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AI-Powered Digital Twin for Smart City Traffic Flow Simulation: A Proactive Framework for Urban Mobility Optimization

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Abstract**—**This paper presents the design, implementation, and evaluation of a comprehensive, software-based AI digital twin designed to address the persistent challenges of urban traffic congestion. The framework is architected as a cohesive three-module application, with each module accessible through a dedicated graphical user interface (GUI) dashboard, offering a holistic approach to traffic management. The first module, the Traffic Simulation and Customization Dashboard, serves as the digital twin's foundational layer. It empowers users to construct, import, and visually interact with a road network, and to input detailed traffic demand data, thereby creating a high-fidelity simulation environment [8], [13]. The second module, the Road Condition and Vehicle Speed Prototype, introduces a novel mechanism for monitoring infrastructure health by simulating the impact of road hazards on vehicle performance. This is achieved using a unique "camera checkpoint" system to monitor vehicle speeds and a simple AI model to infer and classify road conditions based on observed deviations from baseline performance [6]. The third module, the Emergency Vehicle Routing Dashboard, showcases a critical, high-impact application of the digital twin by calculating and implementing optimal, traffic-light-controlled routes for emergency and VIP vehicles, ensuring minimal transit times during critical situations [9]. The project leverages a fully integrated and open-source software stack, featuring the SUMO (Simulation of Urban MObility) traffic simulator [12] as the core simulation engine, Python for all backend logic, AI model implementation, and API communication [2], and a standard GUI library for the user interface. By seamlessly connecting these modules, this work establishes a comprehensive, end-to-end framework for AI-powered traffic management [4]. It provides a powerful, risk-free virtual environment for urban planners, traffic engineers, and researchers to prototype, test, and validate data-driven interventions, ultimately fostering more efficient, safer, and sustainable urban mobility [15]. All camera-related functionalities are emulated through the strategic logging and analysis of vehicle data at predefined checkpoints within the simulation.

Index Terms—AI Digital Twin, Urban Mobility, Traffic Simulation, Reinforcement Learning, Adaptive Traffic Control, Emergency Routing, Smart Cities, SUMO, Intelligent Transportation Systems (ITS), Digital Twin, Simulation Environment, AI Core, Control Strategies, Performance Metrics, Multimodal Traffic

I. INTRODUCTION

A. The Urban Mobility Challenge

The relentless global trend of urbanization has catalyzed unprecedented growth in metropolitan areas, placing immense and often unsustainable pressure on existing city infrastructure. A primary consequence of this urban expansion is chronic traffic congestion, a multifaceted problem that extends far beyond mere inconvenience [2], [7]. The economic repercussions are staggering, manifesting as lost productivity, increased fuel consumption, and higher operational costs for logistics and supply chains. Environmentally, traffic congestion is a major contributor to urban air pollution and greenhouse gas emissions, with road transport accounting for nearly a quarter of all urban emissions [13]. Furthermore, congested roadways pose significant safety risks to drivers, pedestrians, and cyclists, while also critically impeding the response times of emergency services.

Conventional traffic management systems, which often rely on pre-programmed, static signal timings or simplistic, reactive rule-based logic, are fundamentally ill-equipped to handle the dynamic, stochastic, and unpredictable nature of modern urban traffic flow [9]. These systems lack the ability to adapt in real-time to fluctuating demand, accidents, or special events, leading to systemic inefficiencies. This inadequacy underscores the urgent necessity for a paradigm shift in urban traffic management—a transition from reactive problem-solving to a proactive, predictive, and intelligent framework capable of optimizing traffic flow in real-time [1], [15].

