Towards Digital Twin-based Operation and Maintenance: A Virtual Assistant Framework for Creating Guidelines According to Managers' Requirements

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Abstract

Successful implementation of Digital Twin (DT) technology in Operation and Maintenance(O&M) requires deep DT knowledge and extensive O&M experience. To address this challenge, this paper introduces a virtual assistant framework named "DT-GPT" that utilizes Generative Pre-trained Transformer (GPT) to assist managers in creating DT-based O&M guidelines according to their requirements. To determine managers' requirements, an O&M requirements system with DT was developed. Based on the established requirements system, a three-step approach to employ DT-GPT was proposed to dynamically determine guidelines based on the project requirements and details. In a case study, DT-GPT's function is demonstrated through a virtual assistant prototype for campus management. The process exemplifies the potential of DT-GPT in facilitating the successful integration of DT in O&M practices. This paper contributes to the advancement of effective and informed virtual assistants for DT in the O&M stage, significantly reducing knowledge gaps, time, and cost for DT applications.

Keywords

Digital Twin, Operation and Maintenance, Generative Pre-trained Transformer, Virtual Assistant, Large Language Model

1. Introduction

With the integration of information technology (IT) across various industries, traditional sectors have increasingly adopted IT to enhance efficiency and quality, particularly in the Architecture, Engineering, and Construction (AEC) industry [1]. A significant technological advancement in this area is the concept of the Digital Twin (DT) [2], which integrates multi-disciplinary data to support AEC activities, especially in Operation and Maintenance (O&M) management [3]. As the longest stage in the building life cycle, O&M increasingly relies on digital technologies to manage complex building systems, including prediction, anomaly detection, and operational optimization [4]. This application can lead to substantial cost and time savings [5], risk reduction [6], and improved O&M efficiency [7].

AI4DT&CP@IJCAI2024: The Second Workshop on AI for Digital Twins and Cyber-Physical Applications in conjunction with 33rd International Joint Conference on Artificial Intelligence, 3rd-9th August 2024, Jeju, South Korea
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However, due to the novelty of DT in AEC industry, the application of DT and the construction of Cyber-Physical System (CPS) for O&M are still in the early stage. Current DT application strategies and CPS development approaches require managers to possess extensive knowledge and experience with DT, which is often lacking due to the scarcity of successful cases [8]. To address the challenges associated with DT applications, virtual assistants have been proposed as a potential solution [9]. Nevertheless, developing these virtual assistants presents significant challenges, as it demands high levels of automation to accurately interpret diverse natural language queries from various users [10].

The rise of large language models (LLMs) brings new opportunities for DT applications [11]. These models, pre-trained on extensive text corpora, have demonstrated remarkable contextual learning capabilities in natural language processing (NLP) tasks via textual "prompts". Among all LLMs, Generative Pre-trained Transformers (GPT) have shown powerful abilities in generating and understanding natural language [12]. The core idea of the GPT model is to leverage large-scale text corpora for unsupervised learning, gaining deep insights into the structure and semantics of language. During the pre-training phase, the GPT model learns statistical and language patterns from textual data. Subsequently, it enters a fine-tuning phase tailored for distinct tasks like text generation, classification, and question answering [13].

Based on the GPT-4 model, a virtual assistant is developed to assist managers in creating guidelines during the planning stage. The major contributions of this study are as follows:

- A framework for an operation and maintenance requirements system with digital twins has been developed to support the successful implementation of DTs in O&M. This proposed system includes model requirements, function requirements, and nongeometric data requirements;
- A three-step approach to creating O&M guidelines is presented. A novel aspect of our approach is its dynamic determination of guidelines based on the project requirements and details;
- This study utilizes the GPT-4 model to create the DT-GPT assistant, aiding managers in formulating guidelines for digital operational management and identifying the non-geometric data requirements of different projects. The guideline formulation process is integrated with the proposed requirements system and three-step approach.

The paper is organized as follows: Section 2 reviews the related literature. Section 3 presents the framework for the operation and maintenance requirements system with digital twins. Section 4 presents the three-step approach and the DT-GPT assistant. Section 5 describes a case study on campus management. Finally, conclusions are drawn in Section 6.

2. Related Work on LLMs and DT-based O&M

In this section, we perform a comprehensive overview of related research on operation and maintenance with digital twin technology. Meanwhile, we also review some assistants based on GPT models and their applications in different fields.

