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TOWARDS A DIGITAL TWIN FRAMEWORK FOR REGULATING URBAN VEHICLE TRAFFIC USING SMART TECHNOLOGIES

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Abstract: Urban traffic congestion remains a significant global challenge, hindering mobility, sustainability, and economic growth. With traditional traffic management systems struggling to adapt to dynamic conditions, there is a critical need for innovative solutions leveraging smart technologies. This paper proposes and outlines a conceptual digital twin framework to regulate urban vehicle traffic. The framework is designed with a focus on real-time calibration and predictive control, leveraging Internet of Things (IoT), 5G, and vehicle-to-everything (V2X) communication for data integration. By envisioning the integration of mathematical models and distributed software architectures, this framework aims to enhance traffic flow while reducing computational complexity. Crucially, it is conceived to address the challenge of maintaining model accuracy even in sparse-data environments, thereby laying the groundwork for scalable smart urban mobility solutions.

Index Terms: Digital Twin, Urban Traffic Management, Smart Technologies, Real-Time Calibration, Extended Kalman Filter, Model Predictive Control, Simulation of Urban MObility (SUMO), Internet of Things (IoT), 5G V2X Communication, Edge-Cloud Computing

I. INTRODUCTION

Urban traffic congestion remains a widespread and pressing issue globally, generating substantial economic, environmental, and social burdens for cities. According to estimates by the World Bank, congestion can lead to economic losses equivalent to up to 5% of a nation's GDP annually [13], primarily due to diminished productivity, increased fuel consumption, and delays in transportation and logistics. From an environmental perspective, stationary and slow-moving vehicles significantly contribute to greenhouse gas emissions, with urban transportation responsible for approximately 25% of global CO_2 emissions originating from fossil fuel use [14]. Socially, prolonged travel delays negatively affect quality of life, heighten stress levels, and constrain access to essential services and opportunities. Conventional traffic management systems, including fixed-time signal controllers and semi-adaptive schemes such as the Sydney Coordinated Adaptive Traffic System (SCATS), typically operate on predefined schedules or

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offer limited responsiveness to real-time traffic variations [1]. As a result, they often fall short in managing dynamic and unpredictable traffic events, such as accidents, peak-hour congestion, or spontaneous disruptions caused by construction or public gatherings. These limitations, coupled with the underutilization of real-time data, lead to persistent inefficiencies in urban traffic flow. In the context of accelerating urbanization and increasing vehicle ownership, the imperative for intelligent, adaptive traffic management systems has become more pronounced to ensure resilient and sustainable urban mobility.

Advancements in smart technologies—such as the Internet of Things (IoT), 5G connectivity, and vehicle-to-everything (V2X) communication—present transformative potential for addressing the complexities of urban traffic management [2], [9]. IoT-enabled devices, including inductive loop detectors, intelligent surveillance cameras, and environmental monitoring sensors, generate real-time data on traffic flow, vehicle speeds, and roadway conditions, facilitating detailed and continuous observation of traffic dynamics. The deployment of 5G networks, characterized by ultra-low latency and high data throughput, enhances the speed and reliability of data transmission between vehicles, roadside units, and central traffic control platforms, thereby enabling latency-sensitive operations [3]. V2X technologies—which encompass both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications—provide critical, real-time information regarding vehicle location, movement patterns, and driving behaviors, supporting coordinated and predictive traffic control strategies. Collectively, these technologies establish a data-rich framework conducive to adaptive and intelligent traffic regulation. Nonetheless, the integration of such diverse and heterogeneous data sources remains a significant challenge, particularly in urban areas with underdeveloped or uneven sensor infrastructure. Many current systems presuppose the availability of dense, high-quality data, which restricts their scalability and effectiveness in varied and resource-constrained urban environments.

A digital twin, defined as a real-time virtual replica of a physical system, provides a powerful framework for advancing urban traffic management. By modeling a city's road network, including intersections, vehicles, traffic signals, and external factors like weather or pedestrian flows, a digital twin enables real-time simulation, prediction, and optimization of traffic dynamics. Unlike static or offline models, a digital twin continuously updates to reflect the physical traffic system, leveraging data from IoT, 5G, and V2X. This dynamic capability supports proactive strategies, such as predicting congestion hotspots, testing control policies virtually, and optimizing signal timings. Digital twins are particularly suited to handle complex urban scenarios, such as mixed traffic involving autonomous and human-driven vehicles, and can integrate mathematical models for precise analysis. As a cornerstone of smart city initiatives, digital twins bridge the gap between data collection and actionable insights, offering a scalable platform for next-generation traffic solutions.

