# Digital Twin Orchestration: Framework and Smart City Applications

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**Abstract**

The emergence of digital twins as virtual replicas of physical assets has revolutionized various industries, offering unparalleled insights and opportunities for optimization. However, managing and coordinating interactions among digital twins pose significant challenges, necessitating the development of orchestrators. This paper tackles this issue by proposing an orchestrator framework designed to handle interconnected digital twins, examining its effectiveness through applied scenarios in smart city contexts. The framework comprises federation, translation, brokering, and synchronization components. To demonstrate its efficacy, digital twins of smart environments and smart driving were developed and collaborated on applications including hotspot prediction and eco-driving assistance within smart city services.

**Keywords**

Digital Twin, Orchestration Framework, Federated Learning, Smart City Application, Smart Mobility

## 1. Introduction

The concept of digital twins[1] represents a groundbreaking approach in modern technology, offering virtual replicas of physical entities, processes, or systems. These digital counterparts mimic the behavior, characteristics, and functionalities of their real-world counterparts, serving as dynamic models that provide invaluable insights, analysis, and optimization opportunities.

In today interconnected world, the proliferation of digital twins has surged across various industries, ranging from manufacturing [2] and transportation[3] to healthcare [4, 5] and urban planning[6, 7]. These virtual representations enable organizations to monitor, analyze, and optimize complex systems with unprecedented precision and efficiency.

However, as the number and complexity of digital twins proliferate, the need for orchestrators becomes increasingly evident. Digital twin orchestrators serve as the backbone of interconnected digital twin ecosystems, facilitating the management and coordination of interactions among diverse digital twins within a network or system.

In the research context, we refer digital twin orchestration to the mechanism that multiple digital twins can connect and collaboratively work with together. In literature research, the other terms maybe used with the same target such as interconnected digital twins, federated

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digital twins, decentralized digital twins and multiple digital twin collaboration. There have been several works that focus on study to enable interconnection among digital twin including framework for Internet of Federated Digital Twins [8], Web of Digital Twins [9], decentralized digital twin of complex dynamical systems [10], secured digital twins with blockchain [3, 4], linked data and mechanism to facilitate the communication of digital twins [11, 12].

In this research, we investigate digital twin orchestration architecture, propose design of orchestration services, and present the smart city enabler services on digital twin orchestration including environment hotspot prediction and eco-driving assistance.

Toward vision on digital twin orchestration architecture with functionality of federation, translation, brokering and synchronization which addresses challenges in smart city enablers, the key contribution of this paper is summarized as follows:

- We proposed an orchestration framework with detailed functional elements for each orchestration function mentioned above. Each functional element is interconnected with other elements within the orchestration framework and with the digital twin layer (IoT gateway, data management, object management, services) and smart city applications;
- We designed and implemented proof-of-concept applications for smart cities, including Hotspot Prediction and Eco-driving Assistance. These applications leverage the orchestration framework to collaborate on AI model training and simulation outcome sharing;
- We address future research issues in digital twin orchestration, including modeling complex collaborative systems, heterogeneous data, artificial intelligence models, and the computational capacity of the digital twin hosts.

The paper is structured as follows: Section 1 introduces the research. Section 2 delineates the concept of Digital Twin orchestration. In Section 3, we put forward an orchestration framework along with its component design. This proposed concept will be illustrated through a case study on smart city services in Section 4. Subsequently, Section 5 delves into addressing issues and suggesting areas for further research. Finally, Section 6 will provide the conclusion of the paper.

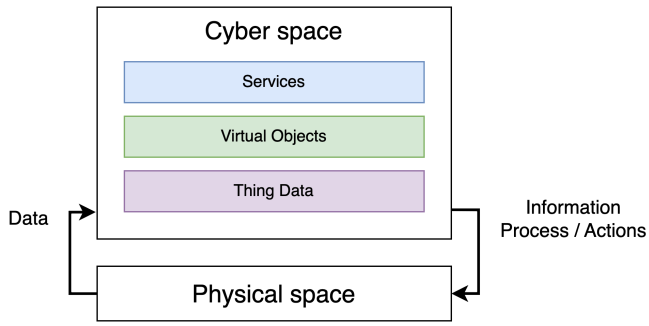


**Figure 1:** A high-level overview of Digital twins with Digital twin components

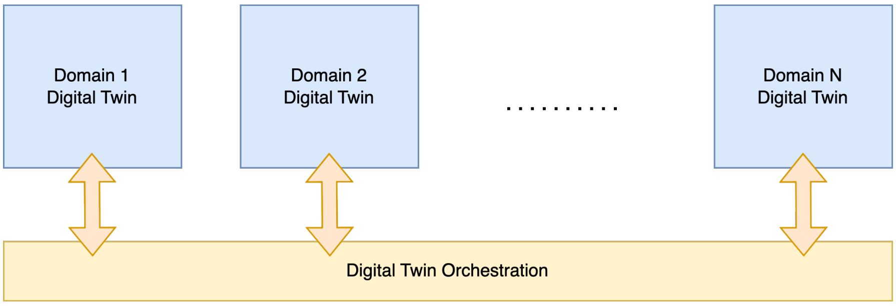


**Figure 2:** Cross domain digital twin orchestration

# 2. Digital Twin and Digital Twin Collaboration

## 2.1. Digital Twin Components

Conventionally, digital twins have fully integrated data flow interaction between the physical and cyber spaces, distinguishing digital twins from digital shadows and digital models [13]. A digital twin is simply a digital representation of an existing physical object. Therefore, not only are physical objects described in cyberspace with their real-time updated information, but the actions of these physical objects are also mimicked in cyberspace. Furthermore, digital twins can be extended to services such as manufacturing, transportation, and urban planning. Thus, digital twins also include service components.