2.1. DT based O&M

The development of O&M can be divided into three stages: the traditional stage which relies on documents and personnel; the platform stage which requires a detection and management platform, and the intelligence stage which integrates Building Information Modeling (BIM), Artificial Intelligence (AI), Internet of Things (IoT) to assist decision-making [14]. Actually, the intelligence stage aligns with the concept of Digital Twin proposed by Michael W. Grieves [15]. Current studies have proved the potential of implementing DT in O&M management [16, 17, 18]. For example, a DT-based framework for automatically detecting and diagnosing faults in facilities was built by Hosamo et al. [19]. Clausen [20] presented a DT framework to control heating and ventilation by using data on weather forecasts, current- and planned occupancy as well as the current state of the controlled environment. Francisco [21] established a DT platform for urban-scale energy management and developed daily building energy benchmarks by leveraging smart meter electricity data. Lombardo et al [2] proposed a multi-layer DT-based architecture aimed to enable the development of machine learning-based intelligent location based services. The platform was evaluated in the complex scenario of healthcare organization, achieving high accuracy and efficiency.

Although the necessity of DT in O&M has been recognized since 2010 [22], managers have not fully embraced its benefits [23]. A main barrier is the challenge of how to employ DT to support management, considering the requirements of managers [4]. To address the issue, Cavka et al. [24] investigated six projects to map the relationship between organizational constructs, owner requirements, and model. It helps owners understand how to approach the handover of digital facility models and determine their model requirements based on specific needs. Chen et al. [25] identified the information requirement and proposed a ontology-based framework for facility maintenance management. A data structure for O&M data requirements was developed by Becerik-Gerber [26] to support successful implementations of DT in O&M.

2.2. LLMs Assistant and Applications in O&M

LLMs are a sophisticated category of Machine Learning (ML) models crafted to comprehend and generate human-like language. They achieve this capability through extensive pre-training on large amounts of text data [27, 28]. Preview studies have explored LLMs assistants and their applications in DT-based O&M. Shamshiri [29] reviewed publications related to text mining and NLP in architectural management, discovering that leveraging pre-trained language models presents a potential research opportunity. Lu [30] evaluated LLMs on the mastery of knowledge and skills in the heating, ventilation, and air conditioning (HVAC) system. Results showed that GPT-4 can pass the ASHRAE Certified HVAC Designer examination with scores from 74 to 78, which is higher than about half of human examinees. Based on GPT-4, an automated data mining framework for building energy conservation was proposed by Zhang [12]. The detection accuracy of GPT is 89.17% for energy waste patterns and 99.48% for normal operation patterns. The response time and cost of GPT are 6747.60s and $17.68, respectively.

In addressing the DT model issue, Jang [31] proposed Natural-language-based Architectural Detailing through Interaction with AI (NADIA). Instead of using menu-based user interfaces, NADIA enables model design detailing using natural language. The validation results showed an average accuracy of 83.33% in generating logically coherent details and 98.54% in complying with ASHRAE standard. A virtual assistant named BIMS-GPT was presented by Zheng et al. [32] to search for information from models efficiently. When evaluated with a BIM query dataset, this assistant achieves a 99.5% accuracy rate in classifying natural language queries while incorporating only 2% of the data in prompts.

2.3. Research Gaps

Based on the above review of DT-based O&M and LLMs assistants, three principal research gaps in previous studies are summarized:

- Although certain studies have investigated the requirements of managers to successfully implement DT in O&M, their established requirements systems are confined to specific aspects such as modeling or data;
- While applying these digital technologies requires professional knowledge, there is limited research focused on assisting managers in creating guidelines to ensure their effective utilization;
- To the best of the authors' knowledge, there is currently no research available on the utilization of LLMs to assist managers in leveraging DT technology for implementation based on their requirements.

3. Operation and Maintenance Requirements System with Digital Twins

As explained in the previous section, the advantages of implementing DTs in O&M stage can be significant. However, due to the novelty of technology, many managers have knowledge gaps in planning, arranging, and applying DTs in O&M stage. We investigated three projects that implemented DT technology during the O&M stage in China. Documents such as standards, guidelines and models were collected and analyzed [24]. Furthermore, we conducted interviews with owners, facility managers and O&M personnel, and followed workers to observe their daily workflows. Three main barriers are concluded as follows:

- There is a lack of modeling standards oriented towards operation and maintenance management, including level of details, component coding and naming rules, model decomposition rules, model color classification rules, and data exchange standards;
- The concept of digital twins and their potential value are not sufficiently understood by managers. They lack clarity on how DTs can integrate with existing O&M processes and the specific functions DTs can offer to improve management and deliver benefits;
- While accurate as-built models containing geometric data serve as the "cyber" part of the CPS, there exist unclear requirements in nongeometric data gathered by IoT from the "physical" part.