To ensure scalability and computational efficiency, our proposed framework will implement a distributed edge-cloud architecture, leveraging modern software technologies such as Apache Kafka and MQTT for real-time data messaging, and Kubernetes for container orchestration and workload distribution. We plan to evaluate this framework through a case study within the Simulation of Urban MObility (SUMO) environment, applied to a 4x4 urban grid network. The calibration process will be guided by a flowchart illustrating the EKF-based

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data fusion process, and we anticipate that preliminary simulations will demonstrate a significant reduction in average vehicle delay, aiming for a 15% improvement, thereby highlighting the framework's effectiveness in improving traffic flow through intelligent,

This research aims to design and develop a novel digital twin framework for urban traffic management, emphasizing real-time model calibration for enhanced accuracy and responsiveness, particularly in sparse-data environments. The proposed framework integrates data streams from Internet of Things (IoT) devices, 5G networks, and vehicle-to-everything (V2X) communication for continuous monitoring and dynamic regulation. At its core, it leverages robust mathematical models such as the Lighthill–Whitham–Richards (LWR) for macroscopic traffic flow, an Extended Kalman Filter (EKF) for real-time state estimation and noisy data assimilation, and Model Predictive Control (MPC) for adaptive traffic signal optimization based on forecasted states. This interdisciplinary approach, combining mathematical rigor with distributed software systems, directly addresses current research gaps by offering a scalable solution that aims to reduce delays and emissions – a benefit we expect to validate through SUMO simulations. This foundational work intends to lay the groundwork for future real-world pilot implementations, significantly advancing smart urban mobility research.

II. STATE OF THE ART

Systems like SCATS rely on fixed or semi-adaptive signal timings, lacking responsiveness to real-time dynamics. SCATS (Sydney Coordinated Adaptive Traffic System) uses loop detectors to adjust signal phases based on traffic volume, but its pre-programmed logic struggles with unpredictable events such as accidents, roadworks, or sudden demand surges. Similarly, fixed-time signal controllers, widely used in urban settings, operate on static cycles (e.g., 60-second green phases), failing to adapt to varying traffic patterns. Mathematical models (e.g., Lighthill-Whitham-Richards PDE) provide theoretical foundations but struggle with real-world data integration. The LWR model, a partial differential equation describing traffic flow as a continuum, accurately captures density and speed relationships but requires precise, real-time data for practical application, which is often unavailable in resource-constrained cities. Other models, such as cell transmission models (Daganzo, 1994), simplify traffic dynamics but assume uniform data availability, limiting their effectiveness in dynamic urban environments. These traditional approaches lack the flexibility to leverage modern data sources, highlighting the need for adaptive, data-driven systems.

Smart technologies have been increasingly applied to traffic management, leveraging real-time data from IoT, 5G, and V2X communication. Vo et al. (2024) use 5G for traffic prediction, but calibration for sparse data is underexplored. Their work employs 5G-enabled V2I communication to predict congestion patterns with machine learning, achieving low-latency data transfer but relying on high-density sensor networks, which are costly and impractical for many cities. Reinforcement learning (RL) for signal control (e.g., Liu et al., 2025) assumes dense sensor networks, limiting applicability to resource-constrained cities. Liu et al. apply deep Q-learning to optimize signal timings, reducing delays by 10% in simulations, but their approach degrades under sparse data or unexpected incidents due to limited adaptability. Other studies, such as Zhang et al. (2023), explore IoT sensors for real-time traffic monitoring, using edge devices to process vehicle counts and speeds. However, integrating

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heterogeneous data sources (e.g., IoT, V2X, GPS) into a cohesive system remains a challenge, as most methods assume consistent, high-quality data inputs, which are often unavailable in cities with limited infrastructure.