Figure 1 illustrates digital twin concepts with components including objects, virtual things, and services. In general, a digital twin will have the following features:

- Real-Time Thing Data Integration: Digital twins continuously receive data from physical assets, ensuring thing data remain up-to-date;
- Two-Way Interaction: Unlike traditional simulations, digital twins facilitate a two-way flow of information between the virtual and physical versions;
- Virtual Thing Models: These accurate models mirror real-world objects and incorporate data from sensors, historical records, and design specifications;
- Analytics and Machine Learning Services: These platforms analyze data, predict maintenance needs, and optimize performance.

## 2.2. Digital Twins Collaboration with Orchestrator

Digital twin orchestration is the process of managing and coordinating the interactions between multiple digital twins that represent physical assets, systems, or processes. Digital twin orchestration enables the creation of complex simulations, scenarios, and optimizations that can improve the performance, efficiency, and resilience of the physical counterparts. Digital twin orchestration can also facilitate the integration of data, analytics, and artificial intelligence across different domains and industries.

Figure 2 illustrates multi-cross-domain digital twin connections. It shows not only how digital twins are interconnected but also how to create an orchestration of digital twins across different domains as an orchestrated instance, such that:

**Table 1**
Functional Requirements for Digital Twins Collaboration with Orchestrator

| Functional | Requirement |
|---|---|
| `Brokering` | Brokering verifies and validates digital twins, manages data transmission and reception, and executes tasks like data filtering, instantaneous delivery, and assured delivery. |
| `Synchronization` | The traditional approach of individually identifying entities and achieving one-to-one synchronization with models is expanded to encompass many-to-many synchronization among digital twins. In such scenarios, preventing collisions is equally paramount. |
| `Federation` | This federation continuously updates shared virtual models while safeguarding the confidential data produced by physical objects within individual digital twins. |
| `Translation` | Transformation guidelines for fostering collaboration among digital twins ought to be devised using established methodologies like ontology. |

- Utilizing data from things or simulators within a context sourced from other digital twins entails context brokering, enabling the creation of applications to operate within more intricate contexts;
- Comprehending data from other digital twins involves a translator that converts data from one digital twin to another;
- Employing analysis models from other digital twins can be achieved through sharing machine learning models or collaboratively training via federated learning;
- To support these functionalities, orchestration requires a synchronization mechanism to align objects and entities across digital twins.

To support digital twin orchestration across multiple domains with various IoT data integration, analysis methods, and artificial intelligence models, a list of functional requirements has been introduced in the NICT B5G white paper [14]. Table 1 briefly summarizes the requirements for digital twin collaboration with orchestrators.

## 3. Digital Twin Orchestration Framework

As discussed in the preceding section, establishing a digital twin federation across diverse domains requires the implementation of a digital twin orchestrator framework. This framework must encompass functionalities such as orchestration, brokering, federation, translation, and synchronization [14] to effectively fulfill its purpose.

In this section, we propose a digital twin orchestration framework and discuss the functional elements of orchestration in detail. Figure 3 presents the digital twin orchestration framework, which includes layers for federation, translation, brokering, and synchronization. Each layer