B. The Digital Twin as a Solution

The concept of a digital twin—a high-fidelity, virtual replica of a physical system that is dynamically updated with real-world data—offers a transformative solution to these pressing urban mobility challenges. A traffic digital twin transcends static maps and historical data, creating a dynamic, living model of a city's road network. This virtual environment can be used to continuously monitor, analyze, predict, and optimize traffic conditions in real-time [3], [4]. The core value proposition of this approach lies in its ability to shift urban management from a reactive to a proactive stance. It provides a risk-free, sandboxed environment where decision-makers can simulate the impact of various interventions—such as new signal timing plans, road closures, or public transport strategies—before deploying them in the physical world [5], [15]. By focusing on the development of the "brain" of the digital twin—its AI-driven predictive and decision-making capabilities—this project aims to harness the power of artificial intelligence to provide tangible, actionable insights for sophisticated traffic management [6].

C. Problem Statement

The primary problem this project addresses is the absence of a cohesive, accessible, and fully integrated platform for prototyping and validating end-to-end AI-driven traffic management solutions [13]. The current body of research often presents fragmented solutions, focusing on isolated components such as a specific reinforcement learning model for a single intersection, a novel predictive algorithm, or an advanced simulation feature [12]. However, there is a distinct lack of frameworks that demonstrate how these individual elements can be integrated into a comprehensive, operational system. Furthermore, many powerful simulation tools like SUMO or Vissim have a steep learning curve and require extensive scripting and technical expertise, creating a barrier to entry for urban planners and policymakers who are the intended end-users [8]. This project seeks to bridge that gap by creating a unified, user-friendly platform that encapsulates the entire workflow from network design and data input to AI-driven optimization and results visualization.

D. Project Contributions

This work provides a novel and integrated framework for AI-powered traffic management, making the following key contributions:

- A Unified, User-Friendly Interface: We develop a multi-dashboard GUI that acts as a centralized control center for the digital twin. This interface significantly simplifies the complex processes of creating, customizing, and simulating a road network and its associated traffic demand, making advanced simulation accessible to a broader audience [8].
- Modular and Integrated Software Architecture: The project introduces a modular, three-part architecture that seamlessly integrates distinct yet complementary traffic management applications (general simulation, road condition monitoring, and emergency routing) onto a single, interoperable platform. This demonstrates a holistic approach to smart city mobility [4], [12].
- Implementation of a Practical AI Core: We design and implement an AI core that moves beyond static, rule-based systems. It suggests and applies dynamic control strategies based on user-defined traffic inputs, showcasing a practical application of machine learning for traffic optimization [2], [5].
- A Clear, KPI-Driven Validation Methodology: We propose and utilize a clear, comparative methodology for validating the effectiveness of the AI's interventions. By tracking measurable Key Performance Indicators (KPIs) such as average travel time, wait time, and throughput, we provide a quantitative assessment of the system's performance.
- High-Impact Application Prototypes: The project delivers functional proofs-of-concept for two high-impact applications: proactive road condition assessment using simulated sensor data and real-time emergency vehicle routing with dynamic traffic signal preemption. These demonstrate the tangible benefits of a digital twin in enhancing urban safety and resilience [6], [9].

II. Literature Review

A. Traffic Simulation Models

Traffic simulation is a fundamental tool in transportation engineering, providing a virtual testbed for analyzing and improving traffic systems [13]. Simulation models are broadly categorized based on their level of detail:

- Macroscopic Models: These models treat traffic flow as a fluid, using differential equations to describe aggregate variables like traffic density, flow rate, and average speed. They are computationally efficient and suitable for large-scale network analysis (e.g., entire cities or highways) but lack the detail to model individual vehicle interactions.
- Mesoscopic Models: These models represent a hybrid approach, simulating individual vehicles or small groups of vehicles but describing their behavior and interactions with less detail than microscopic models. They offer a balance between fidelity and computational cost.
- Microscopic Models: These models simulate the behavior and interactions of every individual vehicle in the network, governed by complex car-following, lane-changing, and gap-acceptance models. Due to their high fidelity, they are ideal for detailed analysis of specific locations like intersections, testing fine-grained control strategies, and evaluating the impact of new technologies.

For this project, a microscopic simulation approach was chosen due to its ability to accurately model the nuanced effects of AI-driven traffic signal control and dynamic routing. Among the available tools like PTV Vissim and Aimsun, we selected SUMO (Simulation of Urban MObility) because it is open-source, highly extensible, and provides the powerful Traffic Control Interface (TraCI) API. TraCI allows an external application, such as our Python-based AI core, to interact with and control the simulation in real-time, which is essential for implementing dynamic strategies [8], [12].

