Realizing Sustainable and Adaptive Smart Cities With AI-Powered Digital Twin

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Abstract

Smart cities incorporating smart grid and intelligent transportation systems are an emerging paradigm that aims to improve the quality of life for residents through ubiquitous networking coverage, automation, and artificial intelligence (AI). However, the emergence of electric and autonomous vehicles (EAVs), the wide expansion of data centers, and the high integration of renewable energy impose heavy burdens on the ossified smart cities infrastructure. In this article, we develop a sustainable and adaptive digital twin (DT) framework to characterize smart cities with high fidelity and real-time synchronization between physical and digital spaces of smart city applications. Different from existing DT models, the developed framework considers the interconnections among multiple subsystems, where each subsystem is connected with real-world physical space to achieve real-time interaction. Considering large-scale system simulations and huge amounts of Internet-of-Things (IoT) data to be processed, we propose a hierarchical computing architecture and a DT update mechanism to decompose and distribute computing tasks according to the capabilities of data centers and local computing devices. Two case studies are presented to validate the adaptability and high fidelity of the developed DT framework that achieves close-to-optimal performance with partially lacking data.

I. Introduction

Smart cities are a promising paradigm that incorporates sensing, networking, and computing techniques to improve the quality of life for city residents as well as to enhance the sustainability and efficiency of city operation [1]. Recently, the prevalence of electric and autonomous vehicles (EAVs) has brought new challenges to smart city planning and operation. First, the operations of EAVs are closely coupled with smart grid (SG) and intelligent transportation system (ITS), making the system modelling complicated. Second, EAV commercialization imposes a burden on the SG loading while raising the bar of on-road networking and computing due to increasing autonomous driving demands. Additionally, the rise of generative artificial intelligence (AI) technology requires a wide expansion of data centers (DCs), which puts pressure on the SG for high carbon emissions. Renewable energy generations (REGs) emerge as potential solutions with net-zero emission but incurs additional challenges due to their intermittent nature. Considering the dynamics and complicity of the system, it is imperative to develop an intelligent operation platform for a precise characterization of smart cities.

Thanks to the advancement of real-time data collection, data analytics, and machine learning technologies, digital twin (DT) emerges as a key enabling technology to realize a high-fidelity and intelligent operation platform for smart cities [2]. Different from existing modelling and operation techniques, DT maps real-time data and response from a physical space into a digital space to offer precise representations of physical entities. With real-time interactions between physical and digital spaces, a DT of smart cities can provide the city operator with valuable data and guidance for operation and planning.

In the literature, applications of DT in smart cities have been explored. For example, a road infrastructure DT was investigated in [3] for road monitoring and object detection in smart cities. In [4], a smart DT platform was proposed to control connected and autonomous vehicles over wireless networks. The application of digital twin in industrial Internet-of-Things (IoT) systems was explored in [5] for ultrahigh-voltage converter station. While existing literature has developed well-modelled DTs for part of smart cities, none of them considered the system-level DT model, which is much more complicated. An attempt at system DT modelling was discussed in [6], where the smart transportation system and smart energy system were modelled together. In [7], a machine learning model was integrated into the digital twin platform to simulate cyber-attacks and evaluate response strategies in smart cities. However, the coupling between subsystems is weak. In [8], a spatio-temporal graph model was developed as the ITS DT with SUMO and OMNET++ network simulator. While the interaction between ITS and SG is considered, the work focuses more on the DT model update rather than its operation optimization.

While existing literature has contributed to various aspects of the smart cities DT development, three major research gaps exist: First, most literature considers a subsystem of smart cities without an explicit characterization of the interconnections among subsystems in smart cities. This research gap is critical, especially with the integration of DCs, EAVs, and

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REGs. These components are highly power-rated with stochastic load profiles that require the coordination of the SG and the ITS for optimal performance. Second, most of the DTs are centrally deployed on one virtualized computing node (potentially for cloud computing), which suffers from limited scalability and low operation resilience. Finally, most DTs utilize existing datasets for model creation, which may not achieve real-time interactions between the DT and the modelled entity in the physical space. Real-time interactions are critical for fundamental infrastructure to provide timely and accurate simulation results.

To bridge the research gaps, we develop a sustainable and adaptive DT framework that can precisely characterize smart cities while capturing the interconnections of subsystems in smart cities. The DT framework will be implemented using emerging hardware-in-the-loop devices [9] and NSF Colosseum [10]. Specifically, our contributions are as follows:

- The proposed framework is one of the first to incorporate SG, ITS and communication subsystems together in the smart city modelling. The framework uses local REGs to achieve net-zero energy provision with detailed communication system modelling to evaluate its impact on system performance.
- A hierarchical DT update mechanism is proposed to decompose and distribute computing tasks to maximize resource utilization, decrease network latencies, and protect user privacy.
- Leveraging synthesized data and machine learning algorithms to implement the proposed DT framework, we can validate the superiority of the developed framework in terms of accuracy and adaptability.