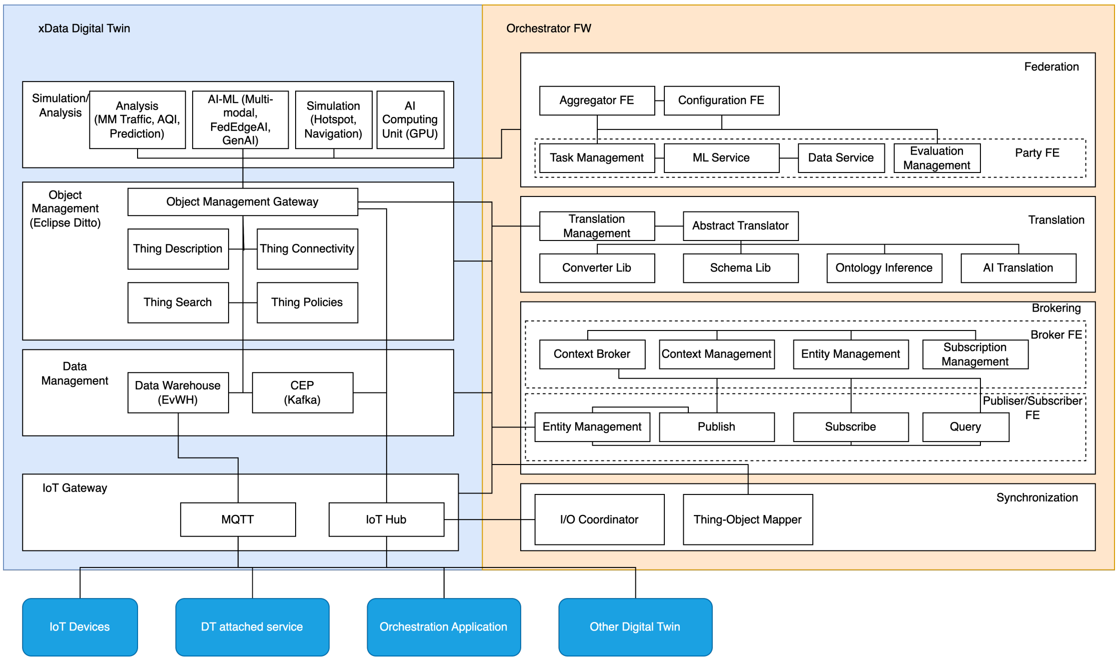


**Figure 3:** Digital twin orchestration framework

displays the functional elements and entities connected to our currently implemented digital twin framework, named xData Digital Twin.

## 3.1. Brokering with Context Information

The brokering function typically resembles an MQTT Broker, receiving all messages from publishing digital twins and then routing them to subscribing digital twins. In the orchestration of brokering, a broker should perform functions such as filtering and combining multi-source data from providers before notifying consumers, akin to a context broker [15]. Therefore, brokering should encompass the following functionalities:

Broker: Structured based on the concept of a Context Broker, where context-aware information refers to the values of attributes characterizing entities relevant to smart applications. The Broker Function Element (FE) manages subscriptions and notifies context consumers when an entity is updated by a context producer.

Publisher/Producer: Structured based on the concept of Context Producers, where a context producer on a digital twin can publish data/context elements by invoking the update operation on a Context Broker. This allows context consumers on other digital twins to receive the updated information.

Subscriber/Consumer: Context consumers can subscribe to context on the broker to receive information that satisfies certain conditions using the subscribe function.

### 3.2. Federation via Federated Learning

Federated Learning (FL) [16, 17] has found application in digital twin collaboration. FL paradigms enable the training of a global machine learning model by aggregating local models trained on separate individual data without sharing private information. Traditionally, federated learning addresses issues related to training on massively distributed and non-IID (Non-Independently and Identically Distributed) IoT data [18, 19]. In the context of digital twin federation, FL has been utilized to train machine learning models for collaborative digital twins, considering both physical and cyber space features. For instance, in [20], the aggregation frequency of federated learning is adaptively adjusted based on reinforcement learning techniques to enhance learning performance under resource constraints, as captured by digital twins. Additionally, in [21, 22], network resources are simulated and optimized by federated learning via digital twins to bridge the gap between physical edge networks and digital systems. Moreover, complex dynamical system digital twins can be decentralized, with models trained using federated learning [10].

In traditional FL research and application, it is typically assumed that the machine learning model and local data among parties are shared across digital twins. However, in the realm of federation orchestration research, our emphasis shifts towards orchestrating cross-domain digital twins through the utilization of federated learning. In the broader scope of federation orchestration design, beyond the core function of federated learning, there is a heightened focus on integrating digital twin features and configuring federation settings.

Aggregator: The aggregator serves two main functions: initially creating or loading the global model for a new federated learning process and aggregating the global model from the feedback models of participating digital twins. In peer-to-peer digital twin orchestration, an original digital twin can act as the aggregator, utilizing a model transfer function to share its model with other digital twins.

Party: Before federation execution, the party function configures the orchestrated digital twin based on the federation configuration provided by the aggregator. During the federation training process, it iteratively collects data from the digital twin, trains the model, and provides feedback to the aggregator. Additionally, the party function connects with the data or machine learning modules of federation participants, including the Data Service Module, Federated Feature Engineering Module, Optimizer Module, and Federated Machine Learning Algorithm Modules.

Configuration: The configuration of the federation is tailored to the analysis objects and parties interested in participating in federated learning, as well as for the model serving aspect of the federation. In the implementation of federated learning, as outlined in IEEE Std 3652.1-2020 [23], configuration serves various functions within the Service Layer, including Participant Coordination and Task Management modules.

### 3.3. Translation

The translation function assists IoT data conversion between different formats or ontologies across orchestrated digital twins. In a smart system orchestrated environment, where IoT data may originate from various digital twins, there are inherent interoperability challenges when applying machine learning models trained on data from one digital twin to data acquired from others [24].

Within the orchestration framework, translations can be pre-defined to handle data conversion tasks using heuristic knowledge, matching data schemas from source to destination, ontology inference [25], and machine translation techniques [26]. These translation functions are essential for data preparation within the federation function, ensuring that data from different sources can be seamlessly integrated and utilized for machine learning tasks.

### 3.4. Synchronization

In the orchestrated digital twin, a physical object may have multiple interact with different digital twins via their IoT data gateway and thing management. For example, transportation digital twin may have direct information from vehicle data access. However, traffic digital twin (for monitoring smart traffic application) may rely on surveillance cameras for its vehicle description. Thus, those data need to be synchronized for more accurately transforming data and training machine learning models.

In the realm of cross-modal digital twins, thing descriptions vary across different instances. When data is transmitted to a digital twin through an IoT gateway, synchronization becomes crucial in recognizing instances where the same physical entity is associated with different cyber objects in distinct digital twins. In the cyber space, objects are characterized by Thing Descriptions (TD). As a result of diverse data collection approaches across different digital twins, the Thing Descriptions (TDs) pertaining to an object may vary, necessitating the involvement of a mapper function to facilitate identification.

