Smart Mobility in the Cloud: Enabling Real-Time Situational Awareness and Cyber-Physical Control through a Digital Twin for Traffic

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***Abstract*—This article presents the design, implementation, and use cases of the Chattanooga Digital Twin (CTwin) towards the vision for next-generation smart city applications for urban mobility management. CTwin is an end-to-end web-based platform that incorporates various aspects of the decision-making process for optimizing urban transportation systems in Chattanooga, Tennessee, to reduce traffic congestion, incidents, and vehicle fuel consumption. The platform serves as a cyberinfrastructure to collect and integrate multi-domain urban mobility data from various online repositories and Internet of Things sensors, covering multiple urban aspects (e.g., traffic, natural hazards, weather, and safety) that are relevant to urban mobility management. The platform enables advanced capabilities for: (a) real-time situational awareness on traffic and infrastructure conditions on highways and urban roads, (b) cyber-physical control for optimizing traffic signal timing, and (c) interactive visual analytics on big urban mobility data and various metrics for traffic prediction and transportation performance evaluation. The platform is designed using a multi-level componentization paradigm and is implemented using modular and adaptive architecture, rendering it as a generalizable and extendable prototype for other urban management applications. We present several use cases to demonstrate CTwin's core capabilities supporting decision-making in smart urban mobility management.**

***Index Terms*—Traffic flow visualization, level of detail, situational awareness, traffic sensor network, urban mobility, traffic monitoring**

I. INTRODUCTION

Urban mobility management entails complex decision-making processes that involve multiple urban management aspects and require advanced capabilities for real-time collection and analysis of urban big data [1, 2]. Taking advantage of advanced information and communication technologies, many recent studies strive to create smart mobility management paradigms and next-generation intelligent transportation systems by building smart city applications [3, 4, 5]. Emerging digital twin technology can provide unique advantages for handling large volumes and varieties of urban data to facilitate complex predictive analytics [6, 7]. They leverage advanced computing and communication technologies to enable digitization and real-time control of complex real-world physical objects, systems, and processes [8, 9, 10]. Originally, the digital twin concept was proposed to promote smart anufacturing [9], and has been recently applied by a few studies to replicate cities for enhancing urban management [11]. With the increasing availability of urban big data and the advent of the Internet of Things (IoT), Artificial Intelligence (AI), and cloud computing, digital twin cities enable unique urban informatics capabilities. These capabilities can inform past and present operation of multiple urban sub-systems (e.g., buildings, transportation, water, and energy) and project the future trend of a urban system from many management aspects [12, 13].

A digital twin city serves as a virtual model of a smart city and is continuously updated through predictive analysis and informed simulation, which are powered by physical-based models and machine learners, to mirror the real-world urban dynamics as it changes. The approach can also create a low-cost virtual environment to simulate a city's behavior and responses to hypothetical urban management conditions (e.g., strategic urban planning, and disaster response management), generating practical insights to support decision making and the optimization of the physical world. Early visions of digital twins for smart and sustainable cities started with the smart city plans of 15 major cities worldwide [14] and New York's strategy for building "the world's most digital city" [15]. Many urban management authorities proposed their vision and plans for digitizing cities to enhance livability and data-driven urban management [16, 17, 18]. Since then, a few research groups in the urban science sector started to translate cities into digital twin representations [11] for a variety of research and prototyping purposes, such as supporting the knowledge discovery of urban data [19], developing intelligent transport systems, and creating smart mobility management strategies [20, 21, 22], facilitating building and infrastructure management [23], and promoting citizen science through volunteered

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geographic information and crowd-sourcing [21, 24, 22].

Despite the great significance and usefulness of these efforts, past digital twin applications rarely focused on optimizing urban mobility from a holistic approach which considers urban sub-systems that can influence (e.g., weather, road hazards, traffic incidents) or be affected (e.g., energy consumption and vehicle emissions) by urban mobility. Although some digital twin prototypes [21] can execute static urban mobility simulation and visualize traffic flows and 3D building environments in townships, they do not enable any optimization of the real-world transportation systems through automated pipelines. Nor do they connect other urban aspects with mobility management. Therefore, they have limited scalability for supporting urban mobility management in large urban areas. In this regard, there is a need to develop a real-time digital twin, which can: (a) enable the situational awareness of urban mobility systems, (b) conduct informed simulation using real-world traffic data in real-time, and (c) optimize transportation systems through a cyber-physical control strategy powered with automated communication pipelines.

This paper follows the vision and methodological aspects of creating a generalized digital twin for urban mobility management and presents a case study for Chattanooga in Tennessee with the Chattanooga Digital Twin (CTwin). CTwin is designed based on a list of desired features and principles [25, 26, 27] for managing urban mobility in the vision of developing smart and sustainable cities. From the urban science perspective, CTwin enables effective and innovative smart mobility management paradigms by providing the following features:

1) real-time situational awareness of the urban transportation system [28].
2) informed traffic simulation models and mobile energy metrics for traffic prediction and vehicle speed controls [29, 30].
3) cyber-physical control for optimizing traffic signal timings [25], and
4) interactive visual analytics dashboards on big urban mobility data [27].

The urban mobility data analyzed in the digital twin are collected and integrated from a wide variety of IoT sensors and online repositories, covering multiple urban sectors (e.g., traffic, natural hazards, weather, and safety) that are important to mobility management. From the informatics perspective, CTwin adopts state-of-art software design conventions (design and architecture patterns) and open-source web technologies, rendering it adaptive, generalizable, and maintainable. We adopted a multi-level componentization strategy during the development to increase its modularity and its code components' reusability, rendering CTwin more flexible and maintainable.

We share our experiences and practices for lowering common software engineering barriers to develop comprehensive and robust digital twin applications. We aim to help would-be-developers, who are often domain experts with a moderate level of coding experience, by presenting the design strategy and software stacks of CTwin platform as a generalized cyberinfrastructure, which provides a software foundation for building modular digital twin city applications for various urban research, planning, and management purposes.