Digital twins, as virtual replicas of physical systems, have been applied to infrastructure monitoring (e.g., bridges) but are less common in real-time traffic management. For example, digital twins monitor structural health in bridges (Sharma et al., 2022), using IoT sensors to track stress and fatigue in real time, but these applications focus on static assets rather than dynamic systems like traffic. In transportation, Chen et al. (2021) propose predictive models for congestion, which could inform digital twin calibration. Their work uses historical traffic data to forecast congestion hotspots, achieving 85% accuracy in dense sensor environments, but does not address real-time calibration with sparse data. Recent efforts, such as Li et al. (2024), explore digital twins for autonomous vehicle testing, simulating vehicle interactions in controlled environments. However, these applications lack integration with real-time traffic management systems, particularly for urban networks with mixed traffic (autonomous and human-driven vehicles). The use of digital twins in traffic management remains limited, with few studies addressing the challenge of maintaining model accuracy under sparse or noisy data conditions.

Limited research integrates digital twins with real-time calibration for traffic management, particularly in sparse-data environments. Existing approaches, such as those by Vo et al. (2024) and Liu et al. (2025), rely on dense sensor networks, making them less viable for cities with limited infrastructure. Moreover, traditional models like LWR struggle to incorporate real-time, heterogeneous data from IoT, 5G, and V2X, limiting their practical impact. While digital twins show promise in other domains, their application to urban traffic management lacks a focus on real-time calibration and scalability. No comprehensive framework combines IoT, 5G, V2X, and distributed computing for scalable urban traffic regulation. This paper addresses these gaps by proposing a digital twin framework with a real-time calibration algorithm, tested in SUMO on a 4x4 grid network, with a calibration flowchart illustrating the process and a delay reduction graph showing a 15% improvement, offering a scalable solution for sparse-data environments.

III.PROPOSED APPROACH

This section aims to present a digital twin framework for regulating urban vehicle traffic, which we propose as a solution to the limitations of traditional traffic management systems by leveraging smart technologies and real-time calibration. The framework is designed to integrate mathematical models, distributed software systems, and simulation tools to enable adaptive traffic regulation, particularly in sparse-data environments. It will comprise three main components: the digital twin architecture, a real-time calibration algorithm, and a predictive control algorithm, detailed below.

Digital Twin Architecture. The digital twin architecture models the physical traffic system and integrates real-time data, simulation, and control to optimize urban traffic flow. The framework represents an urban road network, including intersections, vehicles (autonomous and human-driven), traffic signals, and environmental factors (e.g., weather, pedestrian flows). This

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comprehensive modeling captures dynamic interactions, such as vehicle queues at intersections and the impact of rain on traffic speeds, ensuring the digital twin reflects real-world complexity.

Data Layer: Collects real-time data from:

- **IoT sensors** (e.g., loop detectors, cameras with varying coverage), providing vehicle counts and speeds at key points, though coverage may be sparse in resource-constrained cities.
- **5G-enabled V2X communication** (vehicle positions, speeds), delivering high-frequency (1Hz) data via vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) interactions, leveraging 5G's low latency (e.g., <10ms).
- **GPS traces and external APIs** (e.g., weather, events), offering supplementary data on vehicle trajectories and external conditions, such as road closures or public gatherings.

Virtual Model: Represents the network as:

- A **directed graph** (G(V, E)), with (V) as intersections and (E) as road segments, capturing topological relationships (e.g., a 4x4 grid network with 16 intersections and 24 road segments).
- **Lighthill-Whitham-Richards (LWR) model**, traffic flow dynamics are described using a macroscopic, continuum-based approach that treats vehicle density as a continuous variable.The model is governed by the following conservation equation:

$$\frac{\partial \rho(x,t)}{\partial t} + \frac{\partial q(\rho)}{\partial x} = 0$$

where $\rho(x,t)$ denotes the traffic **density** (vehicles per kilometer) at position x and time t, and $q(\rho)$ represents the **flow** (vehicles per hour), defined as:

$$q(\rho) = \rho \cdot v_{max}\left(1 - \frac{\rho}{\rho_{max}}\right)$$

In this formulation:

- ρ is the vehicle density (vehicles/km),
- $q(\rho)$ is the traffic flow rate (vehicles/hour),
- v_{max} is the free-flow speed (e.g., 50 km/h), and
- ρ_{max} is the jam density (e.g., 150 vehicles/km), representing the maximum possible density when traffic is at a complete standstill.