Another key function of synchronization is to manage the updating of thing descriptions originating from physical entities. This involves initiating synchronization requests with other digital twins upon detecting new updates to thing descriptions. Additionally, synchronization serves to receive notifications for identifying conflicts between thing descriptions from different digital twins and subsequently resolving them through detection and resolution processes.

## 4. Case Study

In this section, building upon the orchestration framework outlined earlier, we embark on designing and deploying digital twins tailored for smart city applications. Our aim is to showcase how orchestration functions can bolster the services offered by these smart digital twins. Within a case study scenario, we introduce two primary digital twins.

The smart environment digital twin, responsible for gathering data from an environment observation network, forecasting Air Quality Index (AQI), and simulating emission plans to improve environmental conditions.

The smart driving digital twin, which monitors data from IoT devices installed on trucks and provides predictions regarding driving risks.

Furthermore, we highlight the existence of a smart application designed to receive contextual emission plans, aiding in eco-driving maneuvers. Through this case study, we demonstrate the seamless collaboration and enhanced functionality facilitated by orchestration, underscoring its pivotal role in optimizing services within smart city contexts.

To implement this, we extend the xData platform [1] to create the xData Digital Twin framework by integrating Eclipse Ditto [2] . This integration enables the platform to effectively manage digital twins and their interactions. To simulate data streaming from IoT devices, we develop a streaming server along with a setup tool. This tool facilitates configuration and data streaming from archived datasets to digital twins using the MQTT protocol. Through this integration and toolset, we can replicate real-time data streams from IoT devices to digital twins, allowing for realistic testing and validation of the digital twin framework functionality.

### 4.1. Smart Environment Digital Twin

**IoT Data:** Environmental data is sourced from environmental observation stations located across the prefectures of the Kanto region in Japan, proved by The Atmospheric Environmental Regional Observation System (AEROS) [3] . These stations conduct hourly measurements of various atmospheric indicators using specialized sensors. Table 2 shows the atmospheric indicators captured by these stations.

**Table 2**
The atmospheric sensing data attributes

| Atmospheric sensing data (hourly measurement) | Unit |
|---|---|
| $SO_2$ | ppm |
| $NO_x$ | ppm |
| NO | ppm |
| $NO_2$ | ppm |
| CO | ppm |
| $O_x$ | ppm |
| NMHC | ppm |
| $CH_4$ | ppm |
| THC | ppm |
| STM | mg/m$^3$ |
| $PM_{2.5}$ | $\mu$g/m$^3$ |
| Wind direction | $^\circ$ |
| Wind speed | m/s |
| Temperature | $^\circ$C |
| Humidity | % |

**Virtual Object:** A virtual object within the smart environmental digital twin is the Observation Station Network within a prefecture. This Observation Network Object comprises a list of observation stations along with their respective data. Figure 4 illustrates observation network objects comprised with observation stations.

**Analysis:** In smart environmental digital twins, a Convolutional Recurrent Neural Network (CRNN) model is deployed to predict Air Quality Index (AQI) [27]. Figure 5 shows the

[1] https://www.xdata.nict.jp/
[2] https://eclipse.dev/ditto/
[3] http://soramame.taiki.go.jp/

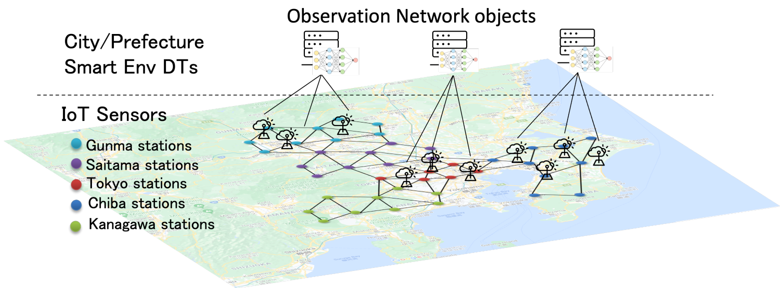


**Figure 4:** Smart environmental digital twins with observation network objects

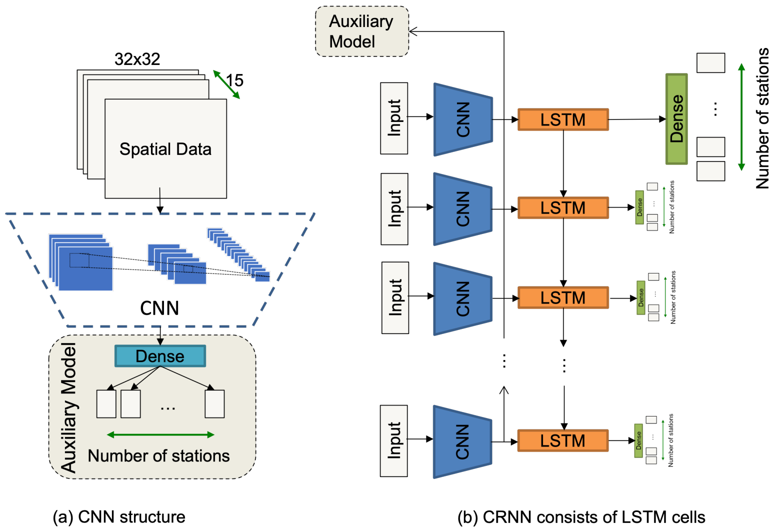


**Figure 5:** CRNN model for predicting Air Quality Index[28]

architecture of CRNN model to predict AQI. To input data into the CRNN model, information from the observation network is first transformed into the spatial representation required by a Convolutional Neural Network (CNN). The outputs of the CNN model across time steps are then continuously fed into the model to predict the temporal sequence structure of air pollution, utilizing the temporal cell of a Long Short-Term Memory (LSTM) network.

