Integrating Crowd-/Service-sourcing into Digital Twin for Advanced Manufacturing Service Innovation

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Abstract**—**In order to support advanced collaborations among smart products, services, users and service providers in a smart product and service ecosystem (S-PSS), this paper proposed a service-oriented hybrid digital twin (DT) and digital thread platform-based approach with embedded crowd-/service-sourcing mechanism for enabling advanced manufacturing services. This approach is well supported by the ecosystem interaction intelligence of digitally connected products, services, users, and service providers via Internet of Beings (IoB) (Things, Users and Service providers). First, driven by industrial application needs in heating industry, a conceptual model of the service-oriented hybrid platform integrated with crowdsourcing mechanism is developed, which supports the concepts of product DT, service DT and human user DT. Second, the key system realization techniques are developed to integrate service crowdsourcing and service recommendation for realizing smart services. Finally, a case study is carried out for evaluating and confirming its feasibility.

Keywords**—** Digital twin, digital thread, Internet of Beings (IoB), service crowdsourcing, smart product-service ecosystem, system intelligence.

1. Introduction/purpose

In the era of Industry 4.0, to better respond to market demand and increase business revenues, manufacturers are extending beyond their traditional pure product offerings to more flexible and complex bundle of smart product-service offerings where service components are integrated with smart product offerings to develop performance- or outcome-based advanced services [1]. So far, to implement manufacturing digital servitization, many studies have conducted on the servitization process from multiple points of view, such as organizational structures and processes [2], and the governance and orchestration of the product-service ecosystem [3], etc. Nevertheless, little research has been investigated on how to link the data in the servitization process and how to use them for advanced manufacturing service innovation.

Servitization is essentially a business model, but it is also an advanced product-service-and-user collaboration technology that can be used to avoid advance payments and the consumption calculation when a smart product is offered in a real ‘pay-per-use’ service mode. However, the fragmented information generated from various departmental teams or business partners/collaborators leads to the discontinuity and inconsistency of design information throughout the product-service lifecycle, making it hard in decision-making at later design phases and product/service improvement in later generations [4]. Therefore, this servitization transformation requires manufacturers to collaborate closely with their partners and customers to create and deliver service value propositions that better meet customer demands. This will uncover insights not only on the way how a product is manufactured, but also on how it is transported, installed, used, repaired, and recycled in real world. The interaction data between the product and various human users must be collected and analyzed. Thus, a service-oriented DT-based system is required to collect a great deal of data from both physical smart products and human users during their interactions with products and services. Human users include human workers (such as repairers, installers, retailers, wholesalers, and transporters) and end-users along the product lifecycle. The DT-based system needs to holistically support concepts of product DT, service DT and human DT. Product DT could be underpinned by IoT and human DT is supported by Internet of Users (IoU) and Internet of Service providers (IoS) [5]. In this paper, the sum of IoT, IoU, and IoS is called IoB that connects the physical, virtual, and social space in cyber-physical-social systems (CPSS). CPSS is an emerging concept developed to understand the bidirectional impact between cyber-physical systems and humans [6,7]. Instead of developing a CPSS, this paper focuses on the development of a service-oriented DT system that can be a part of a CPSS. In the DT-based system, It is important to make joint availability of data generated by machines and by processes involving humans [8].

With the increasing variety of digitally enabled services and business models, the ways of delivering services to end users in collaboration with various service providers (or crowd workers) will be diversified via various service outsourcing or crowdsourcing mechanisms [9]. Based on these business requirements, it is necessary to integrate crowdsourcing mechanisms into a service-oriented DT. On the one hand, this integration can support new business models based on service outsourcing/crowdsourcing for better product/service quality, on the other hand, it can help model human users' behavior and service experience and relationship from service interaction data in DT, in addition to modelling product (machine) behaviors.

Currently, how to develop a service-oriented DT for digitally supporting advanced services is still at its early stage of investigation [10]. Few studies exist on how to design and implement a service-oriented DT platform along the product-service lifecycle to support customer-centric service business models with service outsourcing/crowdsourcing.

The central problem of developing such a service-oriented DT is how products, services, networks of 'players' or stakeholders and supporting infrastructures can be holistically modelled, connected, and interacted in both the physical space and the mirrored cyber space and how the user-generated and product-generated data can be collected and utilized for smart product and service innovations along the product-service lifecycle. This is due to the limitations of existing DT concept that is proposed to support the use of virtual models of physical manufacturing assets for typical physical system monitoring, optimization, and control usages. It lacks human behavior modelling or human DT capability.