II. Background and Motivation

CTwin is developed as a core component of the U.S. Department of Energy's "Real-Time Data and Simulation for Optimizing Regional Mobility in the United States" project [31] and serves as critical information technology infrastructure to mirror the traffic patterns and reduce mobility-related energy use in the metropolitan area of Chattanooga, Tennessee. This paper intends to share the software engineering design and practices, and open-source software suite for creating CTwin with the urban informatics and management communities. We aim to lower both the methodological and technical barriers to the development of smart city applications for urban mobility management.

A. Smart Mobility Management Paradigm through CTwin

At the methodological level, the digital twin is designed to offer a novel and automated paradigm for optimizing urban transportation systems and improving fuel efficiency. Different from a conventional transportation information system or data platform, our digital twin is developed based on the cyber-physical integration concept [10]. The novelty of our digital twin paradigm is its capability to enable a bidirectional cyber-physical connection that creates a digital replica of a physical transportation system in a virtual space in order to simulate its dynamics and behaviors in the real world and provide real-time feedback. Meanwhile, the digital replica can also interact with and alter the physical system through cyber-physical control [32]. In addition to a conventional information system's data management capability, our digital twin is designed to control IoT-connected transportation infrastructure (e.g., traffic signal controllers) using optimized simulation outputs to reduce traffic congestion in the physical world.

Our overall methodological workflow is illustrated in Figure 1. Core features of CTwin include: (1) situational awareness, (2) real-time simulation and metrics, (3) cyber-physical controls, and (4) visual analytics dashboards.

The situational awareness capability is fundamental for other digital twin functionalities. CTwin connects a network of diverse IoT sensors, transportation infrastructure, and third-party data services to discover and assemble large volumes and varieties of urban mobility-related data (e.g., traffic and infrastructure conditions, weather, hazards, traffic incidents) in real-time and near-real-time. With an integrated urban dataset, CTwin can enable the situational awareness from a holistic perspective by creating the foundation for further optimization through the analysis of traffic volume, speed, and lane occupancy on highways and major urban roads, and vehicle queue length at intersections along major traffic corridors.

The information that characterizes urban mobility dynamics is then fed into CTwin's computing environment, where advanced simulation models and urban science metrics are deployed, to produce analyses and optimized strategies for mitigating traffic congestion. The computing environment is deployed on a cloud powered with the capability to handle a

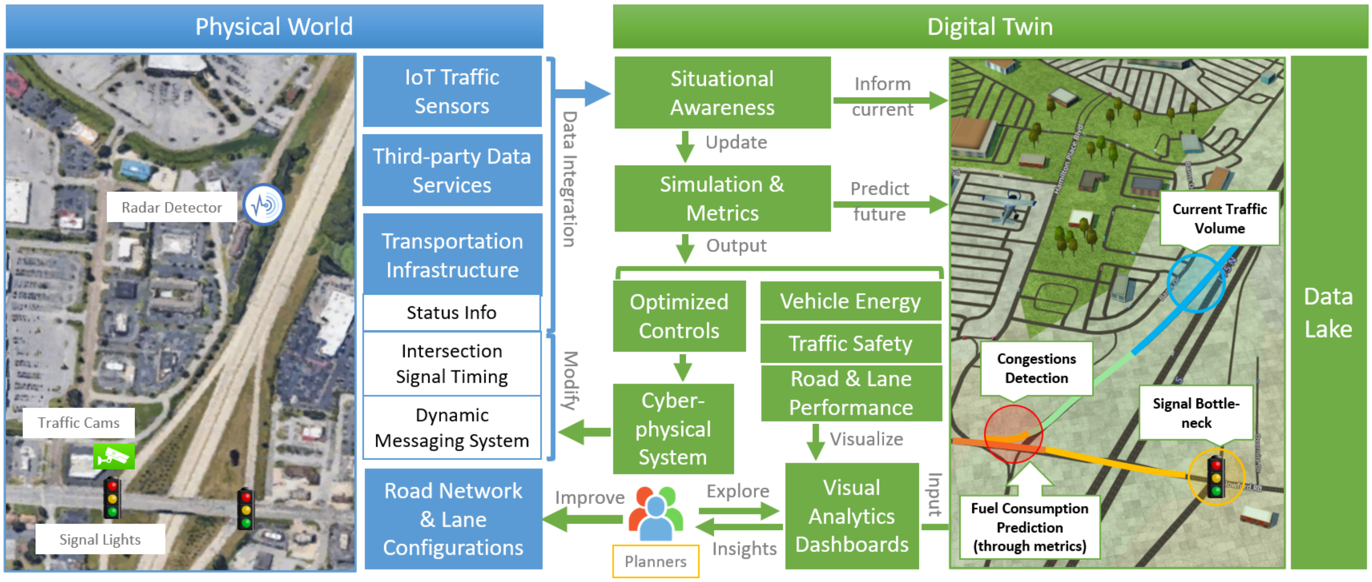

Fig. 1: A smart mobility management paradigm enabled through CTwin's workflow: from virtual to reality.

large amount of urban data. Through simulations and several metrics, CTwin is able to construct lane-based continuous traffic flow using discrete road-side sensors [26], execute a signal-control algorithm in real-time [25, 33], and evaluate the performance of transportation systems.

Outputs from simulations and metrics are employed to change the traffic dynamics in the real physical world. Taking advantage of the state-of-art edge computing technologies, CTwin offers unique cyber-physical capability to establish two-way connections between IoT-enabled transportation infrastructure (e.g., traffic cameras and traffic signal controls at intersections) with a signal timing control algorithm to optimize traffic in corridors and on highways in Chattanooga. This feature aims to reduce traffic congestion and its associated energy consumption in Chattanooga by 20%.