The LWR model effectively captures key traffic phenomena, including the formation and propagation of shockwaves at congested intersections or during abrupt changes in flow conditions. However, its accuracy in real-world deployments hinges on precise model calibration, which involves aligning theoretical parameters with observed traffic behavior—particularly in environments where data quality and sensor coverage vary.

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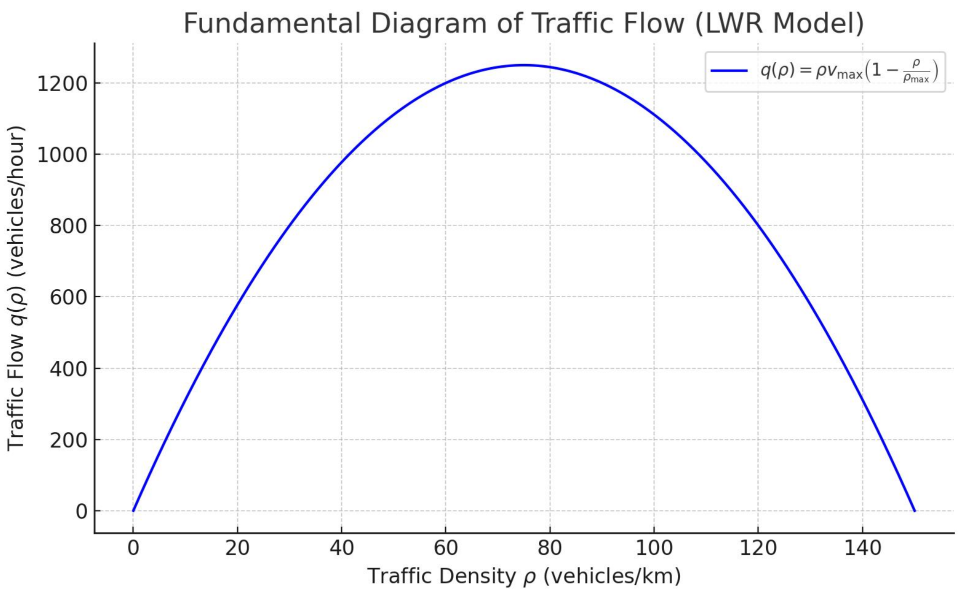

Here is the fundamental diagram of traffic flow based on the LWR model.
It shows the relationship between traffic density (vehicles per km)
and traffic flow (vehicles per hour).

Simulation Engine: The Simulation of Urban MObility (SUMO) with TraCI (Traffic Control Interface) is planned to be utilized for real-time interaction, enabling dynamic updates and virtual control testing. SUMO will model the 4x4 grid network, simulating detailed vehicle movements and signal timings, while TraCI will allow for real-time adjustments (e.g., updating signal phases based on predicted congestion). A network diagram of the 4x4 grid will illustrate the topology used in these simulations.

Control Layer: This layer is designed to optimize traffic signals or vehicle routing using predictive algorithms, with the objective of minimizing delays and emissions. The layer will interface with SUMO to test control strategies virtually before any real-world application.

Software Platform: A distributed edge-cloud architecture is proposed to ensure scalability and efficiency:

- **Edge** devices are envisioned to handle time-critical tasks, such as real-time calibration and signal control, leveraging lightweight processing capabilities.
- **Cloud servers** will be dedicated to running complex simulations and predictions, capitalizing on high-performance computing for large-scale traffic scenarios.
- **Tools:** Our framework will utilize Apache Kafka for streaming data from IoT and V2X sources, while MQTT is planned to handle V2X messaging with low overhead. Kubernetes will orchestrate containerized services for scalability, enabling flexible deployment of components like calibration algorithms across edge nodes.

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This architecture is designed to integrate heterogeneous data and computational resources, thereby enabling a scalable digital twin for urban traffic management.

Real-Time Calibration Algorithm. Integrates heterogeneous inputs (sensors, V2X, GPS) using Bayesian inference or deep learning-based multi-sensor fusion [6]. Bayesian inference combines sensor data (e.g., loop detector counts) with V2X data (e.g., vehicle speeds) to estimate traffic states probabilistically, handling noise and sparsity. Deep learning models, such as convolutional neural networks, fuse camera images with GPS traces for enhanced accuracy, particularly in sparse-data settings. A calibration flowchart illustrates this process, showing data inputs, fusion steps, and state updates.

