

The Role of Digital Twin to Advance Urban Smart Mobility Solutions

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Abstract— Smart cities is an urban concept that offers its residents an advanced technology-driven and data-driven socioeconomic opportunity to improve upon their quality of life, attain sustainability, and initiate a new age of urban functioning-the concept incorporates much from domains like energy, transport, public services, and environmental management. Even though every city has its set of requirements and critical challenges leading to the development of highly customized solutions, they all unite for one common thread-mobility, the main focus of this paper. Smart mobility can only be formed by the interaction of technology, policy, and infrastructure. Integration of IoT into smart mobility is a star that has grown vibrant, a rising Christ in the world of smart transportation in an ongoing attempt to increase the efficiency, safety, and sustainability of the transportation system. Digital twins have likewise spread their wings in the fields of IoT and Industry 4.0, being engaged in real-time observation and control over the physical systems. The deduced objectives of the present research are to develop virtual models (digital twins) to propel advancements in transport systems with the ultimate goal of creating more intelligent, responsive, and energy-efficient mobility solutions.

Keywords— *Smart mobility, IOT, Technology, Smart City, Digital twin*

I. INTRODUCTION

As the world becomes increasingly urbanized, cities are faced with an ever-growing list of challenges, with growing traffic congestion, underdeveloped infrastructure, and air pollution taking the spotlight. To address these persistent challenges, many cities have embarked on utilizing the latest technologies in the field of information systems, contributing to the concept of smart cities. Smart cities are concerned with the optimization of urban services such as transport, energy, and public services by the use of technology and data-driven solutions to generate efficiencies and enhance sustainability, quality of the city, and quality of life for its inhabitants. Within the broad context of smart cities, special significance is given to smart mobility in every urban center. Smart mobility exploits avant-garde technologies in applying improved access, safety, and efficiency to the transportation systems to deal with the most critical problems of contemporary cities.

Through IoT technology, data from vehicles, traffic lights, cameras, and weather sensors can be processed and analyzed in real time. This can help to optimize the technologies in traffic management and render operations more efficient. In addition to this, IoT technology fosters the development of connected vehicles in a bid to create the possibility of an intra-vehicle and vehicle-to-infrastructure communication that facilitates better mobility when fighting traffic. Given the extremely few usable parking spaces, this same technology

might also be used to aim at an IP of parking rights, those parking spots that are susceptible to the hailer coming soon. It is expected that in the future communication technology, IoT technology will therefore play an important role in making transportation more efficient by providing real-time data and connectivity, making transportation systems smarter, and optimizing the overall performance of transportation.

Many propositions have been given on how to leverage IoT to improve various aspects of smart mobility like automation of electric vehicles, Intelligent Transport Systems (ITS), Automatic routing and navigation, parking and transportation management. However, research in many of these areas has faced severe challenges mostly due to the use of data that may not be very reliable. Many of the data sets available suffer inadequacies including precision and systematic bias that make them not very trustworthy for research. Lastly, the problem of privacy and security with the data coming from such systems are critically important as it is evident that these systems draw data from sources like cameras, sensors... and could potentially misuse data generated therein unless there are mechanisms to secure the privacy of the individuals involved. Another big challenge is that IoT based solutions are not necessarily scalable. Most existing systems cannot handle relatively large data distributed between thousands of data points, which results in a gap in real-life traffic scenarios. Similarly, the AI-based systems need to interact with and integrate into the existing systems, such as traffic lights, camera systems, and others. The process involves strenuous multitasking that requires coordination and collaboration among various stakeholders, like governmental entities, private companies, and citizens at random.

Among the ways of achieving one, a digital twin would be a kind of virtual representation of a product, process, or service to simulate, analyze, and optimize the performance of their physical counterparts. In the context of smart mobility, a digital twin would be a complete copy of the transportation system-including roads, vehicles, and public transit networks-allowing the simulation, analysis, and optimization of the physical version of these systems. production of a digital twin for a transportation system means creating a real-time virtual model representing the behavior and characteristics of the actual system. The basic goal of using digital twins would be capturing an array of data. This data becomes another primitive key in the modeling, simulation, and performance analysis of these systems. But one cannot just make them disappear; rather they have great potential in revolutionizing the management and operations of these transport systems.