The rest of the article is organized as follows. Section II introduces the system architecture. Section III presents the proposed DT framework and two use cases for the DT workflow demonstration. Section IV proposes a hierarchical DT update mechanism that incorporates task decomposition and distribution across multiple tiers. Section V presents case studies to demonstrate the effectiveness of the developed DT framework. Finally, we conclude the article in Section VI.

II. System Architecture

A. System Overview

We consider smart cities to be composed of an SG and an ITS, both built on the city topology. The communication system is incorporated into the SG and the ITS through Internet-of-Things (IoT) devices and the HILP system. As shown in Fig. 1, the architecture of smart cities is composed of a digital twin, its counterpart (a physical twin), and a DT modelling block (shown in light blue). The physical twin consists of all the subsystems and devices where the real data are transferred to its DT space via communication systems. The DT mirrors the physical twin with detailed modelling on targeted components such as EAVs, DCs, and roadside units (RSUs). In this section, we introduce the physical twin of smart cities. The main components and functions of each subsystem are elaborated in the following.

B. SG

The SG is a fundamental subsystem in smart cities, aiming to provide residents with green and stable electricity. Compared to the conventional power grid, the SG utilizes advanced sensing, networking, and information technologies to optimize its operation while guaranteeing the reliability and stability of the system. The SG in smart cities is a low-voltage power distribution system that connects with a high-voltage transmission system via a point of common coupling (PCC). In the power distribution system, REGs and loads are connected to different levels of feeders depending on their power and voltage ratings. For example, large-scale REGs (e.g., solar farms) and industrial loads with high load demands are deployed at primary feeders. Meanwhile, lower power-rated generators and loads such as EVCSs, residential loads, and RSUs are deployed at secondary feeders. Communication devices are deployed in both wired and wireless formats to ensure a seamless information exchange in the SG.

C. ITS

Another fundamental infrastructure in smart cities is the ITS, which is composed of transportation, communication, and computing components. In the ITS, RSUs with cameras and sensors monitor traffic conditions and regularly transmit the data to DCs for analysis. RSUs may act as edge computing devices to cache popular content and conduct simple computing tasks with local data. As EAVs become prevalent, EVCSs are widely deployed in the ITS to alleviate EAV range anxiety. EVCSs are equipped with networking and computing devices to perform edge computing tasks. EVCSs couple the operation of SG and ITS by reflecting the traffic flow fluctuation in the form of EAV charging demand in the SG.

D. DCs

Smart cities are a complex system that requires high computation power to maintain its operation. To help alleviate the heavy computation burden, we develop a hierarchical computing architecture that decomposes and distributes tasks to DCs with different computing capabilities. Corresponding to their computing capacities, DCs have different cooling requirements and load ratings, and are deployed at SG's feeders according to their ratings.

As shown in Fig. 1, the hierarchical computing architecture is composed of cloud DCs, edge DCs, and end users. Cloud DCs are responsible for system-level DT operation and thus have high power ratings, usually up to MW level. Additionally, cloud DCs require heavy-duty cooling devices for their servers. Cloud DCs are deployed in the transmission system to fulfill their power demand. Edge DCs are responsible for the regional DT update and data processing. Edge DCs have considerable power demands (e.g., kW level) with moderate cooling requirements. Therefore, edge DCs are usually deployed at primary feeders in the SG. End users with computing capabilities (e.g., EVAs, EVCSs, and RSUs) can provide edge computing services to reduce the data transmission overhead and preserve user privacy. These end users can connect to secondary feeders for power provision.

As the expansion of DCs unfolds, the decade-old SG infrastructure encounters significant loading pressures. As a cost-efficient solution, REGs are integrated with DCs in the SG. For example, cloud DCs are integrated with MW-level REGs to avoid transmission line congestion. For an edge DC with hundreds of kW power demand, a small-size REG is sufficient.