B. Digital Twin as a Cyberinfrastructure

Developing smart mobility features at the regional scale requires labor-intensive and time-consuming efforts. These efforts include collecting multi-domain data, simulating traffic dynamics in real-time for situational awareness and future projection of the transportation systems, optimizing traffic controls for improving intersectional traffic, and supporting urban planners to make informed decisions. Technical challenges associated with developing smart mobility features include collecting and processing big mobility data and integrating different research applications (e.g., simulations, cyber-physical systems, metrics for decision support, and multi-domain urban data) into a comprehensive and automated workflow to support time-critical mobility management applications. To address these challenges, we adopted a cyberinfrastructure approach to building an online research and computing environment for enabling an automated pipeline toward smart mobility features.

In this setting, CTwin is developed as a generalized cyberinfrastructure to assemble and couple individual research applications into a centralized web-based medium to allow integrated usage of these applications as a decision support workflow for mobility management. At the technical level, the cyberinfrastructure aims to facilitate data acquisition, data sharing, communications, multi-domain models and metrics coupling, and collaborative urban mobility management between different planning agencies (e.g., federal, state, and city). It promotes automated machine-to-machine data integration, centralized access to large-scale mobility data and traffic simulation results, and provides a technical framework to integrate various visualizations and dashboards to generate data-driven insights on intersection performance, vehicle energy efficiency, and traffic incident hot spots, etc.

The target users of CTwin include transportation planners, urban scientists, and decision-makers. Its design and features are optimized to match the background and interests of the target users. They should align with its core capability for enabling the holistic situational awareness of urban transportation and allow valuable insights through simulations, metrics, and visual analytics to inform decisions at different urban scales (e.g., regional and corridor) and from various urban mobility aspects (e.g., traffic safety, energy consumption, and weather). To achieve these overall objectives, we have developed the following features:

- Landing page: this first view provides various data visualizations and summary statics to give users an overview of traffic conditions and incidents in the entire region.
- Region: a dedicated geospatial data viewer provides regional insights to the user via a large map. It allows users to query and access a wide variety of urban mobility data, map layers, and simulation outputs at the regional scale. Real-time and historic traffic information measured from roadside sensors can be visualized in this viewer.
- Corridor: a group of visual dashboards present real-time traffic dynamics at different connected signal-controlled intersections along major traffic corridors in Chattanooga. This app integrates traffic camera feeds and signal per-

formance metrics.

- Incidents: this dashboard aims to inform users on the current and past traffic incidents, contributing factors, hot spots, and impacts on the transportation system.
- Metrics: this smarty city app provides an evaluation of the transportation system's performance at the regional scale through metrics, such as the Moving Ahead for Progress in the 21st Century Act (MAP-21)'s system performance and energy metrics, traffic safety metrics, and Mobility-Energy-Productivity (MEP) [34].

These platform features are developed either as a smart city app to deliver a specific core capability (e.g., help a user explore intersection performance at the corridor scale), or as a component of a more comprehensive decision support workflow (i.e., a user flow) to provide users with more comprehensive insights. We will further elaborate on these workflows in Section IV-D.

C. Design Requirements

Embedding multiple big data-driven features in a single cyberinfrastructure is a sophisticated endeavor, which requires our CTwin to fulfil the following technical capabilities and design requirements:

1) Data interoperability: the digital twin should comply with commonly accepted communication protocols and open data standards to ingest unstructured multi-domain datasets and connect with a variety of IoT-enabled sensors and transportation infrastructure.
2) System interoperability: it should adopt industry standards and conventions on system design to ensure its modularity and to enable interfacing with other smart city and mobility applications (e.g., digital twins, web apps, and domain-models).
3) Big-data analytics and simulation capability: the digital twin should be deployable on a distributed computing and storage facility to ensure its capability to analyze the large volume, velocity, and variety of time-critical urban mobility data and to run predictive simulation models.
4) Real-time situational awareness and cyber-physical control: the digital twin should mirror the city's traffic conditions and patterns, identify optimized traffic control strategies through data-informed simulations, and automatically integrate the strategy into traffic control to reduce real-world traffic congestion.
5) Adaptive user flow design: it should offer intuitive user interfaces, user experience design, and user flows for different user groups (e.g., public, urban science researchers, and traffic engineers).
6) Extendibility and maintainability: individual features and functionalities of the digital twin should be developed using open-source web technologies to minimize its development and maintenance cost, and should be free of charge for academic use. It should employ transferable and sustainable web technologies, which comply with the major industrial conventions to facilitate adoption long-term maintenance, and feature extension.
7) Privacy protection: the digital twin should comply with federally mandated cybersecurity requirements, as well as specific data protection requirements by data providers. As such, the system must require user accounts for individuals who have signed the appropriate Non-Disclosure Agreements (NDA). Its Application Programming Interface (API) endpoints for external applications must be protected by API keys.

The development of CTwin follows industry standards for responsive web design to render its web application correctly on a wide range of devices with different screen sizes, resolutions, and technical capabilities. Currently, access to CTwin is only granted to authorized users. The platform access and usage require VPN and API keys to protect data under NDA and critical transportation infrastructure under the platform's cyber-physical control.

D. Data Sources

Our platform integrates various urban mobility-related datasets generated in the Chattanooga metropolitan area using data warehousing methods. These datasets include: (a) real-time, near-real-time, and historic traffic conditions and safety data from sensors, cameras, public entities, and crowd-sourcing platforms [35], (b) real-time traffic control data from TACTICS signal management and control system and Dynamic Message Signs (DMS), (c) real-time and near-real-time information on the weather conditions and hazard warnings (earthquake and wildfires) in the region, (d) performance measures that describe the performance and energy efficiency of the transportation system, and (e) static geospatial data layers that describe the socioeconomic aspects of the city, such as critical urban infrastructure, census data, administrative boundaries (e.g., city, county, and metropolitan area).