This research explores the application of digital twins in systems designed to support mobility. The paper is structured

as follows: Section II reviews the state-of-the-art, Section III introduces the conceptual framework for the digital twin model, and Section IV concludes the paper.

II. STATE OF THE ART

The state of the art provides an overview of the current knowledge, and technologies in developing smart mobility solutions for smart cities. Analyzing existing solutions is an important step in developing effective solutions, as it helps to identify the best practices and understand challenges.

In [1], paper representing two different implementations of the digital twin—Traffic and Air Quality Digital Twin (TAQ) and Graph-Based Multi-Modal Mobility Digital Twin (GBMMM)—viewed the interaction between traffic flows and air quality through the point of city planners to ensure marked reduction in environmental impact. As for GBMMM's focused, it is to investigate multi-modal transportation systems for effectiveness. These solutions improve the monitoring of urban mobility and environmental quality with limitations like technical challenges intrinsic with high computational complexity and real-time data integration.

In [2], The paper addresses, as a priority, METACITIES for urbanization, with several breakthroughs of digital twins of deployment for potential utilities in smart parking, traffic analysis, and emergencies. These potential benefits are in streamlining traffic flow with environmental gains. Concerns are in scale, rate of data processing, and large cities handling this scenario-dependent on multiple layers.

In [3], the topic of digital twin technology discussed relevant applications, stressing how useful they are to enhance urban efficiency and sustainability. Although in depth, the article lacks specific useful tools for addressing urban mobility challenges hence expectedly bare in some applied contexts.

The paper [4] discussed possibilities of Urban Digital Twins (UDTs) in improving sustainability and efficiency in urban areas. It was discovered that problems include interoperability and the absence of standard-framework-based approaches. While the paper built a strong foundation elaborating on applications of UDTs, its recommendations are more conceptual than they are based on anything empirical.

This research [5] introduced the scalable digital twin framework for urban mobility-DTUMOS, aiming to better predict traffic flow and performance. The most obvious benefit it offered, is scalability for large systems, followed by limitations for requiring much computation and difficulties in integrating heterogeneous data sources.

The paper [6] proposed a digital twin system for real-time prediction of traffic and safety risk, which enables the proactive management of transportation. The paper mentions that the strength of a predictive in silico system seems to be where the city is all messed up regarding the IT deployment.

In [7], a navigational system that used digital twin data for automated vehicles are being studied. The solution results in better traffic efficiency and safety, with wireless networks understanding the dependency. The solution is also less preferred as it requires high costs to implement.

We came up with an out-of-the-box initiative named "Dynamic Urban Mobility Digital Twin System (DUMDTS)" to cater to the downfalls of the approaches extant. This

DUMDTS technology will synchronize real-time data from IoT sensors, traffic management systems, and the public transport network, to build a single digital twin. The system dynamically adjusts to the changing city conditions, predict traffic patterns, optimize public transit schedule, and minimize the environmental impact using machine learning algorithms.

Solution	Advantage	Limitation	Proposed Solution Integration
TAQ and GBMMM [1]	Environmental optimization, multi-modal transport analysis	High computational complexity, limited real-time data integration	Enhanced data integration and adaptability
METACITIES initiative [2]	Optimized traffic flow, environmental benefits	Scalability challenges, high data processing demands	Scalable and interoperable architecture
Broad framework for DT applications [3]	Robust framework for DT implementation	Lack of targeted applications	Targeted urban mobility solutions
Conceptual UDTs [4]	Strong foundation for UDT applications	Conceptual solutions, lack of empirical validation	Empirical validation of proposed models
Scalable urban mobility framework [5]	Traffic prediction, operational efficiency	Dependence on computational resources, heterogeneous data integration challenges	Integrated IoT and ML-based system
Risk-aware predictive analytics [6]	Predictive traffic and safety risk management	Deployment challenges in diverse urban landscapes	Comprehensive urban-wide deployment strategy
Navigation system for automated cars [7]	Improved traffic efficiency and road safety	Dependency on next-gen wireless networks, high implementation costs	Cost-efficient and network-agnostic approach
DUMDTS	Real-time adaptability, scalability, interoperability	Initial setup costs, data privacy concerns	Unique adaptive framework for urban mobility