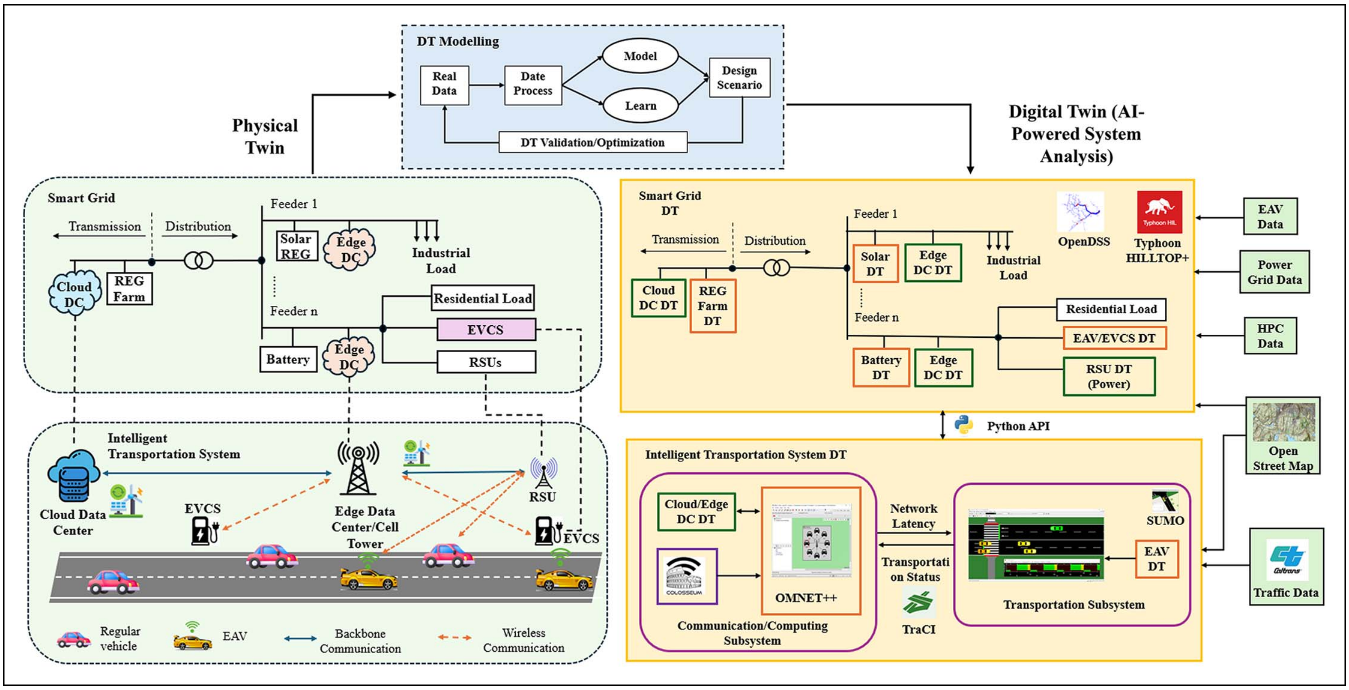

FIG. 1. System architecture and the proposed DT framework.

E. EAVs

EAVs are coupled with the SG and ITS operations through their transportation and charging/discharging features. For example, locations of EVCSs in the SG affect EAV travelling trajectories in the ITS. In return, EAV traffic conditions in the ITS affect their charging decisions, which impacts the EVCS loading status in the SG. The autonomous driving capabilities of EAVs make them ideal candidates for data sensing, networking relay, and edge computing.

III. Proposed DT Framework and Use Cases

In this section, we present the proposed DT framework for smart cities. Then, we showcase the workflow of the proposed framework through two use cases.

A. Proposed DT Framework

The proposed DT framework maps smart cities from the physical space to its digital space through data sensing, processing, and system modelling. Mirroring smart cities in the physical space, the proposed DT framework consists of two subsystems: the SG DT and the ITS DT, which are described in detail. Further, we emphasize on the DT models of key components (e.g., EAVs and DCs) in smart cities.

1) SG DT: As shown in the right part of Fig. 1, the SG in the digital space is created using Typhoon HILLTOP+ [9] and OpenDSS. Typhoon HILLTOP+ is a real-time simulator that connects the SG in the physical space with its DT. In our proposed framework, Typhoon HILLTOP+ connects the SG DT with the SG Laboratory for data sampling, command transfer, and system status monitoring. OpenDSS can simulate quasi-status time series (QSTS) of the power distribution system while interfacing with HILLTOP+ to calculate power flows. HILLTOP+ can interface with OpenDSS through the Python API (OpenDSS Direct) to understand how dynamic control of power system components affects the system-level operation. Such a co-simulation platform can also be leveraged to develop optimization and machine-learning algorithms for the steady-state power grid analysis.

2) ITS DT: In the digital space, the ITS DT model is composed of the transportation subsystem and the communication/computing subsystem. SUMO is employed to model the transportation system, including the road topology, terrain information, and vehicular traffic. The SUMO model is fed with real-time data from the Caltrans Performance Measurement System (PeMS) [11] for model calibration. On the other hand, the communication/computing system is modelled leveraging NSF Colosseum [10] to simulate and test real-life networking scenarios. Colosseum has 128 standard radio nodes (SRNs), a massive channel emulator (MCHEM), a traffic generator, GPU nodes, and management infrastructure which can be reserved and used remotely. Multiple SRNs are reserved to simulate and collect real signal transmission data that are fed into OMNET++ for high-layer networking simulation. Enabled by the traffic control interface (TraCI) and Python interface, the ITS can be co-simulated with the SG.

3) DC DT: In the digital space, DC functionalities such as temperature monitoring, cooling, and load management are modelled to characterize DC's computing, networking, and load statuses. DC DTs are integrated into the SG DT through feeders. DC DTs communicate with the SG DT about their loading forecasting, requested power, and committed power. DC DTs also interact with the ITS DT to perform computing tasks and migrate computing tasks through the communication system when necessary.