The simulation object within the smart environmental digital twin provides information about locations with a high risk of air pollution, such as areas with high levels of oxidants.

## 4.2. Smart Driving Digital Twin

**IoT Data:** For the smart driving digital twin, we gather data from IoT devices mounted on trucks belonging to a transportation company. These devices include dashcam cameras, environmental

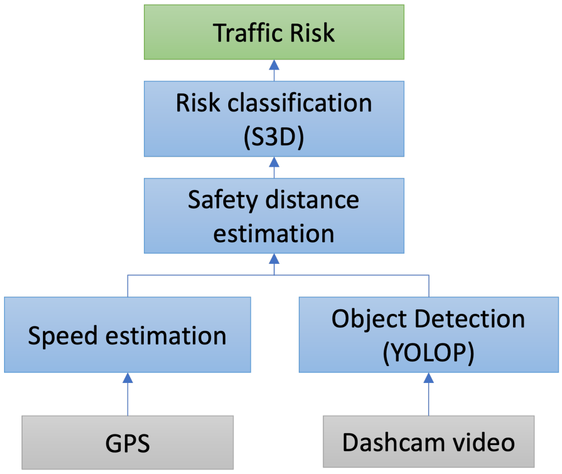


**Figure 6:** MM-TrafficRisk model to predict near-miss accident

sensors (GBIoT [4]) and wearable sensor (Fitbit [5]). The dashcam captures various views such as the front, rear, and position of the truck, while the environmental sensor records air quality metrics similar to those monitored by the observation station network in the smart environmental digital twin. The wearable sensor tracks information about physiological state of the driver while they are driving.

**Virtual Object:** Each physical truck is represented as a virtual object within the smart driving digital twin. These virtual objects include information such as truck vision, position, in-cabin environment, and driver-related data.

**Analysis:** In the implementation of driving risk prediction, we utilize the MM-TrafficRisk model from [29]. The MM-TrafficRisk model described in Figure 6 operates in two stages to predict near-miss accidents using dashcam video data and IoT sensor data. Near-miss accidents refer to incidents where the ego truck nearly collides with another object, such as a vehicle or pedestrian, even though the accident may not actually occur. In the first stage, objects are heuristically detected using YOLOP [30] and vehicle velocity is used to predict the risk. In the second stage, risk events including nearly hitting to pedestrian, cyclist, motorbike, car and truck are classified using the S3D [31] model.

The driving simulation object within the smart driving digital twin includes models for predicting risk events, navigation for the trucks, and providing guidance to the driver for eco-driving practices. These aspects will be discussed further in the later section.

### 4.3. Digital Twin Orchestration

This subsection introduces a proof of concept for orchestration functions that are required for applications, including hotspot prediction and eco-driving assistance.

The hotspot prediction application is deployed on smart city infrastructure to facilitate the

[4] https://gbiot.jp/
[5] https://www.fitbit.com/

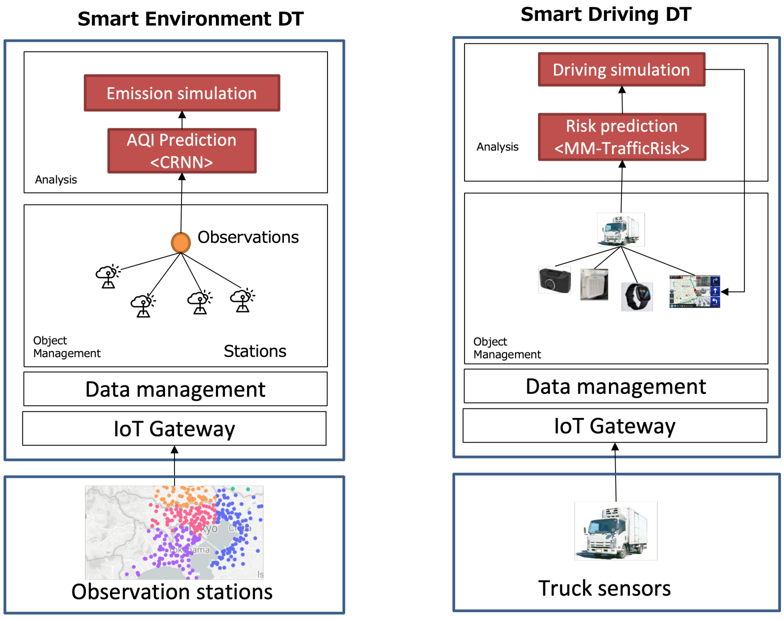


**Figure 7:** Smart Environmental Digital Twin (left) and Smart Driving Digital Twin (right)

prediction of environmental quality in traffic areas. This prediction relies not only on environmental information from observation stations but also on environmental sensors attached to vehicles. Hotspot prediction is particularly relevant to highly congested traffic areas.