This paper presents the Operation and Maintenance Requirements System with Digital Twins that aims to support successful implementation of DTs in O&M. As depicted in Figure 1, the

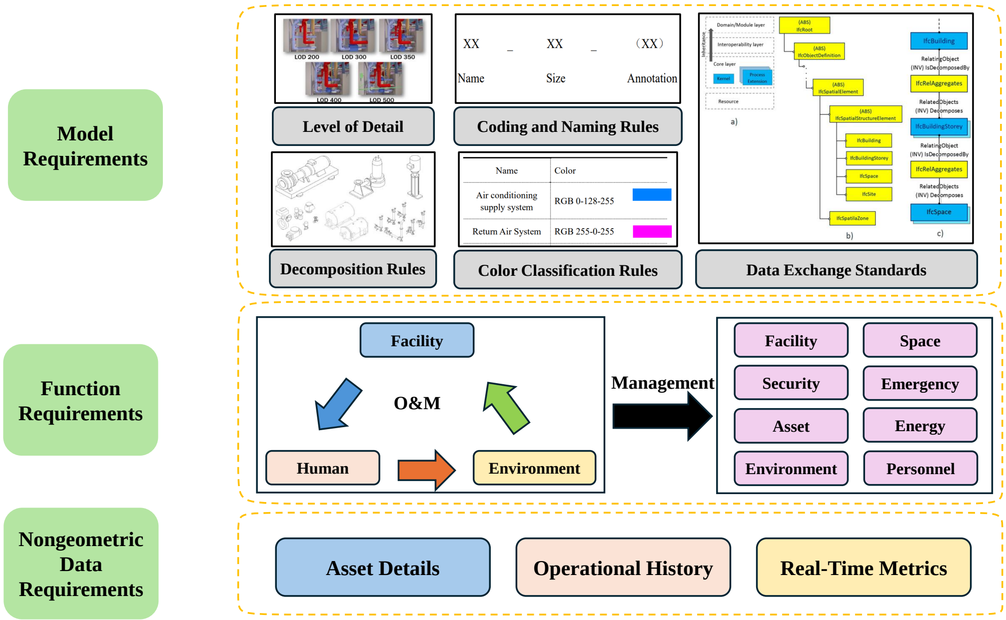

Figure 1: The Framework of The Proposed O&M Requirements System with DTs [33, 34].

proposed requirements system comprises three primary parts: model requirements, function requirements, and nongeometric data requirements.

3.1. Model Requirements

As illustrated in Table 1, model requirements encompass five key aspects to better serve the O&M stage. Level of detail (LOD) describes the precision of components in terms of geometric shape, size, position, and other attributes within the model. Typically, LOD is categorized into different levels, ranging from lower levels (e.g., LOD 100), which represent the basic shape of components in the model, to higher levels (e.g., LOD 500), which signify detailed geometric shape, size, material, and other attributes of components. The appropriate LOD should be determined based on the specific project requirements and objectives, rather than striving for the highest possible level.

Given the multi-participation of projects, it is essential to establish standardized component coding and naming rules to improve the delivery and retrieval of models. UniFormat [35] and OmniClass [36] are commonly utilized standards to identify various types of components by shortcode.

Considering that models for large-scale projects involve a great amount of information and data, model decomposition rules should be established to divide the model into smaller parts to facilitate management and operation. Typically, architectural and structural models are decomposed based on usage and space, while MEP (Mechanical, Electrical, Plumbing) models are decomposed according to disciplines, systems, and subsystems. Due to the complexity of MEP models, model color classification rules should also be established to display models intuitively. Different systems within the model can be distinguished by varying colors and fill patterns. Table 1 presents some examples of color classification rules.

Although models can serve as carriers of data, providing support for management decisions through integrated data, the data must conform to specific standards. This conformance helps to avoid issues such as inconsistent data formats or information loss and facilitates easier exchange and sharing of data among different software and systems. Currently, the Industry Foundation Classes (IFC) [37] and Construction Operations Building information exchange (COBie) [38] standards are internationally utilized for this purpose.

Table 1
Partial Details of Model Requirements.

Model Requirement	Type	Detail
Level of Detail	LOD 100	Simple outline without exact dimensions.
	LOD 200	Approximate geometries and dimensions.
	LOD 300	Precise geometries and dimensions.
	LOD 400	Highly accurate geometries and dimensions, including detailed information required for manufacturing and assembly.
	LOD 500	Completely accurate geometries and dimensions, reflecting the actual conditions post-completion.
Coding and naming rules	Architectural	Name_(Comment, optional)_Dimension
	Structural	Name_Dimension_Comment (such as material and concrete strength)
	MEP	Discipline_System_Dimension
Decomposition rules	Architectural	Decomposed by usage or space
	Structural	Decomposed by usage or space
	MEP	Decomposed by disciplines, systems, and subsystems
Color classification rules	Fresh air ventilation system	RGB 0-255-0
	Sprinkler system	RGB 255-0-255
	High voltage system	RGB 255-0-0
Data exchange standards	IFC	A standard for exchanging and sharing BIM data between different software applications.
	Cobie	A standard for capturing and delivering asset data as part of the project handover process

3.2. Function Requirements

As a new concept, DT is not widely known by managers. DTs involve technologies from multiple fields, including IoT, big data, AI, BIM, etc. These technologies can be too complex for managers with non-technical backgrounds to understand their implementation and application. Moreover, although DTs have been applied in some fields, successful cases in O&M are relatively scarce.