4) EAV and EVCS DT: The EAV DT is constructed with the input of EV driving trajectory data from our EV test drive program. The trajectory data helps the EAV DT to model the EAV driving mechanism and energy consumption pattern. Moreover, EV battery cycling data from our laboratory and

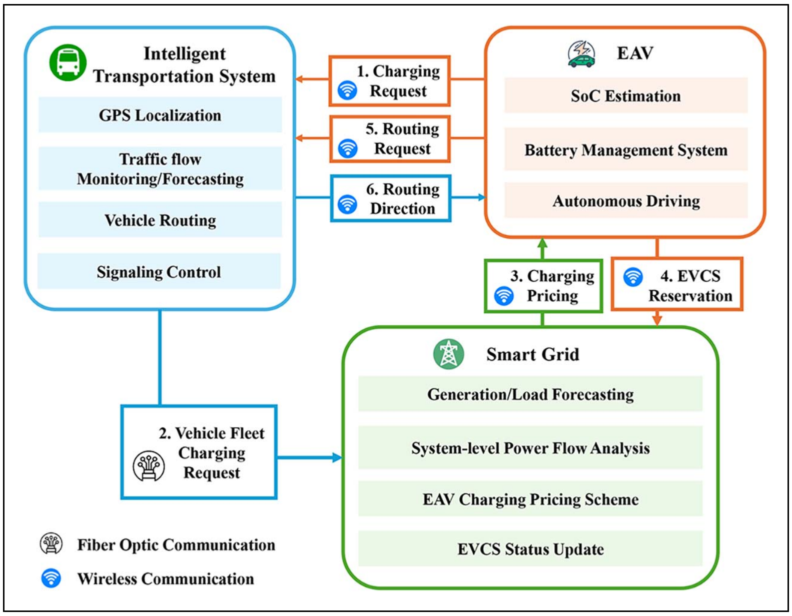

FIG. 2. Use case 1: EAV charging navigation.

emulated vehicular networking data from NSF Colosseum are regularly sampled and fed into the EAV DT for the calibration of EV battery and networking models.

The EVCS DT inputs the ITS traffic data from Caltrans PeMS and the EAV charging data synthesized by [12] to construct its charging load and pricing models. Both EVCS DTs and EAV DTs interconnect with the SG DT and the ITS DT for real-time information exchange while taking into account the networking impact on the system performance.

B. Use Cases

1) Use Case 1: EAV Charging Navigation: Charging navigation is a critical task for both EAVs and smart cities. From EAV perspective, on-time charging helps alleviate drivers' range anxiety. From smart cities perspective, optimal charging navigation on the system level helps guide the traffic flow and mitigate peak electric loads. Additionally, the charging navigation task interconnects the operation between the SG and the ITS as the EVCS pricing could affect the EAV routing plan in the ITS while the traffic conditions could impact the EAV charging plan in the SG.

As shown in Fig. 2, the EAV charging navigation requires cooperative efforts from all entities in smart cities. When an EAV is on the road, its DT regularly monitors and assesses its state-of-charge (SoC) status to evaluate its charging demand given the external environment. When the EAV DT decides to search for EVCSs, the EAV sends the charging request to the ITS DT via vehicular networks. The ITS edge DC collects and aggregates its regional EAV charging requests to analyze the temporal and spatial EAV charging demands. Later on, the regional EAV charging demand is sent to the SG. The SG DT performs a hierarchical EVCS pricing scheme based on the current and forecasted EAV charging demand, power flow analysis, and current load commitment. Once the EVCS price is confirmed and updated, EVAs make reservations to their preferred EVCSs or navigate to the EVCS and be served on a first-come-first-serve basis. EVAs then communicate with the ITS to autonomously navigate to the reserved EVCS.

The charging navigation helps update system data such as ITS traffic conditions, SG loading data, and EAV driving status, which are fed into corresponding DTs for model calibraiton.

2) Use Case 2: Load Shifting for Data Centers: The rapid advancement of generative AI and data-based technologies has boosted the deployment of DCs. In the United States, the electricity load growth was forecasted to jump 81% led by DCs [13]. Multiple countries have started imposing restrictions on DCs with legislation to encourage DCs to become net-positive with REG integration. Our proposed framework can effectively address the heavy loading issues incurred by DCs with a hierarchical load shifting strategy as shown in Fig. 3.

The cloud DT (short for cloud DC DT) evaluates its local REG generation and upcoming task amount to decide the number of tasks to be offloaded to edge DCs. The offloaded tasks are decomposed and distributed to edge DCs according to their available computing resources and REG generation. The locally processed computing tasks are subject to load scheduling and power capping, through which the cloud DC aims to achieve a flattened load profile, which is updated with the SG.

The edge DT (short for edge DC DT) monitors its upcoming computing tasks to assess its available power capacities for task implementation. Different from the cloud DC, the edge DC has fewer servers that require medium temperature control and have a lower power rating. Correspondingly, the computing capability of an edge DC is significantly smaller and therefore, edge DCs may require end users to conduct local computing tasks (e.g., data cleaning and device model update). Once tasks are decomposed and distributed from the edge DCs to end users, the edge DT updates the SG with its load request. Notably, both cloud and edge DCs are integrated with REGs, aiming to achieve a net-positive operation. Therefore, these two DTs need to develop REG integration schemes in accordance with real-time and forecasted electricity consumption and temperature control.