In CTwin, traffic condition data is collected from various types of sensors that include Radar Detection Sensors (RDS) and Closed-Circuit Television (CCTV) cameras. RDS sensors are operated by the Tennessee Department of Transportation (TDOT) and provide lane-specific traffic conditions that include volume counts, average speeds, and occupancy at 30-second intervals [36]. Primary sources for CCTV camera data include GridSmart and TDOT's SmartWay system. The GridSmart system is a network of commercial fish-eye cameras deployed at individual intersections to capture and process vehicle movements in real-time [37]. The TDOT's SmartWay system includes traffic cameras and dynamic message signs across Highways in Tennessee. The system monitors freeways across multiple Tennessee urban areas, including Knoxville, Nashville, and Chattanooga [38]. CTwin uses traffic safety data provided by the TDOT through the Enhanced Tennessee Roadway Information Management System (E-TRIMS) and public sources, such as Waze [27]. Traffic control data, such as the signal timing and DMS information, are retrieved through TACTICS signal management [39] and TDOT's SmartWay system [38].

Weather and hazard information is collected from web services provided by the U.S. Geological Survey (USGS) and National Oceanic and Atmospheric Administration (NOAA).

In addition, the platform also incorporates advanced traffic simulation results, system performance evaluation, and traffic energy metrics as individual smart city apps to provide data- and model-driven insights and forecasting of traffic conditions and traffic-related fuel consumption through multiple simulation scenarios. The performance measures are retrieved from the MAP-21's system performance and energy metrics [40], and National Renewable Energy Laboratory's MEP tool [34].

Figure 2 presents core features and data resources in CTwin and their temporal coverage in the timeline.

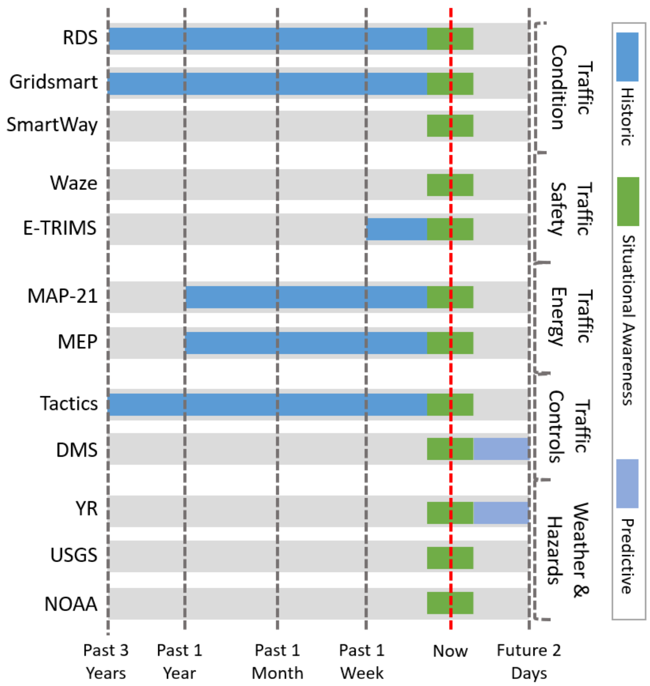

Fig. 2: Temporal range of CTwin features and dynamic data layers.

III. System Design

This section presents the conceptual design of CTwin's features and workflows, and the technical implementation of its cyberinfrastructure. CTwin is a comprehensive web platform that follows a horizontal approach for developing smart city applications. It aims to integrate individual smart city apps and software components, which address a specific sector of urban mobility (e.g., weather, infrastructure, safety, and energy), into a more holistic urban management workflow. This workflow connects different urban mobility aspects to help users generate useful insights between different urban subsystems (e.g., traffic infrastructure performance and energy consumption). CTwin needs to assemble multiple software components (i.e., individual smart city apps) and connect them into logical urban management workflow as user flows. To address the complexity in the cyberinfrastructure design and development, we propose a multi-level component-based paradigm that combines software engineering practices with urban science domain knowledge to facilitate the conceptual design and technical implementation of CTwin.

A. Conceptual Design: Multi-level Componentization

The conceptual design of CTwin includes the design of its core capabilities, user features and their interconnected logic, and user flow. The multi-level componentization strategy proposed in this paper is created to compensate for the standard C4 model (context, containers, components, and code) to incorporate the domain aspect in the user flow and architectural design of a research software tool. Our modified C4-model (as illustrated in Figure 3) offers a conceptual workflow to facilitate the software design.

The workflow starts with the definition of the research objectives, such as exploring the empirical relationships between traffic volume and energy consumption, enabling real-time situational awareness of traffic conditions, and evaluating traffic signal performance along corridors. The workflow breaks different research goals into user flows that are specific to different types of target users (e.g., researchers and traffic engineers), and which are defined based on typical tasks these users perform (e.g., select date and spatial scale, visually compare and correlate variables). We translate these user flows into entities that are specific to the urban science or urban mobility domains. These domain-specific entities include sensors, datasets, analytical pipelines, and simulation models. For example, the user flow for enabling situational awareness of highway traffic dynamics requires the integration of the highway road network with lane information, traffic speed and volume data, an agent-based model for emulating continuous traffic flow along the highway, live camera feeds, and traffic incident data.

To guide the platform's technical implementation, our proposed paradigm helps domain scientists and software developers translate different domain entities into code, addressing the common "model-to-code gap" in urban science software development. Our approach defines three levels of important building blocks: user feature, app, and user flow. A user feature is an atomic and basic element that focuses on enabling a single-objective function (e.g., select date) and user experience (e.g., a visualization of requested simulation outputs. One or multiple user features can be conceptually and logically synchronized to attain a more comprehensive user experience. The synchronization results in a smart city/mobility app.

B. Implementation: Cloud-based Architecture and Software

Guided by the multi-level componentization paradigm, we implemented the platform using the classical multi-tier server-client architecture presented in Figure 4. As CTwin cyberinfrastructure entails many hierarchical components, we choose appropriate software engineering practices to ensure its modularity and interoperability.