Table 1: Comparison Matrix

III. DUMDTS

A. Overview

The Dynamic Urban Mobility Digital Twin System (DUMDTS) is a multi-layered framework developed for the data integration on each instance, analysis for the prediction and most important is simulation to regulate the urban smart mobility. DUMDTS make decisions dynamically for the public transportation optimization, management of traffic and reduction of environmental impact. The system followed from IoT sensors, System for traffic management, Network of public transportation and Machine Learning algorithms to develop solutions between the physical layer and digital layer

as a feedback using closed-loop. Scalability, interoperability standardized protocols and edge computing as a key innovation of its architecture to give the real-time responsiveness.

B. Model

1) Physical Layer:

This is a foundation layer, representing real-world environment, contain terrain features such as waterways and elevation, roads and traffic signals as a infrastructure, and mobility like vehicles and sensors which are getting data from the IoT devices. In this layer, the Data is collected from different sources like IoT sensors, LiDAR and satellite imagery, to make the base for the digital twin. The latency is minimize by preprocessing locally data from Edge devices. In the meanwhile, accuracy of geometric data is checked by Building Information Modeling (BIM).

2) Data Acquisition Layer:

The main focus of this layer is to collect historical as well as real-time data sources. Traffic density, movement of pedestrian and some environmental metrics are collected by the IoT sensors, with this public transportation system helps in trajectories for GPS and occupancy rates. Contextual insights are capture from the social media feed and weather forecasts. To optimize the cloud resources which is one of the main element, Apache Kafka used to manage the data streams high-velocity and Redundant Data is filtered by the edge computing nodes.

3) Data Integration & Processing Layer:

For integration and processing of data, first data is convert into unified format from raw data. In the data processing, outliers are cleaned, adding historical averages in place of missing values and fusing is apply on spatiotemporal datasets to find the correlation in traffic jams whenever rain start. Nodes and edges are interconnected using Graph databases like Neo4j model road networks, meanwhile Geospatial storage is handled by the PostgreSQL with PostGIS. To make sure scalability between the diverse data sources, Apache NiFi is used to automate the workflows.

4) Simulation & Modeling Layer:

To make dynamic simulations, Simulation and Modeling layer is used to transform the processed data. 3D visualizations of terrain integration, infrastructure of the city and follow of real-time traffic, is created using the Tool like Unreal Engine or Unity. SUMO platforms, which are used for Agent-based environment, is used to identify the behavior of every vehicle, capture and match the traffic light policies or during accidents it helps in rerouting path strategies. For commter decisions, MATSIM Models is used, such as selecting between public transit or motorcycle in different weather conditions. Historical patterns and real-time sensor feedback is validating back to back by these simulations to make sure the accuracy.

5) Predictive Analytics & Machine Learning Layer:

This layer give the predictive capabilities of the solution. Congestion of traffic is forecast by Long Short-Term Memory (LSTM) machine learning model, while on the other hand, To predict the transit demand Gradient Boosting Machines (GBMs) is used, like to occupancy of bus in rush-hour. Electric vehicles routing as a eco-friendly and balancing the load of grid with schedules of charging is optimize by the Reinforcement Learning (RL). Without sharing the sensitive data and privacy preserving, Federated Learning model is used to help cities to interconnect train models.