In this use case, we take the EAV as an example that can sense its external and internal environment, process the data, and update its DT locally. Localizing computing tasks not only maximizes resource utilization but also preserves user privacy. Further, with its on-broad battery, the EAV can achieve net-zero computing if charged with green energy.

Upon receiving the load requests from all computing devices, the SG DT responds with the committed generation to each computing infrastructure through careful power flow analysis and load forecasting. In emergency conditions (e.g., power outages or post-disaster scenarios), the PCC may be disconnected between the power distribution system and the transmission system for grid protection. Therefore, DCs that are in the outage-affected areas need to be self-sustained. As such, only critical and necessary computing tasks are implemented at DCs while EAVs are navigated to these power-outaged DCs for temporary energy provision. The previously distributed tasks may be rescheduled by the cloud DT to other normally operated edge DCs.

IV. Hierarchical DT Update

The hierarchical computing architecture and the operation among multiple subsystems in smart cities

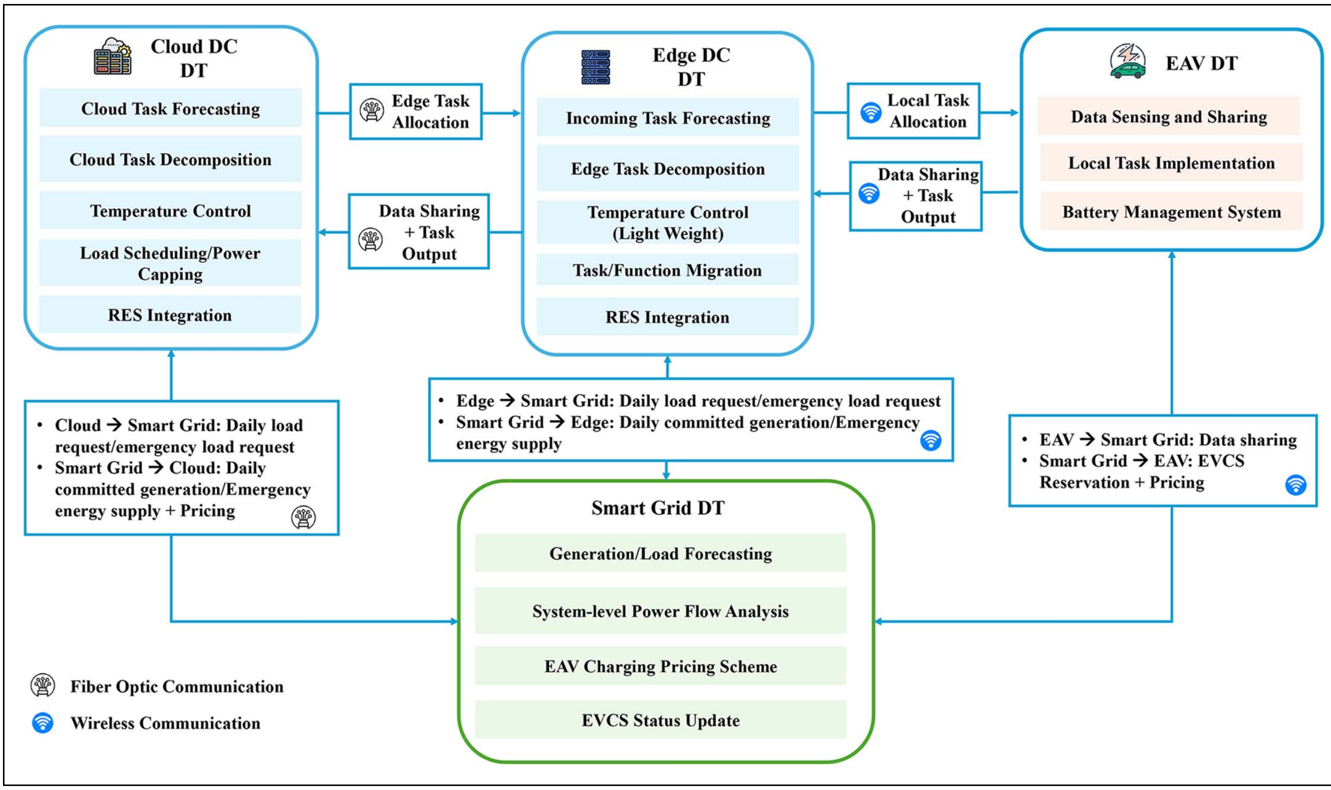

FIG. 3. User case 2: Hierarchical load shifting for DCs.

in the proposed DT framework necessitate an efficient DT update strategy. In this section, we develop a top-down approach to update DTs by illustrating the internal DT update and specify the interconnection between DTs at different layers.