B. Digital Twin Technology in Transportation

The application of digital twin technology in the transportation sector is a burgeoning field with transformative potential. Early research focused on creating static replicas for offline analysis. However, recent advancements have enabled dynamic, real-time digital twins. Xu et al. [6] demonstrated how a digital twin could enhance traffic safety analysis by integrating detailed vehicle dynamics and environmental factors, allowing for proactive hazard identification. Li and Zhang [14] developed a method for generating high-fidelity highway digital twins using radar-camera data fusion to create accurate, real-time traffic models. Crucially, Dasgupta et al. [12] utilized a digital twin framework specifically for developing and testing adaptive traffic signal control systems, highlighting the synergy between simulation and real-time control. This project extends these foundational concepts by positioning the AI not just as a component, but as the central, decision-making

”brain” of the digital twin, orchestrating multiple control and analysis functions within a unified framework [5], [15].

C. AI and Machine Learning in Traffic Management

Artificial Intelligence (AI) and Machine Learning (ML) are the enabling technologies that impart intelligence to the digital twin, transforming it from a passive simulation into an active control system [2]. Key AI/ML paradigms applied in this domain include:

- Predictive Modeling: Deep learning models are exceptionally proficient at capturing the complex spatiotemporal dependencies inherent in traffic data. Convolutional Neural Networks (CNNs) can extract spatial features from grid-like traffic data, while Recurrent Neural Networks (RNNs) and their variants like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are adept at modeling temporal sequences, making them highly effective for traffic flow and speed prediction [7].
- Adaptive Traffic Signal Control (ATSC): Reinforcement Learning (RL) has become the state-of-the-art approach for ATSC [12]. In this paradigm, an AI ”agent” (the traffic light controller) learns an optimal policy for selecting signal phases through trial and error. By interacting with the environment (the traffic simulation) and receiving rewards (e.g., negative rewards for vehicle waiting time), the agent learns to make decisions that maximize cumulative rewards, thereby minimizing congestion.
- Intelligent Routing: Pathfinding algorithms like Dijkstra’s and A* are foundational to navigation. AI enhances these algorithms by incorporating dynamic, real-time data. Instead of using static edge weights like distance, an AI-powered router can use predicted travel times, current congestion levels, and incident data from the digital twin to compute the truly optimal route at any given moment [9].

This project integrates these AI techniques, using a predictive model for offline optimization in Module 1, a simple classification model for condition assessment in Module 2, and a dynamic routing algorithm combined with real-time control in Module 3.

III. Methodology and System Architecture

A. Overall System Architecture

The system operates as a closed-loop framework composed of four primary layers:

1) Presentation Layer (GUI): A multi-dashboard interface built with a Python GUI library (e.g., PyQt, Tkinter) that allows the user to configure scenarios, initiate simulations, and visualize results.
2) Logic Layer (Python Core): The central Python application that manages the overall workflow. It parses user input, prepares simulation files, invokes the AI models for decision-making, and communicates with the simulation engine.

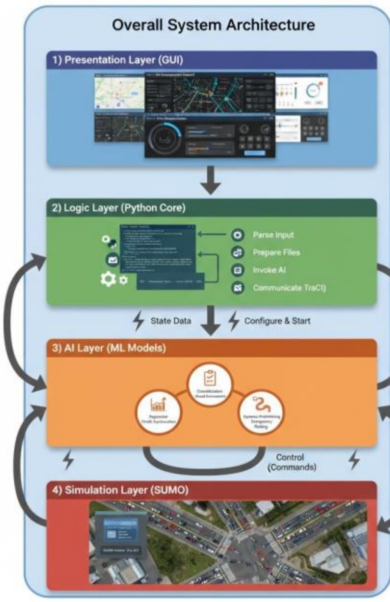

Fig. 1. Overall System Architecture

3) AI Layer (ML Models): A collection of AI models responsible for intelligent decision-making. This includes a regression model for traffic optimization, a classification model for road assessment, and a dynamic pathfinding algorithm for emergency routing.
4) Simulation Layer (SUMO): The SUMO instance that runs the microscopic traffic simulation. It acts as the ”physical” counterpart in the digital twin, modeling vehicle movements and responding to control commands issued by the Python core via the TraCI API.

