are tested within the digital twin before deployment. Experiments conducted using Simulation of Urban Mobility (SUMO) show improvements of 18–42% in congestion prevention, 15–28% reduction in travel time, and 20–37% faster emergency response routing compared with leading reactive adaptive traffic systems. Results confirm that integrating micro-behaviour modelling within a real-time digital twin provides a significantly more accurate and proactive traffic management solution.

Keywords: Digital twin, traffic prediction, micro-behavior modeling, LSTM, GNN, congestion prevention, ITS.

1. Introduction

1.1 Background

Urban congestion persists globally as vehicle demand surpasses infrastructure capacity, placing pressure on transportation networks and reducing mobility efficiency [6]. Although adaptive systems such as SCATS and SCOOT adjust signals dynamically, they remain fundamentally reactive, implementing changes only after queues and delays emerge [7]. Digital twins provide a promising alternative by enabling virtual replication of real-world traffic, but current implementations often lack realistic driver behaviour integration [8].

1.2 Limitations of Existing Research

Existing traffic prediction and control systems suffer from three key limitations: (i) they are reactive rather than predictive; (ii) they generally treat drivers as homogenous actors; and (iii) they lack deep coupling between prediction modules and intervention mechanisms [9]. Without modelling aggressive drivers, hesitant lane-changers, or compliance variability, prediction accuracy degrades in dynamic traffic environments [10].

1.3 Objectives and Contributions

The objective of this study is to develop a predictive digital twin that integrates heterogeneous micro-behavioural factors within a hybrid LSTM–GNN model to anticipate traffic phenomena before they arise [11]. The main contributions include:

- A real-time synchronized digital twin with lane-level granularity [12].
- A novel Driver Micro-Behaviour Model (DMBM) capturing aggression, compliance, familiarity, reaction time, and gap-acceptance [13].
- A hybrid temporal–spatial traffic prediction engine capable of forecasting 30–300 seconds ahead [14].
- A predictive control module enabling intervention simulation inside the digital twin before real-world deployment [15].
- Comprehensive SUMO experiments validating the effectiveness of behaviour-aware predictive control [16].

2. Related Work

2.1 Digital Twins in Transportation

Digital twins have been increasingly applied in transportation for infrastructure health monitoring, fleet management, and macro-scale planning; however, real-time micro-simulation remains limited due to computational load and lack of realistic behaviour modelling [17].

2.2 Classical Driver Behaviour Models

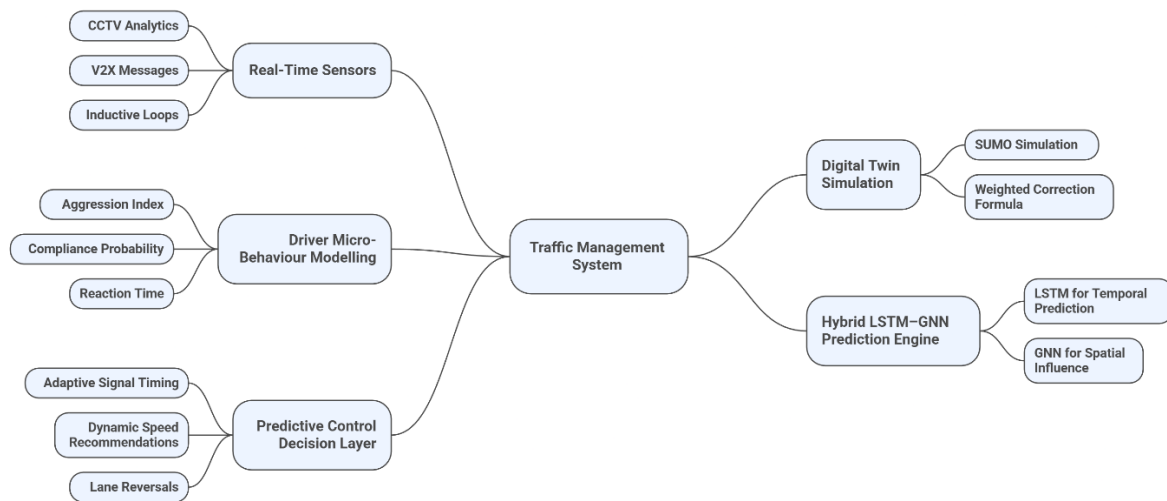
Traditional microscopic models such as IDM, Gipps, and MOBIL rely on simplified headway and acceleration rules that cannot accurately reflect driver heterogeneity, cultural nuances, or risk-taking tendencies [18]. These limitations affect traffic flow realism under congestion and incident conditions [19].