We employ a microservice architecture on the system's server to accommodate our conceptual design strategy. This practice ensures interoperability with other IoT services and data, as well as the system's adaptability and scalability to new datasets, regions, user groups, and management objectives. It allows developers to create a fully independent information system, situational awareness tools, and visual dashboards using adaptive Application Programming Interfaces (APIs)

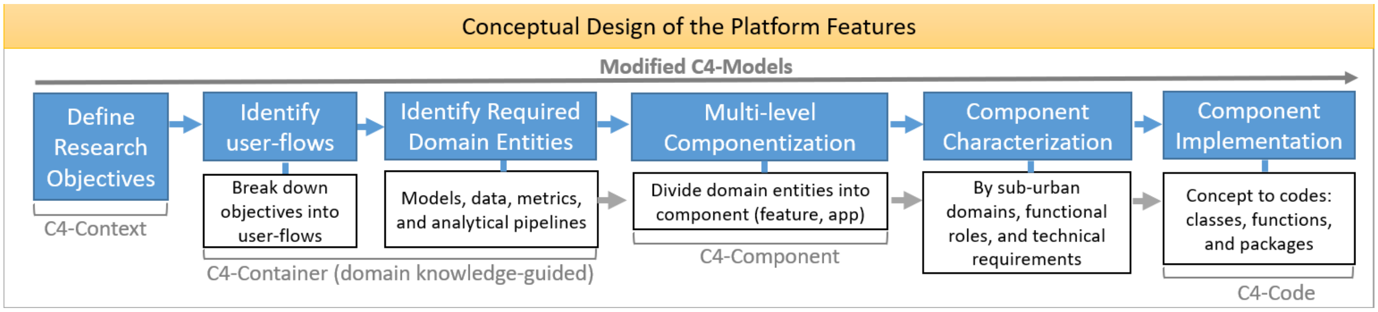

Fig. 3: Multi-level component-based design for improving system modularity and reusability.

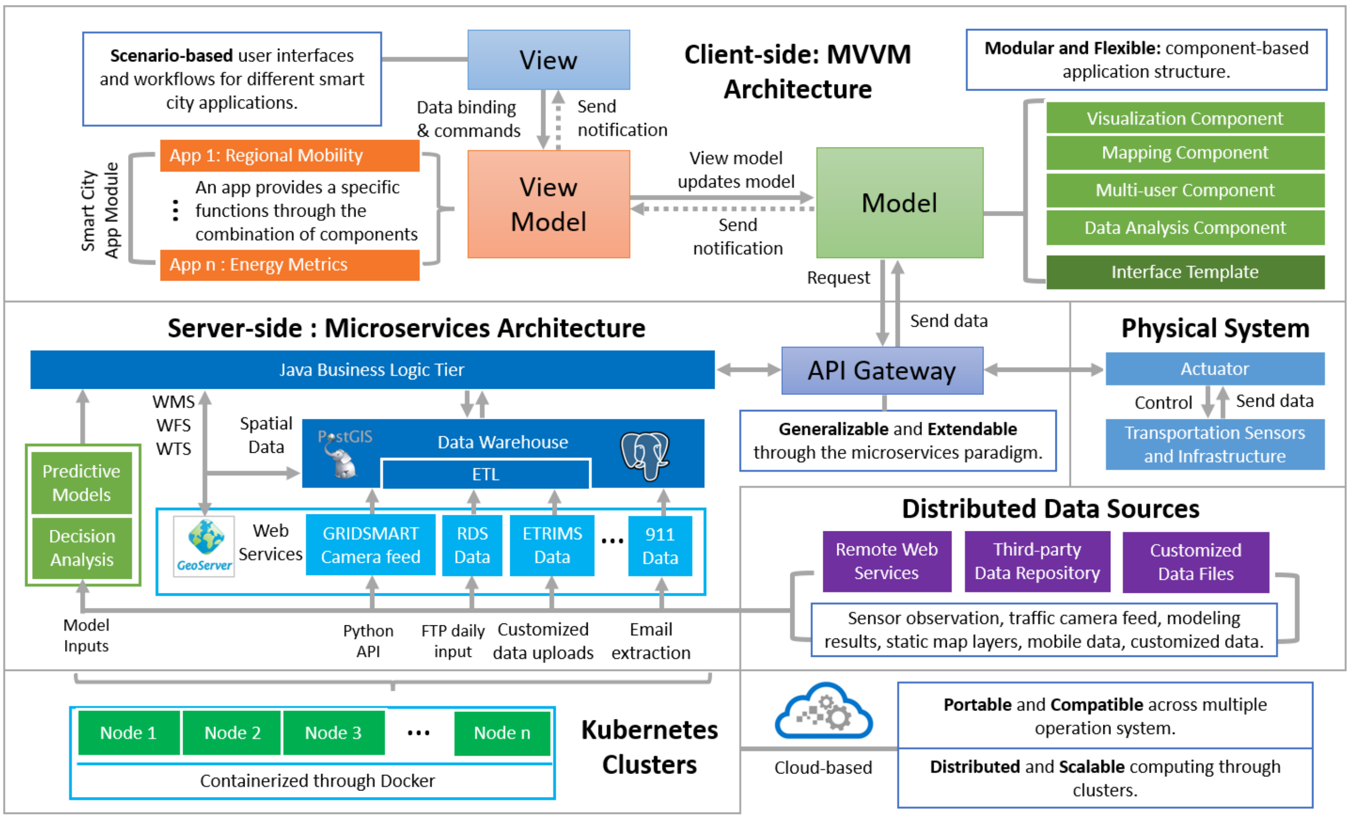

Fig. 4: Multi-tier system architecture of CTwin platform.

to support features and user flows on the client-side. We used the Angular framework to develop the client-side application. Angular is a TypeScript-based open-source web application framework that employs the Model-–View-–View Model (MVVM) design pattern [41]. The MVVM design pattern aligns with our multi-level componentization paradigm. It provides a flexible technical structure to host individual smart city apps and integrate them into user flows. The pattern provides a robust yet flexible web development practice to organize multiple app features into a single-page application.