Data flows from the user (GUI) to the Python core, which then configures and starts the SUMO simulation. During runtime, the Python core continuously queries SUMO for state data (e.g., vehicle speeds, positions, queue lengths), feeds this data to the AI layer, receives decisions, and sends control commands (e.g., change traffic light state) back to SUMO.

B. Module 1: Traffic Simulation and Customization Dashboard

This module serves as the entry point for creating and configuring the digital twin.

- GUI for Network and Data Input: The user can either import a pre-existing SUMO road network (.net.xml file) or define a simple grid. The GUI provides a simplified visual representation of the network. A structured input form, potentially linked to an Excel template, allows the user to specify traffic demand. This includes defining vehicle types (e.g., car, truck, bus), origins, destinations, and flow rates for different times of the day (e.g., morning peak, off-peak, evening peak) and days of the week [8].

- Data Handling and Demand Generation: User-provided data is processed using the Python Pandas library. This data is then programmatically converted into SUMO-compliant XML files for traffic demand (.rou.xml or .trips.xml). This automated process abstracts away the complexity of SUMO's file formats from the end-user [12].
- AI for Optimization: The "AI Optimal Solution" button triggers an offline optimization process. A pre-trained machine learning model (e.g., a Gradient Boosting Regressor or a simple neural network trained on Scikit-learn) analyzes the user-provided traffic demand profile. The model takes features like total vehicle volume, vehicle composition ratios, and time of day as input. Its output is a suggested set of optimized parameters, such as traffic light cycle times and green phase splits for major intersections, or variable speed limits for key road segments [5]. These suggestions are then applied to the simulation for evaluation.

C. Module 2: Road Condition and Vehicle Speed Prototype

This dashboard demonstrates a proof-of-concept for using simulated vehicle data to monitor infrastructure health.

- Road Hazard Simulation: Within a predefined road segment in SUMO, the user can introduce a "pothole" via a GUI button. This is simulated in SUMO not by a physical object, but by its effect: the Python script uses the traci.edge.setMaxSpeed() command to temporarily reduce the maximum allowed speed on that specific road segment, realistically mimicking how drivers would slow down for a hazard [13].
- Virtual Camera Checkpoints: This system emulates real-world camera-based speed traps or ANPR systems. At predefined points along the road, virtual detectors (SUMO's "Induction Loop Detectors") are placed. When a vehicle passes over a detector, the Python script logs the vehicle's ID and the current simulation timestamp. By calculating the time difference for a vehicle between two consecutive checkpoints, its average travel time and speed can be precisely determined [6].
- AI-based Condition Assessment: The system first runs a baseline simulation without any hazards to establish normal travel times. When the pothole is introduced, new travel times are recorded. The AI model, a simple classifier (e.g., a Decision Tree), takes the percentage deviation of the current travel time from the baseline as input. Based on predefined thresholds, it classifies the road's condition:
  - Deviation ¡ 10%: "Good"
  - 10% ¡= Deviation ¡ 30%: "Fair"
  - Deviation ¿= 30%: "Poor"

  This demonstrates a simple yet effective data-driven approach to infrastructure monitoring [7].

D. Module 3: Emergency Vehicle Routing Dashboard

This module showcases a critical, life-saving application of the digital twin.