A. Cloud DT Update

At the top tier, the cloud DT is responsible for the system overall update. The cloud DT is operated through the coordination between the SG and the ITS operators. As shown in Fig. 4, the cloud DT interacts with the physical space through real-time data communication. The DT update requires constant data aggregated sent from edge DC DTs. As smart cities evolve, emerging technologies and devices join the system and thus multi-system coordination is updated accordingly.

Tasks are decomposed in terms of their properties. For example, traffic-related tasks (e.g., traffic flow forecasting and fleet routing) can be decomposed and distributed to ITS DT while power-related tasks (e.g., EAV charging) are decomposed and distributed to the SG DT.

B. Edge DT Update

Smart cities have multiple edge DCs, each responsible for computing tasks of one subsystem for a specific region. Edge DTs can be categorized into regional ITS DTs and regional SG DTs.

1) Regional ITS DT Update: The regional ITS DT characterizes the ITS in a given region (e.g., 20km) with real data collected from the physical space to calibrate the model development (e.g., road topology update) and optimize the operation (e.g., traffic flow guidance). In return, the ITS DT can provide up-to-date traffic guidance and more accurate synthesized data. Upon receiving computing requests from the cloud DT, the regional ITS DT implements tasks locally, further, distributes tasks to lower tiers, or migrates tasks to DCs at the same tiers with redundant computing resources.

2) Regional SG DT Update: Regional SG DT is deployed at edge DCs to monitor and simulate the SG in a given region. The DT is operated by the regional utility company and real SG data in the physical space are fed into the DT model for operation optimization (e.g., REG integration control) and data synthesis. In return, the regional SG DT provides recommended control actions. Upon receiving computing tasks from the cloud DC, the regional SG DT decomposes tasks and distributes tasks to end users under coverage. Different from the ITS, end users in the smart grid are significantly different from each other. For example, REGs can only implement tasks related to their generation and storage control while EAVs may implement tasks for both EAVs and EVCS.

C. End-User DT Update

Considering the complexity of smart cities, there are numerous end users who have their local DTs for data computing. For simplicity, we introduce three representatives of end-user DTs.

1) RSU DT Update: The RSU DT characterizes the operation of RSUs in the regional ITS. The RSU is responsible for sensing the surrounding networking and traffic conditions, which are fed into the RSU DT for model update through learning-based model training. Correspondingly, the updated DT can implement computing tasks accurately to provide local traffic/networking guidance and upload hierarchical data/commands to upper tiers.

2) EAV DT Update: The EAV DT characterizes the operation of EAVs in smart cities. The EAV couples the SG and the ITS, responsible for data sensing,