Managers lack the experience necessary to evaluate the potential and benefits of DTs in O&M.

To address these challenges, function requirements are proposed to assist managers in understanding the capabilities of DTs in O&M. This can encourage managers to apply DTs more actively, thereby enhancing the level and efficiency of management. Table 2 lists the function requirements from eight aspects of management, which were established by literature analysis, on-site survey, and interviews. Based on these function requirements, managers can develop digital twin implementation plans aligned with their management objectives.

3.3. Nongeometric Data Requirements

Data requirements can be divided into geometric data requirements and nongeometric data requirements. Notably, geometric data requirements, such as BIM data, consist of dimensions, shapes, and spatial locations of buildings or equipment. Since geometric data is typically integrated into the model, we categorize it under model requirements as mentioned in Section 3.1.

There is an increasing need to identify nongeometric data requirements to support successful implementation of DTs in O&M [54, 55, 56]. To meet this need, we have established a framework for nongeometric data requirements in Figure 2.

Asset details refer to the static details of components, such as names, locations, materials, models, installation dates, and technical specifications. These data should ideally be gathered at the beginning of a project, with sources including the construction contractors and equipment manufacturers. Once established, asset details remain constant and can be integrated into the components of a model along with geometric data.

Operational history denotes the record-based data of equipment, encompassing activities such as switch adjustments, operational state modifications, fault alerts, and similar logging activities. By analyzing the operational history of equipment, the operational patterns, fault frequencies, and characteristics of the equipment can be identified, thereby formulating effective maintenance schedules. Utilizing data analysis based on historical working records enables the prediction of potential equipment failure times, facilitating the implementation of preventative maintenance measures to mitigate downtime and maintenance costs.

Real-time metrics refer to the various indicators or parameters that characterize the state of equipment during its operation. These data are utilized for monitoring the performance, health status, and operational conditions of the equipment. Real-time metrics are gathered by installing various sensors on the physical equipment, such as temperature sensors, pressure sensors, vibration sensors, flow sensors, etc., selected based on the characteristics of the equipment and function requirements.

The volume of data increases significantly from top to bottom. Nongeometric data requirements must be discerned and captured through a workflow at different stages of a project. Becerik-Gerber et al have listed the continuum stakeholders responsible for data provision [26]. Identifying and gathering the necessary nongeometric data demands a visionary leader who is capable of guiding the entire process. Additionally, forming a Digital Twin team consisting of stakeholders is important to delineate the responsibilities for providing relevant data at each stage. Lastly, supervisory mechanisms should be established to ensure the sufficiency and quality of the collected nongeometric data.

Table 2
Function Requirements of DTs in O&M.

Type of Management	Function	Description
Facility management [39, 40, 41, 42]	Real-time monitoring	Real-time monitoring of the status of equipment or systems, with alarms triggered in case of malfunctions or anomalies.
	Remote control	Remote control of equipment or system status through a platform or mobile application.
	Routine maintenance	In case of faults, maintenance work orders can be promptly dispatched to maintenance personnel.
	Predictive maintenance	Utilizing simulation and machine learning to forecast potential faults.
Space management [43, 44]	Space planning	Planning room size and interior spatial layouts. Allocating rooms to users that meet their needs.
	Space occupancy	Analyzing space occupancy and vacancy rates.
Security management [45, 46, 47]	Behavior monitoring	Issuing alarms for behaviors such as unauthorized entry, theft, and falls.
	Digital patrolling	Planning patrol routes and schedules. Issuing alarms for anomalies.
	Smart Parking	Integrating recognition, positioning, tracking, monitoring, and management into smart parking systems.
Emergency management [48, 6]	Fire monitoring	Monitoring the status of sensors. Issuing alarms and notifications upon detecting a fire.
	Evacuation planning	Planning evacuation routes in the model based on monitoring of corridors, stairs, and emergency exits.
Asset management [49]	Asset database	Recording asset entry, exit, inventory, and depreciation to manage assets more efficiently.
	Asset tracking	By integrating RFID tags with the model, assets can be swiftly located and tracked.
Energy management [50, 51]	Consumption monitoring	Monitoring energy consumption data and setting up energy consumption plans by zone.
	Simulation and forecast	Integrating models and energy consumption data for stimulating and forecasting energy consumption.
	Operation optimization	Optimizing equipment operation strategies based on energy consumption forecasts to minimize energy usage and costs.
Environment management [52]	Environment monitoring	Monitoring the environment and issuing alarms when indicators exceed predefined limits.
	Operation optimization	Optimizing lighting and HVAC systems' operation strategies based on environmental monitoring results.
Personnel management [53]	Personnel database	Establishing a personnel database to record daily attendance information.
	Visitor Appointment	Supporting online submission of visitor appointment requests and maintaining a record of historical data.