The CTwin platform adopts free and open-source libraries/software suites, which are proven to be deployable and interoperable with many industrial applications. Individual technologies are summarized in Table I. In our architecture, we defined several software building blocks based on required functions for our platform, such as data storage, web mapping, geoprocessing, visualization, and graphical user interface generation. One or more software packages and libraries are

TABLE I: Software packages

Package Name	Descriptions
Angular	TypeScript-based web application framework
Java Spring	Back-end web application framework
Docker	Container platform for packaging software
Kubernetes	Orchestration system
PostgreSQL and PostGIS	Relational database with geospatial extensions
GeoServer	Java-based server written in Java that allows users to share, process, and edit geospatial data

selected to fulfill the functional roles of each building block. For example, we chose GeoServer for our web mapping building block. It enables many geospatial features, such as web map services, web feature services, web tile services, and online geo-processing services. Individual building blocks have well-defined data standards, input and output formats. As they are connected through a microservices architecture, any chosen software packages can be readily replaced by other packages and technologies to incorporate new features and improve performance for specific research needs. For example, the GeoServer could be swapped with CartoDB or ArcGIS servers. This flexibility is enabled through our multi-level componentization strategy and Docker containerization.

The CTwin platform is hosted in a cloud environment managed by ORNL. The edge-computing paradigm adopted by our platform follows the vision of Cloud of Things (CoT) that promotes the integration of various IoT devices and sensors as distributed resources for data processing and management.

C. Data Access Through APIs

Databases are excellent storage for large amounts of data. To better manage these data and improve access speeds, we store the original data alongside their aggregates for commonly requested time intervals (i.e., 1 minute, 5 minutes, 15 minutes, 1 hour, and 1 day) and other aspects (e.g., traffic by travel direction, and turn movements). Furthermore, we store derivative data (e.g., fuel use and energy consumption) separately. This speeds up data access, and provides a smoother user experience while exploring the data through CTwin.

For easier access to the data, we developed data services for several of the most relevant datasets, including RDS, GridSmart, and incident data. These services enable us to use URL-based queries to specify type of data, date and time ranges, and level of aggregation required for a given task. Within CTwin, these services are used to provide data for the user interface in a format that is optimized for the use in charts or other visualizations. The date and time ranges are chosen by the user through the date selector in the user interface, while aggregates are determined by the type of chart.

In addition to this internal use, the data services can also serve data to users and components outside the CTwin's infrastructure through the use of API keys, which serve as a convenient alternative to authentication with username and password. This enables project members to perform research and develop prototypes for new features on their own machines, without interfering with CTwin's functionality. It also mitigates integration concerns as it is easy to test new functionality without fully integrating changes on the server.

IV. Use Case Demonstration and Discussion

CTwin serves as a generalized cloud-based cyberinfrastructure to integrate individual smart city applications into a holistic urban mobility management and decision-support workflow. Many of these smart city applications are published as independent studies and incorporated into CTwin to enable the platform's core capabilities for real-time situational awareness of the urban transportation system [26], informed simulations and metrics [34], traffic control optimization [30, 25], cyber-physical controls [42], and visual analytics for exploring multi-scale traffic dynamics [27, 43].

A. Situational Awareness

We demonstrate CTwin's situational awareness capability at multiple spatial scales through three selected cases. Two cases present urban mobility patterns at the regional scale, as depicted in Figure 5. These two cases are demonstrated using the "region page" of CTwin, which offers an interactive web map with options for showing many data layers related to urban mobility near Chattanooga. Examples include traffic infrastructure locations (e.g., interstates, U.S and state highways, county roads, ramps, traffic signals, and DMS), civil infrastructure locations (e.g., fire stations, law enforcement, hospitals, and schools), traffic sensor locations (e.g., CCTV cameras, GridSmart cameras, and radar detection sensors) weather and natural hazards (e.g., precipitation, wildfire, and earthquake), and demographic attributes (population). CTwin functions as an adaptive big-data cyberinfrastructure to assemble these datasets and provides centralized access and visualizations to allow users to explore them. The spatial coverage of these two use cases includes four major highways in the vicinity of Chattanooga: I-75, I-24, US-27, and US-153.

The first case demonstrates CTwin's capability to mirror continuous emulation of highway traffic flows in near-real-time [26]. This feature is enabled through an agent-based traffic emulator and RDS sensors. Figure 5a demonstrates an animated Kernel Density map to visualize the traffic density at the regional scale. RDS measurements are displayed at individual sensor locations using color-coded circle symbols. Users can zoom in on the map to view animated vehicle movements along the highway at the lane level, where color-coded dots are employed to represent individual vehicles and their driving speeds. The CTwin platform offers an effective online computing environment to host the emulator and connect it with 214 IoT-connected RDS sensors on interstate and state highways near Chattanooga through an automated data pipeline. Relying on CTwin's data acquisition and management capability, the traffic emulation can be readily expanded to highways in Tennessee's three other urban areas (e.g., Knoxville, Nashville, and Memphis) in Tennessee that are equipped with the same type of RDS sensors.