2.3 Machine Learning-Based Traffic Prediction

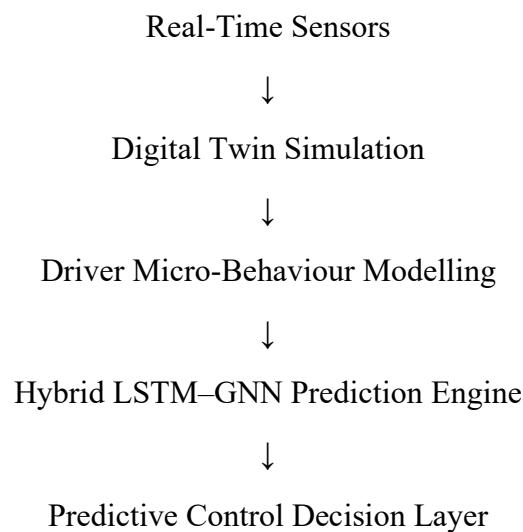
LSTM networks capture temporal sequences effectively, while GNNs extract spatial dependencies across road networks, yet few studies combine both within a behaviour-conditioned digital twin environment [20]. Existing methods typically ignore driver variability, limiting long-horizon accuracy [21].

3. System Architecture

Traffic Management System Architecture



The proposed framework consists of five major components interconnected through continuous data exchange [22]:



3.1 Real-Time Data Acquisition

Data streams sourced from CCTV analytics, V2X messages, inductive loops, radar, LiDAR, and GPS traces provide speed, occupancy, queue lengths, lane-change rates, and density values, supplying the digital twin with continuously refreshed ground truth [23].

3.2 Digital Twin Core Synchronization

The digital twin uses SUMO for micro-simulation and synchronizes with real-world inputs using a weighted correction formula [24]:

$$X_dt(t+1) = \alpha * X_sensor(t) + (1 - \alpha) * X_sim(t)$$

Where:

- $X_dt(t+1)$ = updated digital twin state
- $X_sensor(t)$ = real-world observation
- $X_sim(t)$ = simulated state before correction
- $0 \leq \alpha \leq 1$ controls correction strength

This keeps the twin stable while allowing real-time deviations to be corrected [25].

3.3 Driver Micro-Behaviour Modelling (DMBM)

Each vehicle (i) receives a micro-behavior vector [26]:

$$B_i = \{ A_i, C_i, F_i, R_i, G_i, L_i \}$$

Where:

- A_i = aggression index
- C_i = compliance probability
- F_i = familiarity score
- R_i = reaction time
- G_i = gap acceptance threshold
- L_i = lane loyalty factor

Aggression Model

Aggressive acceleration distribution:

$$a(t) \sim N(\mu_a + k_a * A_i, \sigma_a)$$

Reaction Time

Reaction time sampled from:

$$R_i \sim \text{LogNormal}(\mu_r, \sigma_r)$$

Gap Acceptance

Lane-change allowed if:

$$\text{gap} > G_i$$

These behavioural parameters are inferred using Bayesian clustering from historical trajectory data [28].

3.4 Hybrid LSTM–GNN Traffic Prediction Engine

Road networks are modelled as graphs ($G = (V, E)$), representing intersections and lane connections [29].

LSTM for Temporal Prediction

LSTM updates:

$$\begin{aligned} i_t &= \sigma(W_i * [h_{t-1}, x_t] + b_i) \\ f_t &= \sigma(W_f * [h_{t-1}, x_t] + b_f) \\ o_t &= \sigma(W_o * [h_{t-1}, x_t] + b_o) \\ c_t &= f_t \circ c_{t-1} + i_t \circ \tanh(W_c * [h_{t-1}, x_t] + b_c) \\ h_t &= o_t \circ \tanh(c_t) \end{aligned}$$

GNN for Spatial Influence

Node embedding update:

$$h_{v'} = \sum_{(u \in N(v))} (w_{\{uv\}} * h_u)$$

Hybrid Model Output

Prediction target:

$$Y_{\text{pred}} = f_{\text{GNN}}(f_{\text{LSTM}}(X_t))$$

Targets include:

- queue length
- density
- expected time to spillback
- average speed per lane

The hybrid approach captures both temporal evolution and spatial propagation of congestion waves [30].