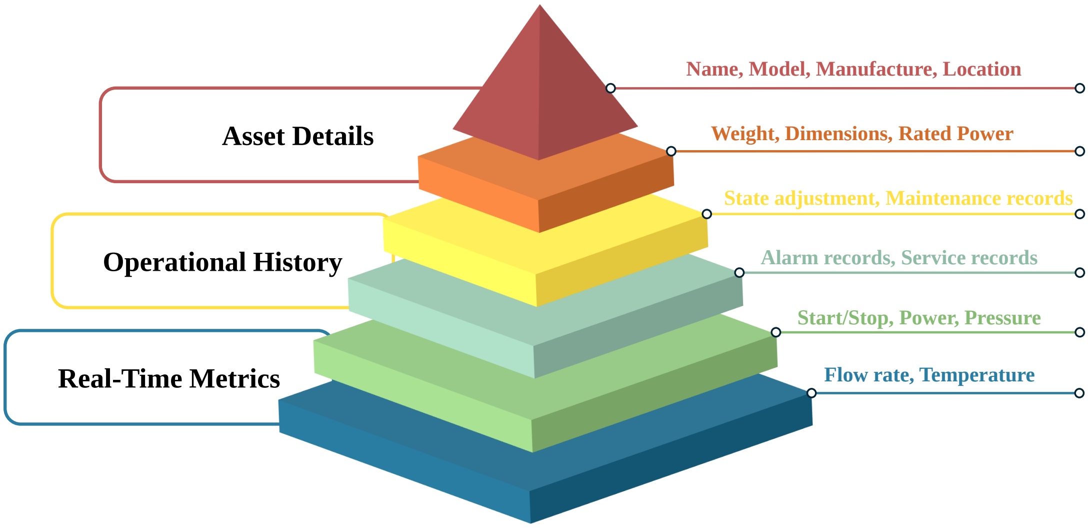

Figure 2: The Framework of Nongeometric Data Requirements.

4. LLMs-based Assistant

The overall framework of proposed DT-GPT Assistant, which is based on the operation and maintenance requirements system in Section 3, is depicted in Figure 3. DT-GPT Assistant can assist managers in creating guidelines for digital operational management and identifying the nongeometric data requirements of different projects. It comprises three main modules: the function module, the component module, and the data module. Every module was developed based on the GPT-4 model, enabling interaction through natural language.

4.1. Function Module

The function module is designed to meet function requirements, assisting managers in establishing the goals that a project needs to achieve during O&M management at planning stage. It facilitates subsequent workflows such as building models and deploying CPS. Considering various O&M management requirements, the function module proposes three versions of function lists: Basic, Advanced, and Intelligent versions.

Basic Version includes fundamental functions such as routine maintenance schedules, equipment monitoring, energy management, and safety inspections. It caters to managers requiring essential maintenance and monitoring to ensure operational efficiency and compliance with safety standards.

Advanced Version is built upon the Basic Version by incorporating system interconnectivity and O&M management data analysis. It is designed for managers seeking to enhance operational insights and efficiencies through more sophisticated data-driven strategies and system integration, facilitating proactive maintenance and optimization.

Intelligent Version elevates the Advanced Version by integrating intelligent functions powered by artificial intelligence algorithms. It is dedicated to assisting forward-thinking managers in