The second case is developed to monitor and analyze the occurrence of traffic incidents along the highway using real-time and historic emergency response data and CCTV camera feeds. Through an adaptive map view, users can identify the locations and hotpots of current and past traffic incidents. CTwin provides a user-friendly interface and visualizations that can display a large number of traffic incidents on a web map through cluster markers (as shown in Figure 5b). Furthermore, users can access the real-time camera feeds via the CCTV layer to monitor current traffic conditions on the highway. Users can retrieve time-critical information regarding traffic incidents and congestion details in real-time. These details reflect the traffic dynamics (e.g., how other vehicles respond and the change in driving behaviors) near the occurrences of

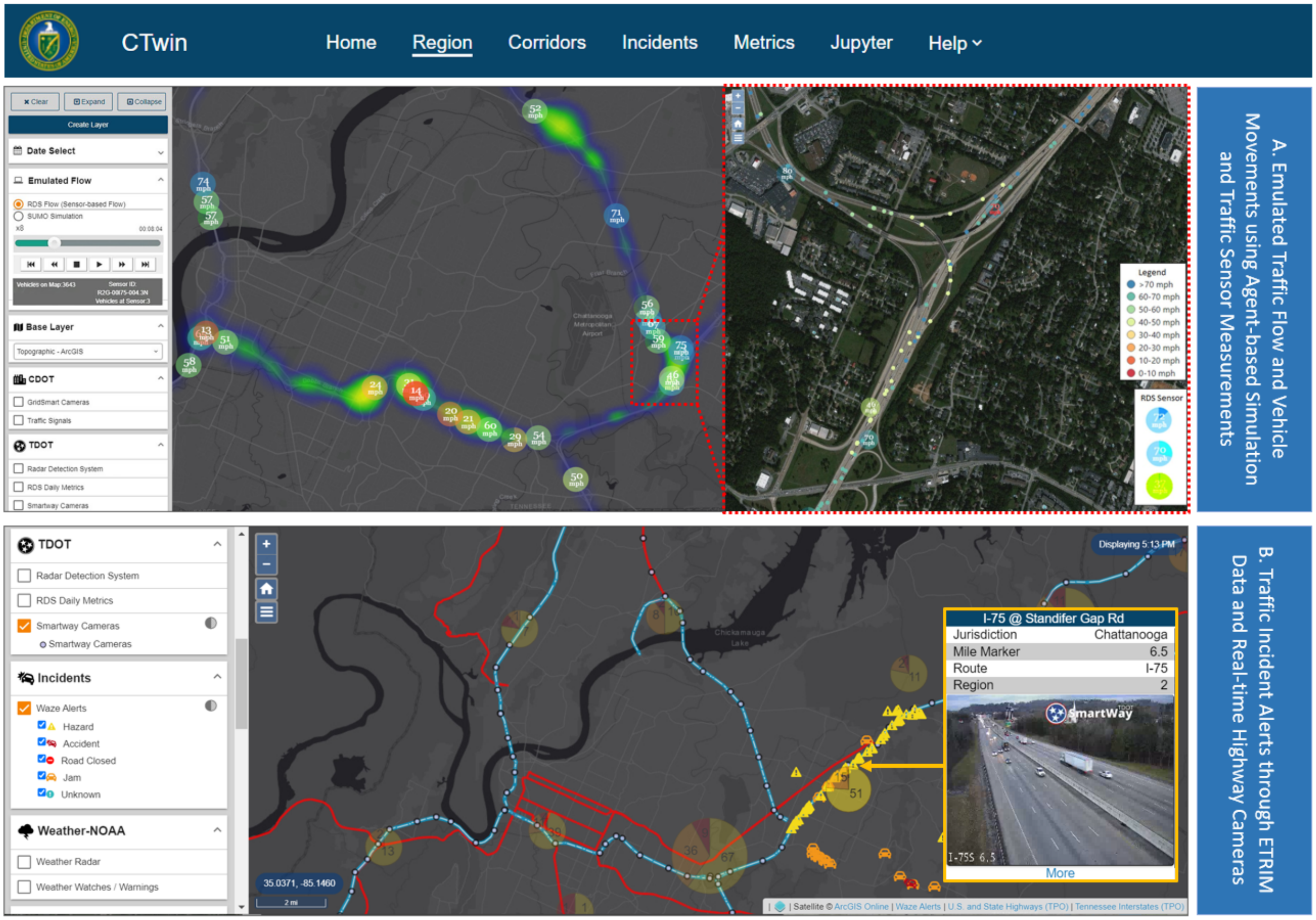

Fig. 5: The demonstration of CTwin's situational awareness capability through selected cases at the regional scale: (a) the construction of continuous traffic flow using near-real-time traffic sensor measurements and an agent-based simulation model, (b) traffic incident alerts through real-time incident data and CCTV cameras.

the incident. In this case study, there are 114 CCTV cameras near highways near Chattanooga, and 554 cameras throughout Tennessee which could contribute to incident monitoring in other urban areas.

B. Cyber-Physical Control

Typically, urban mobility systems rely on preset traffic signal timing plans which use estimates of typical traffic for different times of day (e.g. morning peak and afternoon peak) and days of the week. Unlike these systems, CTwin enables a cyber-physical control mechanism that can respond to traffic scenarios in real-time by simulating corridor-level traffic dynamics based on the real-time traffic data provided by CTwin to identify optimized traffic timing plans, and send them back to the real-world signal controllers to change the physical world (as illustrated in Figure 6). CTwin uses the National Transportation Communications for Intelligent Transportation Systems Protocol (NTCIP) to ensure compatibility with the majority of signal controllers deployed across the United States. To complement the control mechanism, CTwin also provides a series of data visualizations to inform users on the most updated state (e.g., traffic volume and speed), operating condition, and performance of individual signalized intersections within a traffic corridor (as depicted by the blue boundary in Figure 6).

We take advantage of CTwin's cyberinfrastructure to conduct a cyber-physical control experiment within the Shallowford Road traffic corridor in Chattanooga (as depicted by the green boundary on the map in Figure 6). The control experiment is designed to establish two-way communication between the traffic controls, such as traffic light controllers and traffic camera observations (measuring traffic conditions), and signal timing optimization algorithms deployed in a cloud environment. The optimization algorithms take the real-time traffic condition information (e.g., vehicle counts, speeds, and turn movements) and identify the best signal timing plan for each signal along the corridor in real-time. The optimized signal timing plan is returned back to the signal controller in response to the current traffic scenario captured by CTwin's situational awareness capabilities. Details of the real-time control algorithms are elaborated in [42] and [33].