Eco-driving assistance refers to an application designed to improve environmental quality by guiding drivers through polluted areas. This application utilizes information from emission simulations conducted by the smart environmental digital twin. It then provides guidance to drivers while they navigate through restricted areas.

To enable the services provided by these applications, we implemented the system using the proposed digital twin orchestration framework. Figure 8 illustrates the interaction between components of digital twins and applications using orchestration functions. In the deployment of smart city applications, the hotspot prediction application and eco-driving assistance application receive emission restriction plans from the smart environmental digital twin. They process this data and provide support to application users.

Additionally, in the smart driving digital twin, virtual mobile environmental observation objects and AQI prediction models are deployed to provide environmental services through digital twin orchestration.

Figure 8 illustrates the implementation of smart digital twins and smart applications with orchestration functions between the components of digital twins. It depicts the interaction between various elements, including observation stations, IoT devices, environmental sensors, and the applications themselves. The orchestration functions facilitate seamless communication and data exchange between these components, enabling the efficient operation of the smart city applications.

**Federation:** In general, it is crucial to maintain data privacy and security among digital

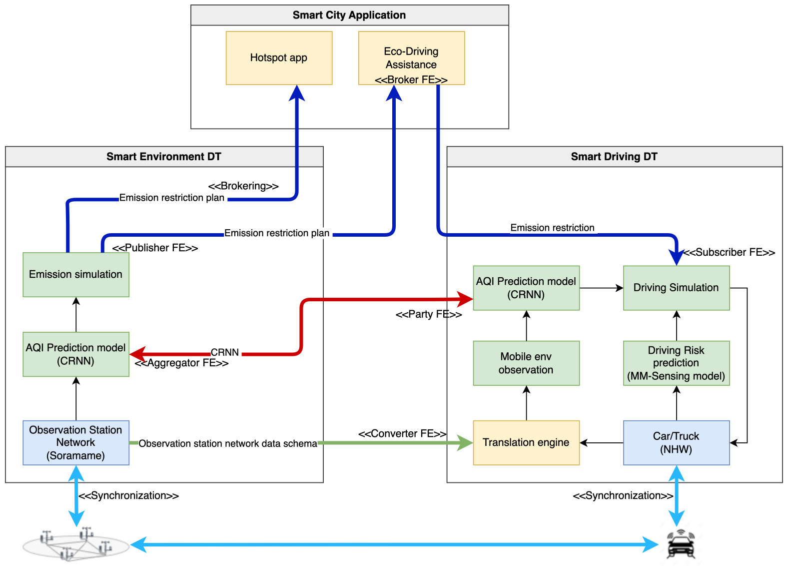


**Figure 8:** Digital Twin orchestration for Smart Mobility Services

twins. However, for hotspot prediction, where the hotspot may be related to traffic areas and environmental conditions, leveraging data from environmental sensors attached to trucks could significantly enhance prediction accuracy. To address privacy concerns while utilizing this valuable data, instead of directly sharing truck environmental data between digital twins, CRNN model can be trained using federated learning [28] techniques on spatial-temporal data, enabling it to learn from distributed datasets across different digital twins.

**Translation:** For training the AQI prediction model on the smart driving digital twin, we utilize environmental information collected by environmental sensors attached to trucks. However, the environmental data captured by the trucks is not directly inputted into the model from the smart environmental digital twin. To address this, a translation function is heuristically developed to convert data schemas and facilitate exchange between these smart digital twins.

**Brokering:** In the context of emission reduction, when a vehicle enters a hotspot area, its driving digital twin simulation is automatically detected by the smart city eco-driving assistance system. This triggers actions to mitigate aggressive driving behaviors such as harsh accelerations and braking, idling, and speeding. In some cases, the system may also suggest alternative routes to the driver.

To facilitate communication between the smart city eco-driving assistance system and the smart driving digital twin, a context broker is installed within the smart city application infrastructure. This broker receives emission restriction plans from the smart environmental digital twin, creates emission entities within its system, processes the information, and subsequently notifies the smart driving digital twin. This enables the smart driving digital twin to adjust its simulation and provide appropriate guidance to the vehicle in real-time.

**Synchronization:** To facilitate the sharing and training of models through federation, as well as to notify the appropriate smart driving digital twin within each smart city digital twin