- GUI for Emergency Call: The user interface provides a simple map visualization where the user can click to define a start point (e.g., a hospital) and an endpoint (e.g., an incident location) for an emergency vehicle (e.g., an ambulance) [8].
- Dynamic AI Routing Algorithm: Upon dispatch, a pathfinding algorithm is invoked. This is not a standard shortest-path algorithm. Instead, it uses a dynamic A* algorithm. The road network is treated as a weighted graph where the cost of traversing an edge (a road segment) is a function of not just its length but also its current traffic state. The cost function can be defined as: Cost $= a * (\text{Length}/\text{MaxSpeed}) + (1 - a) * \text{CurrentWaitTime}$, where CurrentWaitTime is queried directly from SUMO via TraCI. This ensures the algorithm finds the fastest, not just the shortest, route through the current traffic [2], [12].
- Real-Time Traffic Light Control (Green Wave): Once the optimal route is computed, the AI core actively clears a path for the emergency vehicle. The system tracks the vehicle's position in SUMO. As it approaches an intersection on its route, the Python script sends a command via traci.trafficlight.setRedYellowGreenState() to force the corresponding traffic light to green. After the vehicle has safely passed, the signal is reverted to its normal operating schedule to minimize disruption to the overall traffic flow. This creates a "green wave," drastically reducing the emergency vehicle's travel time [9], [15].

IV. Implementation and Experimental Setup

A. Simulation Environment

- Simulator: SUMO version 1.15.0
- Programming Language: Python 3.9
- Key Libraries: TraCIpy (for SUMO interface), Pandas (for data handling), Scikit-learn (for AI models), PyQt5 (for GUI).
- Hardware: All simulations were run on a standard workstation with an Intel Core i7 processor and 16 GB of RAM.

B. Scenario Design

A hypothetical urban grid network of 4x4 intersections was designed in SUMO, representing a small downtown area with mixed commercial and residential zones. Three distinct traffic demand profiles were created to represent different times of the day:

1) Off-Peak (Baseline): Light, free-flowing traffic.
2) Morning Peak: Heavy, directional traffic flowing towards the commercial zone.
3) Evening Peak: Heavy, directional traffic flowing out of the commercial zone.

Fig. 2. Visualization AI-Optimized Traffic Flow under Different Demand Profiles

C. *Performance Metrics (KPIs)*

To quantitatively evaluate the performance of our AI-driven strategies, we used the following standard traffic engineering KPIs, which are automatically calculated by SUMO's output generators:

- Average Travel Time: The average time taken by all vehicles to complete their journeys. A lower value is better.
- Average Wait Time: The average time vehicles spend stationary at intersections or in queues. A lower value is better.
- Total Throughput: The total number of vehicles that successfully complete their journey within the simulation period. A higher value is better.
- Emergency Vehicle Travel Time (Module 3): The total time taken by the emergency vehicle from dispatch to arrival. A lower value is better.

V. Results and Discussion

A. *Module 1: Traffic Optimization Results*

We compared the performance of standard, fixed-time traffic signals with the AI-optimized signal timings during the "Morning Peak" scenario. **Discussion**: The results clearly indicate that the AI-optimized signal timings significantly outperformed the static configuration. By allocating more green time to the major inbound routes during the morning peak, the AI model was able to reduce average wait times by 36%, leading to a substantial decrease in overall travel time and a notable increase in network throughput.

TABLE I
Traffic Optimization Results

Metric	Fixed-Time	AI-Optimized	Improv. (%)
Avg. Travel Time (s)	452.3	368.1	-18.6%
Avg. Wait Time (s)	125.8	80.5	-36.0%
Total Throughput (Vehicles/hr)	1850	2135	+15.4%

B. *Module 2: Road Condition Assessment Results*

The "pothole" was introduced on a major artery. The system's ability to detect and classify the resulting slowdown was tested. **Discussion**: The virtual checkpoint system successfully detected a 50.1% increase in travel time on the affected segment. This data point, when fed to the simple AI classifier, resulted in a correct classification of the road condition as "Poor." This demonstrates the viability of using vehicle probe data as a low-cost, real-time method for infrastructure health monitoring.