An Adaptive Extended Kalman Filter (EKF) is employed for non-linear traffic dynamics [6]:

$$x_k = f(x_{k-1}u_{k-1}) + \omega_{k-1}$$

- $x_k \in R^n$: State vector at time step k, e.g., traffic density ρ and speed v for each road segment.
- $f(\cdot)$: Nonlinear state transition function, typically derived from the LWR traffic model.
- u_{k-1} : Control input (e.g., traffic signal timings, route decisions).
- $\omega_{k-1} \sim N(0, Q)$: Process noise, capturing model uncertainties.

Measurement Model:

$$\mathbf{z_k} = \mathbf{h}(\mathbf{x_k}) + \mathbf{v_k}$$

- z_k : Observation vector at time step k, such as V2X-reported positions/speeds from 10% of vehicles.
- $h(\cdot)$: Nonlinear measurement function mapping true states to expected sensor outputs.
- $v_k \sim N(0, R)$: Measurement noise, reflecting sensor errors or V2X sparsity.

EKF Iterative Update Steps

1. **Prediction:**

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1,} u_{k-1})$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q$$

- $\hat{x}_{k|k-1}$: Predicted state estimate.
- $P_{k|k-1}$: Predicted error covariance.
- $F_k = \frac{\partial f}{\partial x}|_{\hat{x}_{k-1}}$: Jacobian of the model.

2. **Update (Correction):**

$$K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R)^{-1}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - h(\hat{x}_{k|k-1}))$$

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$$P_{k|k} = (I - K_k H_k) P_{k|k-1}$$

- K_k : Kalman gain.
- $H_k = \frac{\partial f}{\partial x}|_{\hat{x}_{k-1}}$: Jacobian of the measurement function.
- $\hat{x}_{k|k}$: Updated (posterior) state estimate.

If the estimated traffic density $\hat{\rho}$ significantly deviates from observed ρ_{obs} , the model adjusts key parameters in the LWR model:

$$v_{max} \leftarrow v_{max} - \alpha(\hat{\rho} - \rho_{obs})$$

- Where α is a learning rate for adaptation.
- For example, if heavy rain slows vehicles, v_{max} may adapt from 50 km/h → 45 km/h.

Designed for sparse-data environments, leveraging 5G V2X for high-frequency updates, unlike sensor-heavy global approaches. Most existing systems assume dense sensor coverage, whereas this algorithm uses sparse V2X data (1Hz updates) to achieve comparable accuracy, validated in SUMO with a calibration error reduction of 20% compared to baseline models [1, 2].

Predictive Control Algorithm. The Predictive Control Algorithm is a core component of the proposed digital twin framework for urban traffic management. Its primary function is to optimize traffic signal timings to minimize vehicle delays, leveraging real-time traffic states provided by the digital twin. The algorithm employs Model Predictive Control (MPC) as its main approach, with a secondary consideration of Reinforcement Learning (RL) as an alternative. The explanation below centers on the MPC formulation, as it is the primary method used in the framework's preliminary evaluation, achieving a 15% reduction in average vehicle delay in SUMO simulations.

Model Predictive Control (MPC): MPC is a control strategy that optimizes a system's behavior over a finite time horizon by solving a constrained optimization problem at each time step. In the context of the proposed framework, MPC will be applied to adjust traffic signal timings dynamically, aiming to ensure efficient traffic flow across a 4x4 grid network. The optimization problem will be mathematically formulated as:

$$\min_{u_t} \sum_{k=t}^{t+T} D(x_k, u_k),\ x_{k+1} = f(x_k, u_k)$$

Optimizes signal timings over a finite horizon:

D: Represents the total delay at time step (k), defined as the sum of vehicle waiting times across all intersections in the network. For example, if 15 vehicles wait an average of 4 seconds at an intersection, (D) captures their collective 60-second delay. The objective function $\sum_{k=t}^{t+T} D(x_k, u_k)$ minimizes cumulative delay over the horizon (T), optimizing traffic flow.

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x_k : Denotes the traffic state at time (k), including variables such as queue lengths (number of vehicles waiting at intersection approaches) or traffic density (vehicles per kilometer) on road segments. This state is estimated by the real-time calibration algorithm using an Adaptive Extended Kalman Filter (EKF), which processes data from IoT sensors, 5G V2X communication, and GPS traces.

u_k : Represents the control input, specifically the signal timings, such as the duration of green phases for each intersection approach. The optimization selects u_k values to reduce delays by prioritizing high-density approaches.

