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SMART-TWIN: Systematic Modeling and Real-Time Transportation with Digital Twins

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Introduction

Urban traffic systems are becoming increasingly complex, making it harder for transportation agencies to quickly spot problems and respond. Many current traffic management approaches rely on limited data and respond only after issues occur, which can delay responses to events such as lane closures or signal failures. This research introduces SMART-TWIN, an Artificial Intelligence (AI)–driven Digital Twin framework designed to model, analyze, and predict traffic conditions in real time. By integrating detailed traffic modeling, simulated travel patterns, and machine learning to detect disruptions early and quantify their impacts using interpretable performance metrics such as congestion buildup, delay, and user cost. The system provides a scalable and practical foundation for proactive, data-driven transportation management.

Study Methods

To understand how traffic problems develop and how they can be detected early, researchers built a detailed digital model of a real intersection and tested it under different conditions. Using traffic data collected over time, they recreated everyday conditions and common disruptions—such as lane closures and traffic signal failures. They then trained artificial intelligence (AI) models to recognize patterns in the data and identify what was happening on the road in near real time, similar to how a traffic operator might monitor conditions. The team also measured how each disruption affected traffic flow by tracking variables such as how long cars were delayed and how congestion built over time. By combining AI detection with these real-world impact measures, the system could quickly detect problems and quantify their impact. This approach helps translate complex traffic data into measurable, actionable insights that can enable agencies to better respond to issues before they become major delays.

SMART TWIN enables near-real-time detection of traffic disruptions and quantifies their impact, providing a powerful tool for proactive, data-driven traffic management.

Findings

- High-Accuracy Disruption Detection: The AI model achieved near-perfect accuracy (~99.9%) in identifying traffic conditions, including lane closures and signal failures, demonstrating reliable operational state classification.
- Early Warning Capability: Disruptions such as signal failures were detected within one analysis interval (approximately 10 minutes), enabling proactive intervention before severe congestion develops.
- Nonlinear Congestion Growth: Traffic disruptions led to disproportionately large increases in congestion and delay, particularly under higher demand conditions, underscoring the importance of early detection.
- Scalable Decision Metrics: The system successfully translated traffic conditions into measurable impacts, including queue buildup, delay, and user cost, providing actionable insights for traffic management.

Policy/Practice Recommendations

- Adoption of Digital Twin Technology: Transportation agencies should incorporate AI-driven Digital Twin frameworks to enhance real-time traffic monitoring and decision-making capabilities.
- Proactive Traffic Management Strategies: Agencies should leverage early-warning detection systems to implement timely interventions such as signal retiming, lane management, and traveler information updates.
- Investment in Data-Driven Infrastructure: Policymakers should support the integration of simulation, AI, and sensing technologies to improve traffic system resilience and operational efficiency.
- Phased Deployment Using Synthetic Data: Agencies can begin deploying Digital Twin systems using synthetic datasets and gradually integrate real-time sensor data, reducing barriers to adoption.
- Cross-Agency Collaboration: Collaboration between transportation agencies, researchers, and technology providers is essential to scale Digital Twin solutions across corridors and regional networks.

About the Author

Dr. Hovannes Kulhandjian is a tenured full Professor in the Department of Electrical and Computer Engineering at California State University, Fresno. His current research interests are in applied machine learning, wireless communications, and networking with applications to unmanned aerial vehicles, autonomous vehicles, and Intelligent Transportation Systems (ITS). He has secured multiple competitive research grants from federal agencies and industry, including funding from the U.S. Department of Defense to establish the Secure Communications and Embedded Systems Laboratory at Fresno State. Dr. Kulhandjian is the recipient of several research and innovation awards, including the Claude C. Laval III Award for Commercialization of Research, Innovation, and Creativity. He is a Senior Member of the Institute of Electrical and Electronics Engineers (IEEE) and actively contributes to the research community through editorial and leadership roles in intelligent transportation systems, wireless communications, and artificial intelligence.

To Learn More

For more details about the study, download the full report at https://transweb.sjsu.edu/research/2537

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