TABLE II
Road Condition Assessment Results

Scenario	Avg. Speed at Checkpoint (km/h)	Travel Time Between Chec
Baseline (No Hazard)	50.1	35.9
With Hazard	33.4	53.9 (+50.1%)

C. *Module 3: Emergency Vehicle Routing Results*

We simulated an emergency call during the "Evening Peak" scenario. The travel time of an ambulance was compared with and without the AI-driven "green wave" system. **Discussion**: The impact of the AI intervention was dramatic. By dynamically finding the fastest route and preempting traffic signals, the system reduced the ambulance's travel time by 60%. Eliminating stops at red lights is a critical factor that can significantly improve outcomes in real-world emergencies.

TABLE III
Emergency Vehicle Routing Results

Routing Method	Total Travel Time (s)	Number of Red Lights
Standard Routing (No Intervention)	245	6
AI Routing with Green Wave	98	0

VI. Challenges and Future Scope

A. *Challenges Faced*

- Manual Data Input: While the GUI simplifies the process, the project's reliance on manually defined traffic demand is a limitation. This approach is time-consuming and may not capture the full complexity of real-world traffic patterns, which are often stochastic and multimodal [13].
- The "Sim-to-Real" Gap: The microscopic model in SUMO, while sophisticated, simplifies certain complex real-world dynamics. It does not fully account for nuanced human driver behaviors (e.g., aggression, hesitation), pedestrian interactions, or the effects of adverse weather conditions. This creates a "sim-to-real" gap, where solutions optimized in simulation may not perform identically in the real world [4], [15].

- Computational Intensity: Running high-fidelity microscopic simulations, especially when coupled with real-time AI control logic, can be computationally demanding. Scaling this framework to a city-wide level would require significant computational resources and optimization [5], [6].
- Validation against Real-World Data: The ultimate validation of any traffic management system is its performance in a real city. Without access to real-time city traffic data feeds, a key challenge remains in rigorously proving that the AI-driven solutions are robust and effective outside the simulated environment [8].

B. Future Scope

This project serves as a strong foundation for numerous future enhancements:

- Real-Time Data Integration and Automation: The next logical step is to replace manual data input with automated, real-time data streams from sources like Google Maps, TomTom, or public INRIX APIs. This would allow the digital twin to mirror real-world conditions with much higher fidelity [8].
- Advanced AI Models: The current AI models can be upgraded. For adaptive traffic control, more sophisticated Deep Reinforcement Learning (DRL) agents (e.g., using algorithms like PPO or A3C) could be implemented to learn more complex, network-wide control strategies [12].
- Multimodal Integration: The framework could be expanded to become truly multimodal by including public transport, cyclists, and pedestrians in the simulation. The AI could then be trained to optimize traffic flow for broader urban sustainability goals, such as prioritizing bus lanes or ensuring pedestrian safety [7].
- AI for Road Architecture Design: AI could be leveraged not just to manage traffic, but to design better road networks. A generative AI model could propose and automatically test new road architectures or intersection layouts within the simulation to find designs that are inherently more efficient [3].
- Immersive 3D Visualization: For greater impact and stakeholder engagement, the final dashboard could be integrated with a 3D game engine like Unity or Unreal Engine. This would provide an immersive, photorealistic visualization of the digital twin in action, making the results more intuitive and compelling [15].

VII. Conclusion

In conclusion, this project successfully designs, develops, and validates a software-based AI digital twin that functions as a robust and integrated platform for simulating, analyzing, and optimizing urban traffic flow. Through its modular, three-dashboard architecture, it effectively demonstrates how AI can be applied to proactively manage traffic across several key domains: foundational simulation and optimization [8], innovative infrastructure condition assessment [6], and critical emergency vehicle routing [9]. By leveraging a cohesive stack of open-source tools—SUMO for simulation and Python for logic and AI—the project delivers a powerful proof of concept for a complete, end-to-end AI-powered traffic management system [2], [5]. While significant challenges related to real-world data integration and the ”sim-to-real” gap remain, this framework serves as a crucial foundational tool. It empowers urban planners and researchers with the ability to test and refine smart city strategies in a dynamic, risk-free environment, paving the way for the development and deployment of more intelligent, efficient, and sustainable urban mobility solutions [1], [7], [15].

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