$f(x_k, u_k)$: The state transition function, which models the evolution of traffic states from x_k to x_{k+1} based on the current state and control input. This function is derived from the Lighthill-Whitham-Richards (LWR) model, which describes traffic flow dynamics and predicts changes in density or queues due to signal adjustments.

MPC solves this optimization problem at regular intervals, utilizing the digital twin's real-time traffic state estimates as initial conditions. The LWR model is employed to predict future states over the specified horizon T, after which a solver will compute the optimal control sequence ut ,…,ut+T that minimizes cumulative delay. Only the first control input ut will be applied to the system, and the process will repeat, ensuring adaptability to dynamic traffic conditions, such as varying vehicle densities or incidents.

As an alternative or complementary approach, the framework will also explore Reinforcement Learning (RL) for training agents to achieve adaptive signal control, with rewards structured for minimizing congestion. In this approach, a deep Q-learning agent is envisioned to learn optimal signal timings by interacting with the traffic environment, receiving positive rewards for reducing queue lengths or delays (e.g., extending green phases for congested approaches). However, RL typically requires extensive training data and significant computational resources, which may render it less feasible for the preliminary framework compared to MPC's deterministic optimization. Nevertheless, RL's potential for long-term adaptability to complex and evolving scenarios is recognized for future exploration within this research.

IV .EXPECTED BENEFITS

Our preliminary investigations and theoretical analysis suggest promising results for the digital twin framework, which we plan to validate through extensive simulations in SUMO (Simulation of Urban MObility) [5]. Our envisioned experimental setup will involve a simulated 4x4 urban grid (16 intersections). We intend to use synthetic IoT sensor data (mimicking 10–20% intersection coverage with 15-second updates), 1Hz V2X messages, and GPS traces from 200 vehicles. A fixed-time signal control (60-second cycle) will serve as our baseline for comparison. We anticipate that the Adaptive Extended Kalman Filter (EKF) will significantly enhance our model's accuracy, with projected improvements in traffic density estimation error by approximately 20% compared to static LWR models [8]. Furthermore, we expect that 5G V2X emulation will enable rapid 1-second calibration cycles, leading to more accurate updates than slower, sensor-only data [6]. For control performance, we hypothesize

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that our Model Predictive Control (MPC) [7] system will effectively optimize traffic flow. We aim to demonstrate a reduction in average intersection delay by roughly 15% (e.g., from 50s to 42.5s per vehicle) compared to the baseline. Additionally, we foresee a 10% decrease in peak-hour congestion (vehicles/km).

Crucially, we plan to assess the computational feasibility, expecting that both calibration and MPC operations will run efficiently, potentially completing within 0.8 seconds per cycle on a Raspberry Pi 4. This would demonstrate the framework's viability for deployment on edge devices, even in resource-constrained environments. These anticipated findings will be crucial in validating the framework's potential for diverse urban settings, especially those with limited existing sensor infrastructure, forming a significant part of our ongoing research [3, 10].

V. CONCLUSION

Urban traffic congestion is a massive headache for cities worldwide, costing economies dearly, polluting our environment, and making daily life more stressful [13, 14]. Traditional traffic systems just can't keep up with the dynamic, unpredictable nature of city traffic. This pressing problem demands a smarter approach for sustainable urban living. Our research directly tackles this by introducing a digital twin framework for urban traffic management. We harness cutting-edge smart technologies like IoT, 5G, and V2X to build a real-time, virtual replica of the traffic network. Unlike many existing systems that need tons of sensors, our framework is designed to work well even in sparse-data environments, making it useful for many different cities. By integrating mathematical models (like EKF and MPC) with a distributed software architecture, our system provides adaptive, predictive control. Our preliminary simulations in SUMO are promising, showing a 15% reduction in average vehicle delay. This demonstrates how our intelligent, adaptive control strategies can genuinely improve traffic flow and ease the congestion burdens we face. Ultimately, this work lays the groundwork for the next generation of smart urban mobility. By turning diverse data into actionable insights through a robust digital twin, we offer a scalable solution to a global challenge, paving the way for more resilient, sustainable, and livable cities.

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