Typically, urban mobility systems rely on preset traffic signal timing plans which use estimates of typical traffic for different times of day (e.g. morning peak and afternoon peak)

Fig. 6: Cyber-physical control experiments conducted through the CTwin's cyberinfrastructure: Connecting traffic light controller at intersections with signal timing optimization algorithms.

and days of the week. Unlike these systems, CTwin enables a cyber-physical system that can respond to traffic scenarios in real time by simulating intersection-level traffic dynamics in a virtual computing environment to identify optimized traffic timing plans, and send them back to the real-world signal controllers to change the physical world. Our approach follows the National Transportation Communications for Intelligent Transportation Systems Protocol (NTCIP) to ensure CTwin's compatibility with the majority of signal controllers deployed across the United States. The same practice could be applied to other traffic controls and infrastructure, such as the dynamic messaging displays that are deployed on roadways, to inform drivers on traffic conditions, incidents, road hazards, as well as to reroute traffic.

This paper highlights CTwin's merit as a cyberinfrastructure to mirror the traffic dynamics by retrieving traffic information through IoT connections and hosting the control algorithms in a digital twin environment. It enables researchers and practitioners to conduct predictive analysis to optimize signal timing. The effort aims to improve traffic signal efficiency to reduce congestion, as has been tested through a SUMO (Simulation of Urban MObility)-based traffic simulation conducted during a control experiment in the Shallowford Road corridor to reduce 18% of vehicle energy consumption [44].

C. Metrics and Visual Analytics for Decision Support

In addition to situational awareness of urban mobility systems through visualizing traffic sensor observations, CTwin also provides advanced decision support capabilities. The platform integrates metrics for road and traffic infrasturcture performance, traffic safetys, and energy efficiency. Intuitive and interactive visual analytics dashboards allow users to explore the vast variety of data and metrics that characterize different aspects of the urban mobility system in Chattanooga. Useful insights regarding the multiscale traffic dynamics and traffic safety are derived through these visual analytics dashboards and are detailed in [27] and [43].

The critical contribution of CTwin in supporting informed decisions is to facilitate the dissemination of useful insights through various urban mobility data, metrics, and simulation outputs, as well as the collaborative inter-agency urban planning through easy-to-access visual analytics interfaces. This cyberinfrastructure serves as a foundation to create a multi-sector smart city platform that utilizes the horizontal approach to integrate individual smart city applications into a centralized platform. Through such a platform, users can collectively use different smart city apps to derive more holistic insights that rely on multiple aspects (e.g., energy and traffic safety) of urban mobility management.

D. Decision Workflow for a Use Case

This section presents a decision workflow for mitigating a traffic congestion scenario based on the level of detail principle. Other workflows can be devised to support decisions for reducing traffic incidents and road hazards.

- Step 1 - Daily Overview: Users start with the "landing page". CTwin provides the user an overview the traffic conditions and traffic incidents at the regional scale within a defined interval of time. The landing page provides summaries of traffic volume and speeds, traffic incidents, and weather conditions at the regional level to give the user an overall idea of the transportation system condition in Chattanooga. Through the graphical interface, users can explore the performance and conditions of the transportation system for the current day and historically. This high-level overview helps users get the general idea of the temporal variability in mobility-related data to select the date of interest.
- Step 2 - Regional Insights: Users identify a date with unique overall traffic patterns, such as dates with abnormal traffic volume or special events (e.g., holidays and the introduction of COVID-19 travel bans). Users can then switch to the "region page" to explore the urban infrastructure and contributing factors (e.g., incidents, weather, and population distribution) that may affect the mobility patterns and cause traffic congestion. Following the previous example, users can activate the traffic flow emulator and the NOAA weather radar layer to explore in detail how traffic flow dynamics and vehicle movements vary in response to precipitation. The region page helps users get a more detailed view of traffic and environmental conditions on a selected date of interest. Following the same example, users can identify traffic corridors of interest (e.g., areas with high traffic volume or which are affected by special weather) through the region view.
- Step 3 - Corridor Insights: Users switch to the "corridor page" to examine the traffic corridor or signalized intersections that have been identified through the previous step. Through a group of visual dashboards, users can explore traffic dynamics at different signal-controlled intersections that are connected within a selected corridor. They can examine mobility patterns for the corridor and individual intersections through real-time traffic camera feeds and charts which summarize turn movements and other signal performance metrics. This helps them to identify traffic bottlenecks (signal phases and lane configurations that can be improved) which they need to understand to mitigate congestion.
- Step 4 - Metrics: After understanding the multi-scale traffic dynamics through previous steps, users switch to the "metrics page" to explore how the measures of traffic safety, energy consumption, and road performance change in response to urban mobility patterns. The visualization of MAP-21 system performance and energy metrics can guide the users back to the region page or corridor page to explore the potential causes through CCTV camera feeds, and summary statistics for intersection traffic.

V. Conclusion

This paper illustrates the implementation of a smart city digital twin at the example of CTwin, an urban mobility management in Chattanooga, which considers mobility-reladed aspects across different scales. Our urban informatics approach maintains a holistic and automated approach to integrate and analyze urban big data, and reduce traffic congestion and excessive fuel consumption in urban areas. The design and development of our comprehensive smart city platform, can integrate individual smart city apps into complex workflows to support decision-making for urban mobility management.

As a cyberinfrastructure that makes urban big data and its analytics easily accessible, our platform enables advanced capabilities which include real-time situational awareness of traffic and infrastructure conditions, cyber-physical control to optimize traffic signal timings, and interactive visual analytics of big urban mobility data with various metrics for traffic prediction and transportation performance evaluation. The intuitive and user-friendly interface allow users to prepare a systematic plan for smart mobility monitoring and offer means for quantitative assessment of the transportation system performance through informed simulation and metrics.

The platform can be accessed anytime from anywhere through the internet and thus such can be updated as information is produced, allowing for a central repository and access that can inform users about the the state of the transportation system. CTwin is developed in a flexible and extendable structure to address similar urban mobility management concerns at the national level. The platform is designed using multi-level computation and built with open-source technologies that make the system adaptive and generalizable.

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