6) *Decision Support & User Interaction Layer:* At last, the decision support and user interaction layer plays an important roles between the insights and user end. To prevent from congestion, Traffic manages able to use the dashboards with signal controls adaptation and heatmaps on real-time data. On the other hand, to combine the motorbikes, buses and riders, recommendation of personalized routes is received by commuters via mobile app. Scenarios is simulated by the Policymakers, it helps to make decisions like addition of bike lane and also, access to real-time traffic and environmental impacts. System is integrate with third-party apps using REST APIs integration, like navigation and privacy safeguards.

The layer flows from bottom to top- from data collection in physical layer to predictive analytics and feedback of the user, that create a closed-loop system. For example, Accident occur, detected by a sensor which reroute the traffic by trigger the simulations, congestion forecasts is updated by Machine learning model, and real-time alerts is received by commuters via mobile app. DUMDTS revolves around two key capabilities: modularity, which enables DUMDTS to adapt to cities later on (e.g., swapping simulation tools), and interoperability built on standards-e.g., MQTT-aiming at achieving both scalability and privacy, answering back to the cities' sustainable aspirations too.

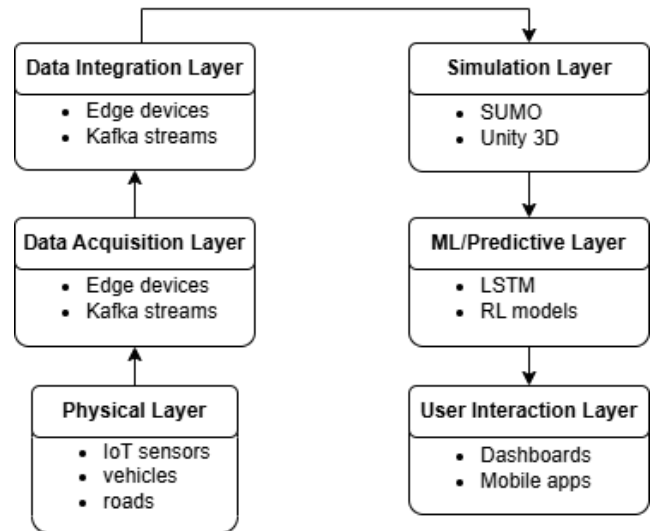


Figure 1: System Architecture

C. Implementation

1) Data Collection & Preprocessing:

For the implementation of DUMDTS, it starts with deployment of IoT sensors in the critical urban infrastructure

such as public transit hubs, intersections and roads. The focus is to collect real-time data like density of traffic, speed of vehicles and air quality. To enable low-latency preprocessing, retrofitted the existing traffic cameras or GPS trackers with modules of edge computing modules (e.g., NVIDIA Jetson or Raspberry Pi). Apache Kafka is used to ingest Data Streams from Wi-Fi/Bluetooth sensors to make sure high-throughput handling of inputs like movement of pedestrian, alerts on social media and weather forecasts.

2) Digital Twin Construction:

In the construction of Digital Twin model, photogrammetry and GIS data is used to build the Digital Twin 3D city model, traffic simulations are integrated with the help of SUMO and Unity is used to replicate real-world dynamics.

3) Machine Learning Integration:

Long Short-Term Memory (LSTM) Machine learning model is used to find the congestion prediction on the road, model is trained on previous years of data, such as traffic log files of previous 5 years and this model is deployed on the Kubernetes clusters using docker containerization for the cloud edge inference and scalability.

4) Deployment & Monitoring

During the deployment of DUMDTS, Rest APIs is used to connect the infrastructure of the city with the Twin model. Basically it's the data coming from the difference devices installed such as electric vehicles chargers, transit fleets and traffic lights and make the real-time adjustment enable like buses rerouting during accidents or via social media alerts.