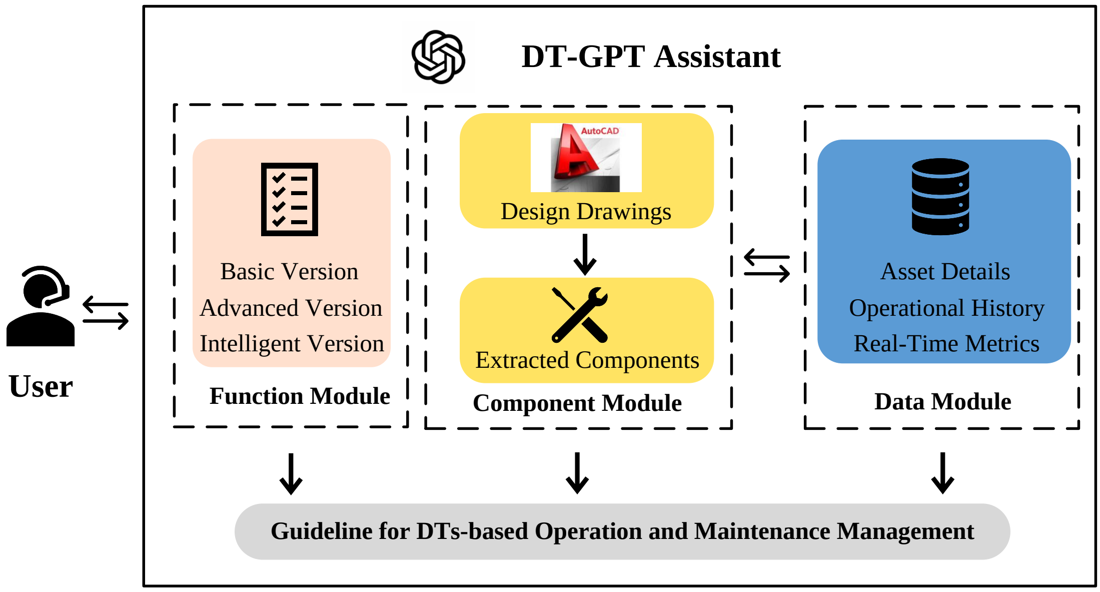

Figure 3: The Framework of Proposed DT-GPT Assistant.

utilizing AI for predictive maintenance, energy optimization, and advanced security solutions, thereby achieving the highest level of efficiency, sustainability, and occupant comfort.

4.2. Component Module

Considering the variability of each project and ensuring the completeness of the component list, we have developed the component module to extract components directly from design drawings. This module can read design drawings of various disciplines. Each component is extracted and its relevance to O&M process is identified using the GPT-4 model. Finally, component lists for various disciplines are generated.

The component module ensures that all components in the design are accounted for and aids the O&M teams in better comprehending the system's structure and composition. This understanding is crucial for developing appropriate maintenance management strategies and procedures. Additionally, by generating these component lists, managers can determine the data needed to be collected during different project stages.

4.3. Data Module

Based on the nongeometric data requirements mentioned in section 3, the data module is designed to provide the asset details, operational history, and real-time metrics of components extracted by the component module. Components capable of interfacing with the CPS via IoT technology include all three types of non-geometric data: asset details, operational history, and real-time metrics. Conversely, components unable to access the CPS through IoT technology have non-geometric data that include only asset details and operational history. By leveraging the data module, managers can specify the necessary data according to the attributes and operational requirements of different components. This structured approach optimizes the data collection process, ensuring that the collected data matches subsequent analysis and management needs. Additionally, managers can selectively gather essential data instead of conducting indiscriminate large-scale data collection, thus conserving resources and reducing costs.

5. Case Study: LLMs-based Digital Twins in Campus Management

To validate the feasibility of the proposed O&M requirements system and the DT-GPT assistant, we applied them in the project of the International School of Medicine, Zhejiang University (ISM-ZJU). ISM-ZJU started construction in 2020, leveraging a diverse array of technologies including cloud computing, big data, IoT, AI, and DTs. These technologies facilitated the integration of data from individuals, spaces, and equipment within the campus, thereby enhancing the digitization and intelligence of campus management.

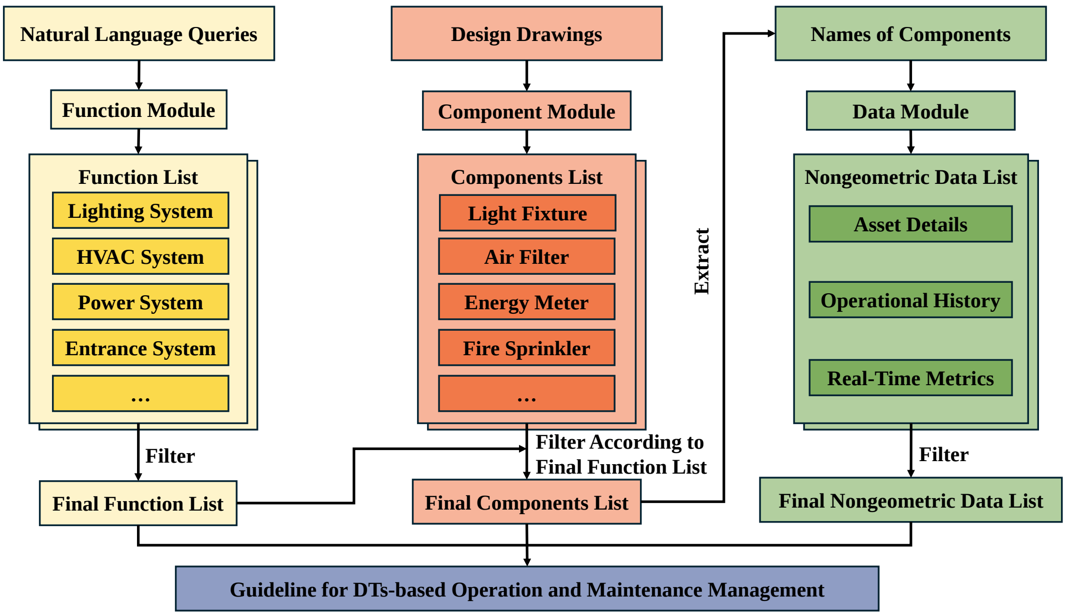

Figure 4: The Process of Employing DT-GPT in ISM-ZJU.