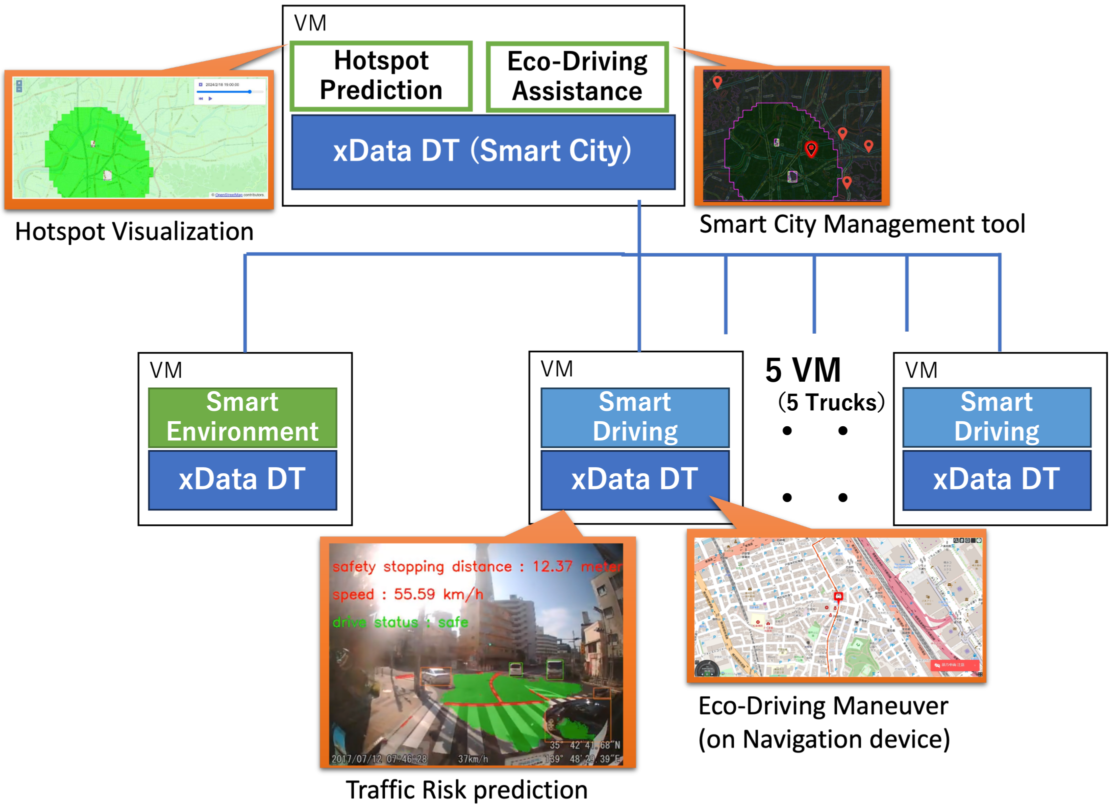


**Figure 9:** Demonstration system setup

application, we have implemented a synchronization function. This function ensures real-time spatial and temporal information updates between the observation station network and vehicles. Through this synchronization process, the latest data from the observation station network, including environmental conditions and traffic-related information, are continuously updated, and shared with the smart driving digital twins. This enables the digital twins to remain informed about current conditions and make real-time adjustments as necessary, contributing to improved prediction accuracy and decision-making in various smart city applications.

Figure 9 illustrates our demonstration system setup. We have configured seven virtual machines to deploy digital twins and orchestration applications. Among these, five virtual machines are dedicated to hosting smart driving digital twins, with each digital twin corresponding to one of the five trucks in our simulation.

Through our proof of concept demonstration, the orchestration framework successfully facilitated collaboration between the smart environment digital twin and the smart driving digital twins. This collaboration provided additional training data for the AQI prediction model, enabling hotspot prediction by the smart city application. As a result, the smart city application can help reduce emissions by guiding drivers away from hotspots. While the orchestration concept has been validated with the framework, we also identified several issues and challenges that require further technological advancements. These will be discussed in the next section.

## 5. Discussion and Open research

In the preceding section, we introduced the concept of digital twin orchestration and demonstrated its application through Hotspot prediction and Eco-driving assistance scenarios. These applications relied on the collaboration between Smart environmental digital twins and Smart driving digital twins. While we have validated the concept through orchestration, there are still research issues to address to enhance accuracy and deploy these solutions in real-world environments.

In this section, we will delve into analysis related research, address research issues and explore potential solutions to further improve the effectiveness and applicability of digital twin orchestration in practical settings.

### 5.1. Related research and comparison

The research in [3, 4] proposed a framework for Blockchain-based collaborative digital twins for pandemic alerting and smart transportation use cases. It focuses on providing an autonomous, secure alerting service with trusted and transparent data exchange among digital twins. The framework consists of four layers to facilitate digital twin collaboration: the physical layer, blockchain-based layer, data analytics layer, and digital making layer. The blockchain-based layer primarily connects digital twins, enabling multiple digital twins to collaborate through a blockchain network that ensures secure data exchange and maintains registered information of digital twins.

Focusing more on communication, the research in [8] presents a vision of the "Internet of Federated Digital Twins (IoFDT)." It describes how digital twins, such as those for smart agriculture, smart factories, smart mobility, and smart logistics, can integrate heterogeneous DTs through a hierarchical architecture of collaboration involving horizontal and vertical interactions. For example, in a lower layer, smart mobility, smart power plants, and smart manufacturing are connected before serving higher-layer applications like smart green city or smart logistics services.

For collaborative training between AI models from multiple digital twins, San et al. introduced an application of federated learning [10]. The proposed federated learning framework for digital twin collaboration focuses on spatiotemporal reconstruction of dynamical systems with various computational frameworks, enabling the learning of an aggregated model while keeping training data on the devices of participants.