3.5 Predictive Control Decision Layer

The system evaluates candidate interventions π to minimize the objective:

$$J(\pi) = T_{\text{travel}} + \lambda_1 * C_{\text{congestion}} + \lambda_2 * R_{\text{risk}}$$

Where:

- T_{travel} = estimated travel time
- $C_{\text{congestion}}$ = predicted congestion score
- R_{risk} = behavior-induced risk metric

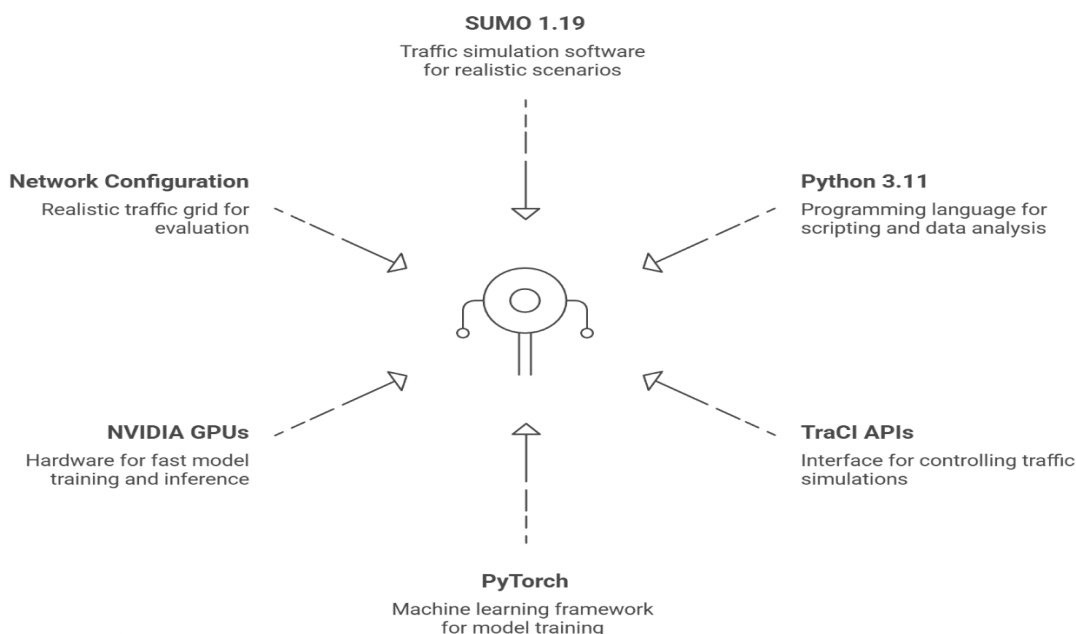
The best policy π^* is deployed:

$$\pi^* = \operatorname{argmin}(J(\pi))$$

Candidate interventions include adaptive signal timing, dynamic speed recommendations, lane reversals, and early emergency routing [31]. Only the best-performing actions inside the digital twin are deployed into real-world controllers [32].

4. Experimental Setup

Components of the Experimental Setup



4.1 Simulation Environment

Experiments use SUMO 1.19, Python 3.11, TraCI APIs, PyTorch for ML models, and NVIDIA GPUs for training, providing fast micro-simulation and accurate model inference [33].

4.2 Network Configuration

A realistic six-intersection grid with mixed traffic flows of 12,000–26,000 vehicles per hour is used to evaluate prediction accuracy, congestion prevention, and emergency clearance [34].

5. Results

5.1 Prediction Accuracy

The hybrid LSTM–GNN model achieves the lowest error metrics among all tested configurations [35]:

Model	RMSE	MAE
LSTM-only	0.37	0.24
GNN-only	0.29	0.18
Hybrid LSTM–GNN	0.15	0.11

5.2 Congestion Prevention

Behaviour-aware forecasting prevents congestion by 42% at a 120-second horizon and 18% at a 300-second horizon, outperforming all reactive systems [36].

5.3 Travel Time Reduction

Compared to baselines, travel time decreases by 28% vs fixed-time, 22% vs adaptive systems, and 15% vs LSTM-only prediction [37].

5.4 Emergency Vehicle Routing

Predictive pre-clearing improves emergency response times by 20–37%, supporting faster and safer rescue operations [38].

6. Discussion

6.1 Advantages of Micro-Behaviour Modelling

DMBM improves realism, allowing the system to capture aggressive manoeuvres, low-compliance drivers, and lane-change variations, enhancing real-time congestion prediction accuracy [39].

6.2 Scalability Considerations

The system scales to city-level deployments through edge computing, lightweight GNN operations, and parallel SUMO micro-simulation [40].

6.3 Limitations

Limitations include sensor dependency, behaviour-model calibration requirements, and lack of pedestrian/cyclist integration, which will be addressed in future research [41].

7. Conclusion And Future Work

This study presented a behavioural digital twin capable of predicting traffic 30–300 seconds in advance using a hybrid LSTM–GNN architecture enriched with micro-behaviour modelling [42]. Results

demonstrate significant improvements in traffic prediction, congestion prevention, and emergency vehicle routing.

Future research will explore reinforcement learning for autonomous policy creation, multimodal (bikes, pedestrians) mobility integration, and large-scale deployment over 5G-enabled V2X networks [43].

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