Figure 4 presents the process of employing DT-GPT in ISM-ZJU. At the project's outset, managers opted to integrate DT technology into the O&M stage. The function module of DT-GPT assistant was employed to generate function lists according to natural language queries inputted by managers. Function lists involved functions of various systems that the CPS could achieve. Managers filtered these functions based on their management objectives. Consequently, the final function list was made.

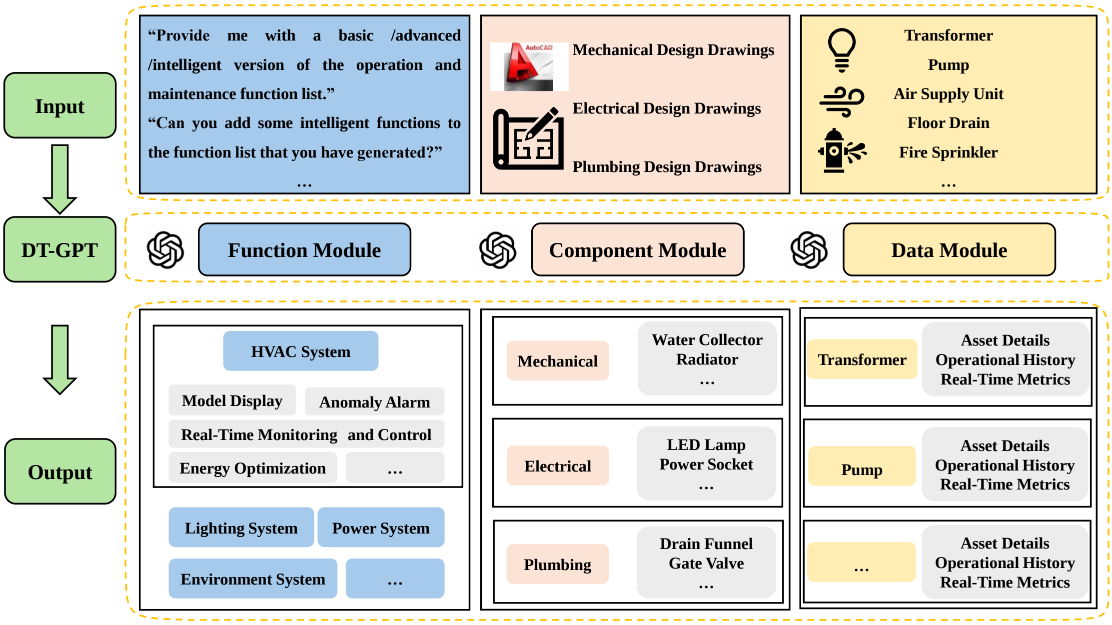

Figure 5: The Inputs and Outputs of DT-GPT.

Table 3
Partial Functions of Electrical Distribution System Generated By DT-GPT.

Functions	Description
Model Display	Display different operational states of equipment through colors and animations. Establish an interface displaying schematic diagrams of the electrical distribution system. Filter and display equipment models based on profession, system, floor, space, status, and other conditions. Click on the equipment model to display the ledger. Real-time display of equipment operating parameters within the model.
Data Statistics	Organize equipment operation and maintenance records by year, month, day, and other time intervals. Attach QR codes to equipment surfaces. Scanning the QR code with a mobile device will automatically link to the relevant equipment data.
Anomaly Alarm	Alarm and log abnormalities in the distribution transformer system. Automatically send alarm events to management personnel via SMS, app notifications, etc. Generate work orders automatically when alarms occur and provide the option to send the work orders through selection. The alarm data can be categorized and summarized by system, alarm type, location, etc., and can be exported in Excel format.
System Interconnection	The model displays camera locations in the electrical distribution area. Clicking on a camera allows to view the video surveillance feed.

Subsequently, the component module of DT-GPT assistant was utilized to extract components relevant to O&M from various design drawings. Managers filtered components based on the final function list and their management objectives, thus identifying the final component list.

Following this, names of components in the final component list were inputted into the data module of DT-GPT assistant. As a result, asset details, operational history, and real-time metrics of each extracted component were provided. Considering management requirements and costs of arranging sensors, managers filtered nongeometric data and determined the final nongeometric data list. Finally, three lists were organized to form a DT-based campus O&M guideline.

Figure 5 illustrates the specific inputs and outputs of DT-GPT. For the function module, examples of natural language queries are as follows: 1) Provide me with a basic/advanced/intelligent version of the operation and maintenance function list. 2) Can you add some intelligent functions to the function list that you have generated? 3) Create a basic operation and maintenance function list for me that covers the lighting system, HVAC system, etc. Table 3 presents the results of electrical distribution system generated by DT-GPT.