In the context of data exchange between digital twins, Javier Conde et al. [11, 12] presented a data flow architecture by extending FIWARE and validating it with a combination of linked open data. Data representing physical or logical objects are termed context entities. Each context entity has a set of attributes, and the metadata of these attributes represent its properties. Based on this, the reference architecture is compatible with FIWARE [6] generic enablers (GE), which

[6]https://www.fiware.org/

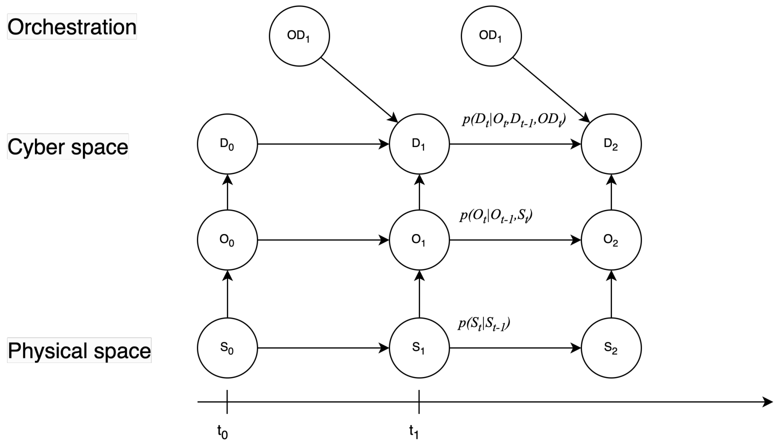


**Figure 10:** Probabilistic models of digital twin orchestration over time step $t$. In the physical space, the state $S$ represents the state of the physical object being monitored. In the cyberspace, $O$ represents observations, and $D$ represents the state of virtual objects within the digital twin. When orchestration occurs, $OD$ represents the observation of linked objects from other digital twins. Directed edges in the figure denote conditional dependencies between the various components and observations, illustrating the complex interactions and dependencies within the digital twin orchestration framework.

include Management of Context Data, Data Acquisition and Persistence, Data Analysis, and Security.

Our study closely aligns with the concept of the Web of Digital Twins [9]. In this framework, a digital twin is depicted as a Knowledge Graph structured with entities and relationships defined by an ontology. Expanding on this idea to encompass interconnected digital twins, the Web of Digital Twins utilizes Distributed Knowledge Graphs [32], where links between digital twins are described using the Relational Description Framework.

In general, most studies focus on how data and models can be securely exchanged between digital twins while maintaining data privacy. In particular, Web of Digital Twin address the model and relationship among digital twins, yet not provide a mean to orchestrate those connected digital twins. Our proposed framework also addresses these functions. More importantly, we integrate all functionalities into a single framework, allowing digital twins to interpolate exchanged data, share and adapt analysis and simulation objects, and serve context information to smart applications as illustrated with prove of concept applications.

## 5.2. Issues and Open Research

Digital twins consist of various components, including virtual objects, analysis models, and simulation objects. These digital twins continuously observe data and update their internal components to represent models for analysis, prediction, optimization, and control of physical objects [33]. When digital twins collaborate via digital twin orchestration, the models inside each digital twin receive additional observations acquired from other digital twins. Consequently, transitioning between models and calculating components becomes more challenging.

Figure 10 illustrates probabilistic models of digital twins, showcasing the complexity and interconnectedness of the various components within the digital twin orchestration.

In our current focus on digital twin federation with federated learning, we recognize that the accuracy of federated learning is heavily reliant on consistency in data distribution and computational resources among digital twins. In our proposed orchestration applications, one significant challenge lies in enabling collaborative training between static observations (such as those from observation station networks) and mobile observations (from truck sensors). Addressing this challenge requires leveraging conventional methods [18, 19] to ensure effective collaboration despite the disparities in data sources and computational resources.

To address the limitations posed by computing devices for federated learning, we have implemented offload learning techniques for federated edge AI [34, 35]. However, a persistent challenge arises with digital twins that require additional capacity for components other than machine learning. This is particularly evident in small, embedded computers, such as those mounted on trucks, where resources are constrained. Finding effective solutions to optimize the performance of digital twins on such devices remains an ongoing issue.

In our latest study, we have demonstrated the concept of digital twin orchestration by linking a smart environmental digital twin with a smart driving digital twin, facilitating collaboration through orchestration functions. Although the analysis models and simulation services are already operational, further investigation is required to enhance the performance and accuracy of these models. This effort involves optimizing the models, conducting experiments, and evaluating the performance of machine learning models within these digital twins when orchestration is enabled.

## 6. Conclusion

In this paper, we have discussed how digital twins collaborate via an orchestrator with functions including federation, translation, brokering, and synchronization. **Federation** with federated machine learning enhances collaboration by sharing models while maintaining the privacy of sensitive original data. **Translation** supports conversation and data conversion between digital twins for cross-domain communications. **Brokering** with context allows for relaying data transmission and filtering with context. **Synchronization** is utilized to identify entities and ensure the up-to-date status of virtual things.

Based on this discussion, we proposed an orchestration framework with functional entities and demonstrated its application in a smart city context, including **Hotspot prediction** and **Eco-driving assistance**. In the demonstration, smart environmental digital twins and smart driving digital twins were created to capture environmental information and collaborate for hotspot prediction. Leveraging location and time context, smart driving simulations can maneuver drivers to reduce emissions.

Furthermore, we discussed research issues and challenges in the implementation of digital twin orchestration. Combining multiple digital twins, especially across domains, makes modeling digital twins and orchestration for evaluation difficult. Collaborative training among digital twins with federation also faces challenges due to non-identical data distribution and limitations of edge computing devices equipped on vehicles.

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