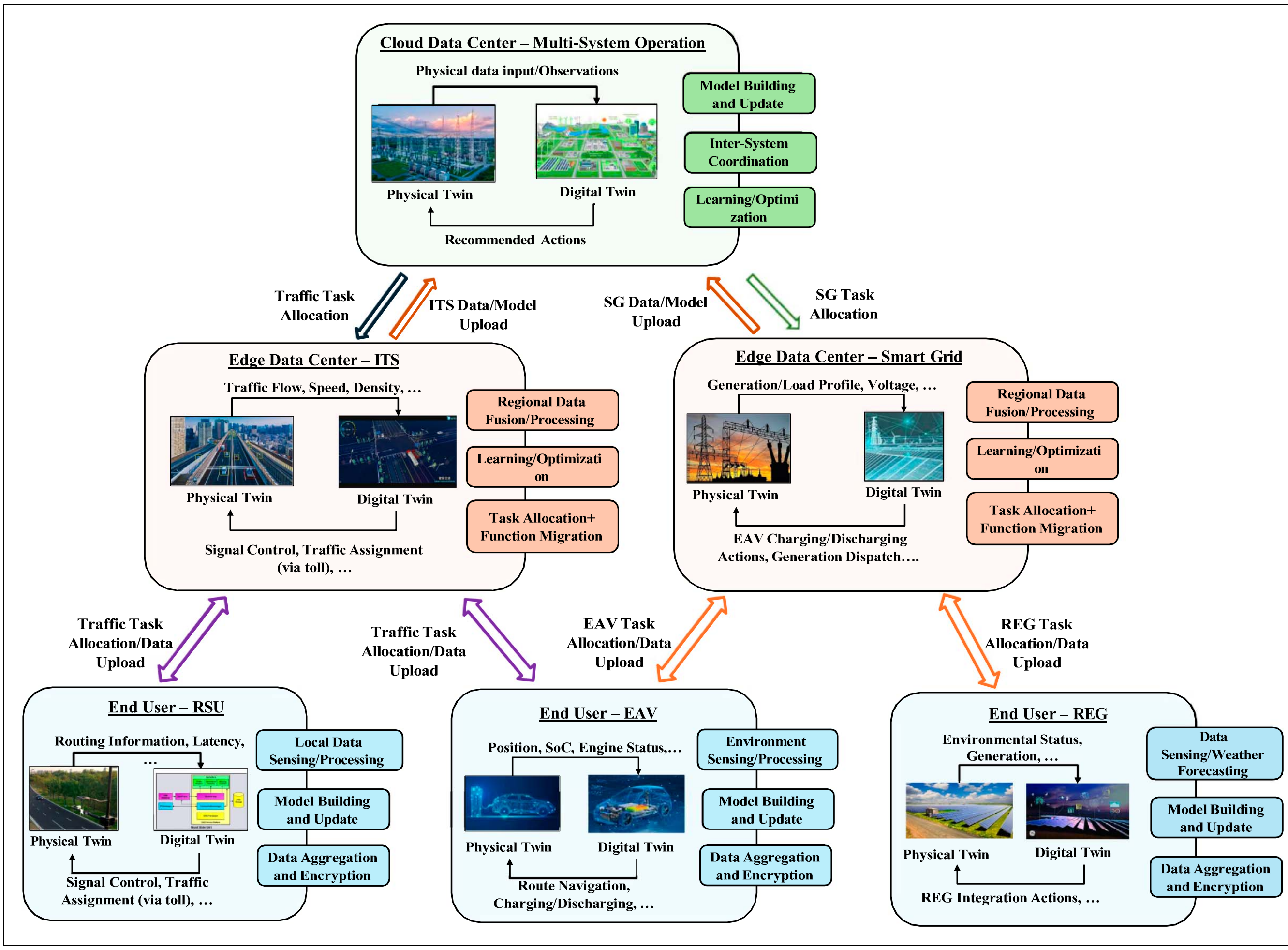

FIG. 4. Hierarchical DT update.

transportation, networking relay, edge computing, charging and discharging services. EAV sensing data are fed into the EAV DT for its model calibration and data synthesis and in return, the updated DT helps improve the autonomous driving performance as well as the battery management. EAVs can perform tasks in a fleet manner as an aggregated computing device/battery pool.

3) REG DT Update: The REG DT characterizes the operation and control of REG in the regional SG. The REG generates electricity using local RES with detailed control schemes tailored to each RES. The real generation data along with the REG environmental data are transferred to the REG DT to calibrate the REG generation forecasting profile as well as the REG control strategy. Then, the REG DT helps improve the REG generation through its model's forecasting and optimized control. The REG DT can undertake computing tasks from the smart grid, especially the ones related to REG control and environmental data sensing.

V. Case Study

To demonstrate the effectiveness of our developed DT framework, we conduct two case studies. First, the high fidelity and adaptability of the developed DC DT are showcased using real performance data of virtual machines from distributed DCs from Bitbrains [14]. Then, the DC loads are integrated into smart cities, in cooperation with EAVs and REGs, to perform a cooperative economic dispatch in the SG for peak load mitigation. Here, we demonstrate how such a DT framework can achieve near-optimal results while outperforming other benchmarks.

A. Forecasting Performance on CPU Usage

The forecasting performance on the CPU usage using the proposed DT framework is shown in Fig. 5, in comparison with the real data and model-based forecasting (i.e., auto-regression model). We show the forecasting results on two different virtual machines. It is observed that the proposed DT framework achieves high forecasting accuracy compared to real data while the model-based forecasting has a much lower forecasting accuracy as it cannot well track the sudden impulses of incoming computing tasks. Statistically, the proposed DT framework achieves a mean squared error (MSE) of 0.008578, much better than the model-based forecasting for Machine 1. Similar statistics apply to Machine 2 results: the DT framework has an MSE of 0.0005228 which is negligible.

It is also observed that the proposed DT framework can achieve high forecasting accuracy even on virtual machines with significantly different CPU usage patterns. Therefore, we have validated the framework's adaptability as the DT framework can be adaptively adjusted to achieve good performance under different operation scenarios.