The component module read mechanical, electrical, and plumbing design drawings. Components in drawings were extracted. The module traversed all components and assessed their relevance to the O&M process. Consequently, the components list was generated. Table 4 presents a partial list of mechanical, electrical, and plumbing components extracted using the component module in ISM-ZJU.

Table 4
Partial list of Extracted MEP Components in ISM-ZJU.

Professional Category	Extracted Components
Mechanical	Water collector, radiator, manual air vent valve, water filter, pressure gauge, electric air damper, outdoor unit, fresh air handling unit, kitchen exhaust unit, thermostat, fan coil unit, horizontal centrifugal pump, submersible pump.
Electrical	Single-tube LED lamp, double-tube LED lamp, standard ceiling light, three-hole concealed safe socket, fire emergency lighting fixture, single/double two-way switch, power distribution box.
Plumbing	Drain funnel, pressure reducing orifice plate, Y-type strainer, gate valve, angle valve, outdoor fire hydrant, hot water return pipe, fire hydrant water supply pipe, domestic wastewater pipe, domestic wastewater pipe, siphonic rainwater hopper.

Names of components in the components list were inputted into data module. The module traversed every name and generated their asset details, operational history, and real-time metrics. Besides, managers could request the data module to add or adjust nongeometric data if they were not satisfied. Table 5 presents a partial nongeometric data list generated by the data module in ISM-ZJU.

Since the DT-GPT assistant always offers more information than necessary for actual O&M needs, a DT team involving members of different disciplines was built to help managers filter functions, components, and data. In addition, this team plays a role in facilitating the implementation of DTs, such as verifying data collection situation and inspecting the completion of

Table 5
Nongeometric Data of Different Components provided by Data Module.

Name	Basic Information	Working Records	Operational Parameters
Transformer	Name, production date, manufacturer and contact information, product model, installation date and location, rated voltage, rated current, rated power, connection group label, cooling method, short-circuit impedance, weight.	State adjustment, maintenance and service records, alarm records (fault, overload, high temperature, voltage abnormality, current abnormality).	Communication status, start/stop, power factor, voltage, current, power, temperature.
Pump	Name, production date, manufacturer and contact information, product model, installation date and location, execution standard, license number, weight, rated voltage, rated current, rated power, diameter, flow rate, head.	State adjustment, maintenance and service records, alarm records (fault, motor fault, overload, high temperature, low water level, high pressure).	Communication status, start/stop, flow rate, pressure, manual/automatic mode, rotation speed, power.
Air supply unit	Name, production date, manufacturer and contact information, product model, installation date and location, dimensions, interface dimensions, airflow, static pressure, power, wind speed, noise, efficiency, weight.	State adjustment, maintenance and service records, alarm records (fault, abnormal wind speed, abnormal temperature and humidity, abnormal pressure, abnormal flow rate).	Communication status, start/stop, flow rate, pressure, manual/automatic mode, power, temperature, humidity, pressure, wind speed, flow rate.
Floor drain	Name, production date, manufacturer and contact information, product model, installation date and location, execution standard, diameter, depth, core material.	maintenance records, replacement records.	None.

the CPS. Figure 6 presents the interface of the CPS for the project. Figure 7 shows the interfaces of mobile applications for workers and residents. As of now, a total of 13 subsystems and 9638 equipment have been integrated into the system.

Figure 6: The Interface of Cyber-Physical System for ISM-ZJU.

Figure 7: The Interfaces of Mobile Applications for Workers and Residents.

6. Conclusions and Future Work

This paper introduces DT-GPT, a virtual assistant framework for creating DT-based O&M guidelines according to managers' requirements. To determine the requirements of managers, operation and maintenance requirements system with digital twins is established, including model requirements, function requirements, and nongeometric data requirements. The framework of DT-GPT consists of three major parts: function module, component module, and data module. Combining DT-GPT, a three-step approach is proposed for dynamically determining guidelines based on the project requirements and details. The implementation of this framework is demonstrated through a virtual assistant prototype developed for ISM-ZJU, serving as a case study. The results illustrate that the prototype efficiently assists managers in supporting successful implementation of DT in O&M.

Although the results of our framework appear promising, several limitations need to be acknowledged. The current framework of DT-GPT requires evaluation using objective metrics, such as accuracy in generating guidelines. Additionally, the DT-GPT deployment process still needs managers to filter information according to their management objectives. Future work can focus on improving the automation level in guideline generation. Finally, since the case study was focused on the application of campus management, future research could explore its adaptation and optimization for various project types.

In conclusion, DT-GPT represents a significant advancement in the field of virtual assistant frameworks for DT in O&M, offering practical solutions to bridge the gap between technology and management requirements. By facilitating the seamless integration of DT into operational practices, this framework holds promise for driving innovation, improving decision-making, and maximizing efficiency in a wide range of industries.

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