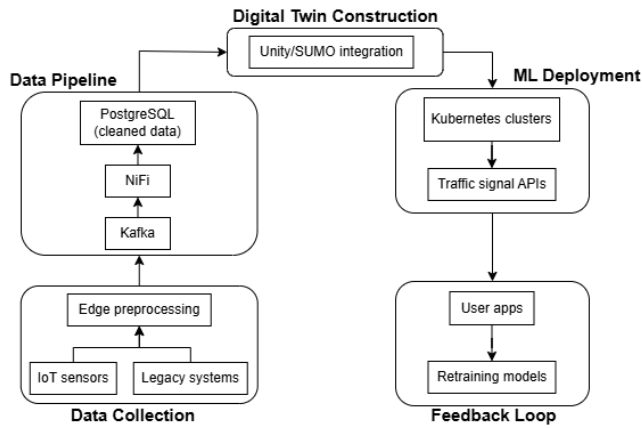


Figure 2: DUMDTS Implementation

D. Validation

This is an iterative process, interconnected pilot testing in mid-sized cities like Helsinki, which is used in this paper to develop the solution, with performance monitoring. Consider Historical traffic data as a baseline to benchmark the simulations such as comparing predicted vs. actual

congestion during rain. Machine learning accuracy is validated using A/B testing: like Reinforcement Learning is used to optimize the traffic signal policies which are tested in controlled zones, with traditional timer-based systems in measured against outcomes. Real-Time system health is tracked using tools like Prometheus and Grafana, mobile apps are used to get citizen feedback to refine models. Incremental rollout is prioritized in Polit phases, which start from single districts to identify scalability.

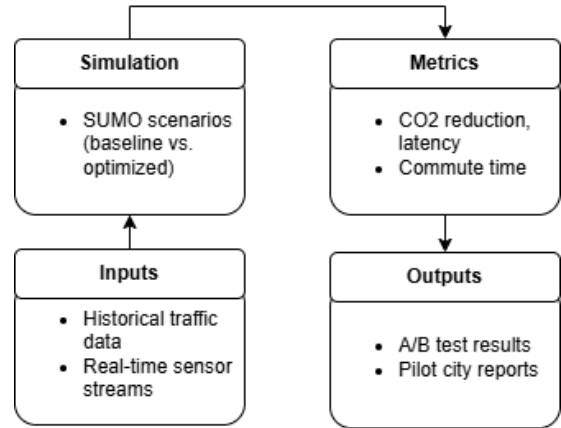


Figure 3: System Validation

REFERENCES

- [1] "Digital Twins for Urban Mobility," *ResearchGate*, Dec. 2024, doi: 10.1007/978-3-031-15743-1_61.
- [2] E. Faliagka *et al.*, "Trends in Digital Twin Framework Architectures for Smart Cities: A Case Study in Smart Mobility," *Sensors*, vol. 24, no. 5, Art. no. 5, Jan. 2024, doi: 10.3390/s24051665.
- [3] R. F. El-Agamy, H. A. Sayed, A. M. AL Akhatatneh, M. Aljohani, and M. Elhosseini, "Comprehensive analysis of digital twins in smart cities: a 4200-paper bibliometric study," *Artif. Intell. Rev.*, vol. 57, no. 6, p. 154, May 2024, doi: 10.1007/s10462-024-10781-8.
- [4] S. Mazzetto, "A Review of Urban Digital Twins Integration, Challenges, and Future Directions in Smart City Development," *Sustainability*, vol. 16, no. 19, Art. no. 19, Jan. 2024, doi: 10.3390/su16198337.
- [5] H. Yeon, T. Eom, K. Jang, and J. Yeo, "DTUMOS, digital twin for large-scale urban mobility operating system," *Sci. Rep.*, vol. 13, no. 1, p. 5154, Mar. 2023, doi: 10.1038/s41598-023-32326-9.
- [6] T. Li *et al.*, "Digital Twin-based Driver Risk-Aware Intelligent Mobility Analytics for Urban Transportation Management," Jul. 03, 2024, *arXiv*: arXiv:2407.15025. doi: 10.48550/arXiv.2407.15025.
- [7] K. Wang *et al.*, "Smart Mobility Digital Twin Based Automated Vehicle Navigation System: A Proof of Concept," *IEEE Trans. Intell. Veh.*, vol. 9, no. 3, pp. 4348–4361, Mar. 2024, doi: 10.1109/TIV.2024.3368109.