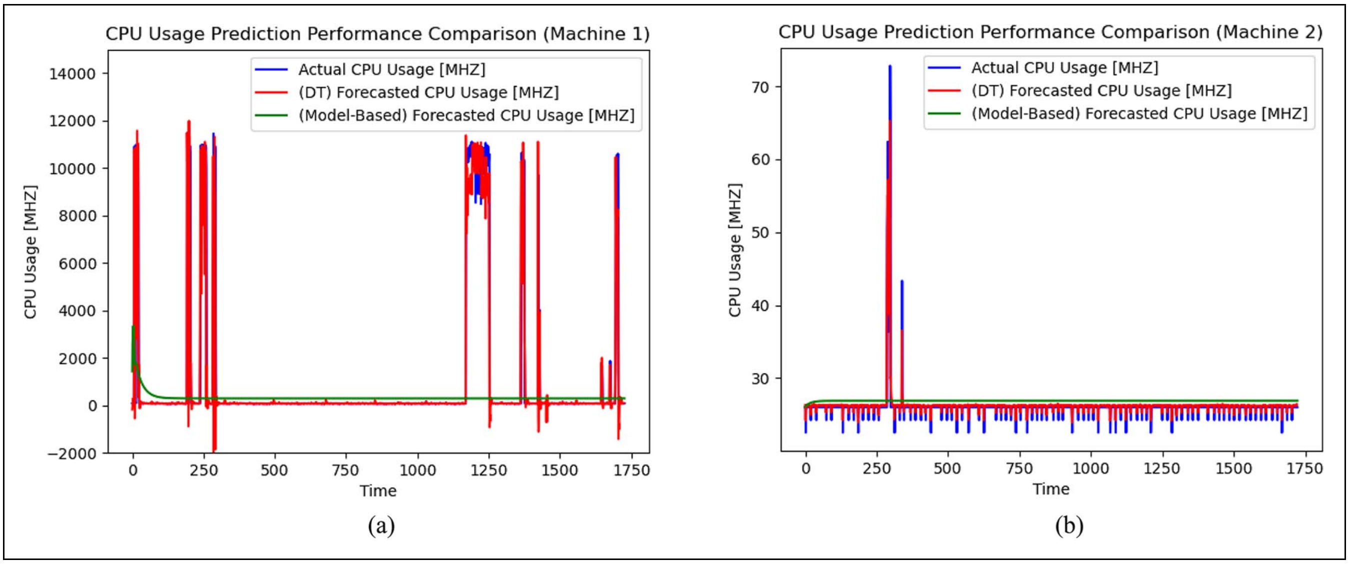

FIG. 5. Forecasting performance on CPU usage.

B. Performance Comparison of the Cooperative Economic Dispatch

This case study considers the joint optimization of the SG DT and the ITS DT with the integration of DCs, EAVs, and REG. Specifically, we consider using EAVs as mobile energy storage that can charge and discharge in corporations with the SG demand to achieve a cost-efficient power generation. As such, the joint optimization problem is formulated to reduce the generation cost C_{gen}, EV fleet travelling cost C_{tra}, and battery degradation cost C_{bd} as follows:

$$\min\ (\delta C_{gen} + \epsilon C_{tra} + \zeta C_{bd}) \qquad (1)$$

The optimization problem is subject to constraints of power balance, EV mobility and battery capacities. Due to the space limit, we omit the discussion on constraints. The simulation is conducted on IEEE 14-bus system with one REG integrated and two edge DCs deployed. Two EAV fleets travel in smart cities (modelled in the ITS DT) to provide on-demand energy considering the uncertainty of loads and the REG. Due to the uncertainty of the SG components, it is critical to have the proposed DT framework for data synthesis and forecasting.

The performance comparison of the cooperative economic dispatch scheme using real data, data forecasted by the proposed DT framework, and data provided by the model-based forecasting is shown in Fig. 6. It can be observed that the economic dispatch cost of the real data (i.e., without uncertainty) is minimal while the proposed DT framework achieves a relatively low cost compared to the model-based forecasting result (i.e., the auto regression-based forecasting). The results show the promise of using the proposed DT framework for data synthesis and forecasting.

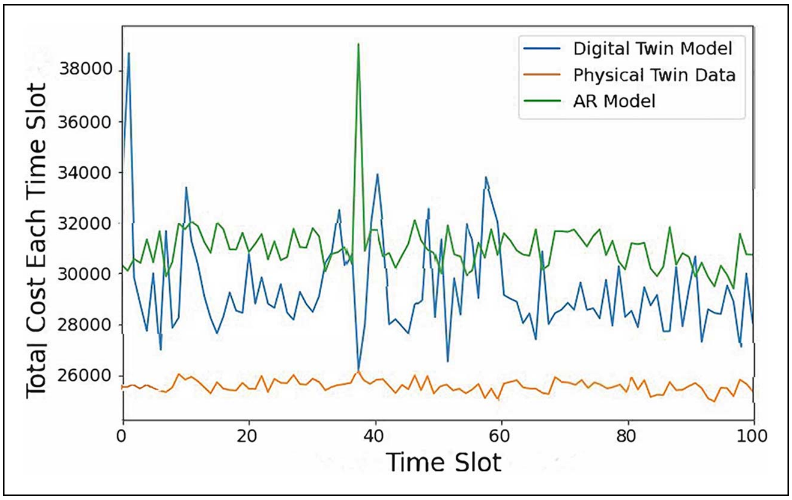

FIG. 6. Performance comparison of the cooperative economic dispatch.

VI. Conclusion

In this article, we have developed a sustainable and adaptive DT framework for smart cities that integrates SG with ITS. The emerging paradigms such as EAVs, DCs, and REGs are also characterized and incorporated into the proposed framework to meet the net-zero/net-positive goal for a highly intelligent and automated city operation. Further, a hierarchical computing architecture has been developed to improve the resource utilization of local computing resources, strengthening the resilience of the smart cities operations, while preserving user privacy with limited data uploading to the centralized operator. Two use cases have been introduced to demonstrate the necessity of the proposed framework for emerging paradigms. A hierarchical DT update mechanism has been proposed to achieve an efficient and privacy-preserved DT update through task decomposition and peer-to-peer task migration. Two case studies have been presented to demonstrate the effectiveness of the developed DT framework on adaptability and high-fidelity modelling to achieve near-optimal performance.

For future work, we plan to develop a full-scale well-rounded DT platform to provide guidance on long-term smart cities planning and operation.

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