This research applies advanced service needs in heating industry [11] to explore and demonstrate how to design and prototype a hybrid DT and digital thread platform for supporting manufacturing servitization with embedded service crowdsourcing and human behavior and service-relationship modelling capabilities. The main research contributions are as follows.

(1) A holistic service-oriented DT design supporting the concepts of product DT, service DT and human (user) DT.

(2) Integrating service crowdsourcing and service recommendation for realizing smart manufacturing services.

The paper is structured as follows. Section 2 reviews related work in DTs for manufacturing services, digital thread and digital shadow, and crowdsourcing for service innovation, Section 3 presents the industrial requirements for a service-oriented platform and the development of the service-oriented hybrid DT and digital thread platform in terms of its conceptual model and the overall architecture. Then the implementation of service provider coordination mechanism on the hybrid DT and digital thread platform is demonstrated in Section 4. Section 5 evaluates the feasibility of coordinating service providers to deliver the requested service and the evolutionary updating of DTs around 'maintenance as a service' concept. Finally, the paper is discussed and concluded in Section 6.

2. Related Work

2.1 Digital Twin for manufacturing services

DT is one of the key building blocks for smart manufacturing [12]. Underpinned by Internet of Things (IoT), Big-Data analytics and other Industry 4.0 technologies, DT is potentially applicable for many fields that involve the mapping, bidirectional interaction, and co-evolution of physical and virtual spaces. Currently, DTs are mainly applied in smart city, construction, aerospace, automobile, and manufacturing, etc. [13,14]. For enterprises, DTs can serve as living testbeds for various products and manufacturing process scenarios, allowing themselves to learn from continuous real-world data for better evolution.

From a manufacturing perspective, DTs are defined by ISO/DIS 23247-1 as living digital representations of observable manufacturing elements including personnel, equipment, materials, manufacturing processes, facilities, environment, products, and supporting documents that updates and changes as the physical counterpart changes. They not only consist of design, as-built manufacturing and operational data for their physical counterparts in the virtual space, but also include models, simulations and algorithms describing its physical counterpart including features and behaviors in the real world. Different from IT-driven innovation generated only from data, the DT-enabled service innovation emphasizes more on the cyber-physical interactions [15]. So far, as indicated by Lu et al. [16], 85% DT applications are developed for manufacturing assets, and 11% are developed for factories.

In smart manufacturing, due to the capability of grasping the state of manufacturing systems in real-time and predicting system failures, DT is regarded as a disruptive concept in implementing smart manufacturing systems with better quality, higher productivity, lower cost, and increased flexibility [17]. The existing research mainly focuses on how to apply DT into manufacturing practice from various perspectives. For example, Qi et al. [13] analyzed the enabling technologies and tools for implementing DTs for potential applications. Tao et al. [18] proposed a DT-driven product design framework for redesigning or improving existing products. The mechanisms for modeling and implementing connections between physical and virtual models is studied by Jiang et al. [19]. To improve productivity and efficiency, DTs are also applied into the manufacturing process to gain a clearer picture of the real-time performance and operating conditions of manufacturing systems, such the production management and control of complex product assembly shop-floor [20] and the scheduling optimization [21].

In addition, DT can also be combined with other technologies, such as Artificial Intelligence and Big-Data analytics to form new models of DT-based services including product fault diagnosis, predictive maintenance, performance analysis, training, and lifetime forecasting in the product lifecycle [13,18,22]. By gathering the real-time parameters of sensors and control systems, and the real-time user inputs, the digital model is built to analyze the state of smart products with Artificial Intelligence to discovering potential mistakes and warnings.

Benefited from the increasing connectivity and amount of usable data, DTs are shifting the businesses from analyzing the past to predicting the future, achieving data-driven development of innovative product and services [18] and diversifying value creation and business models in an iterative manner [15]. With the product-service integration in all aspects of modern society, the importance of service is recognized by more and more enterprises under the paradigm of Everything-as-a-service (XaaS). To meet the increasing service demands from different application fields, different levels of users, and different businesses, a product-service system consisting of various DTs of products, services, customers, and stakeholders on the supply chain shows great potential for supporting and speeding up this servitization process [5,10], appliable from smart product (appliance) to smart factory [8]. So far, DTs are mainly used to ensure well-defined services, such as real-time asset monitoring, asset failure analysis and prediction, intelligent optimization and update, user behaviour analysis, and asset maintenance [4]. For example, in asset maintenance, the maintenance strategy can be classified into proactive maintenance (including preventive, condition-based, predictive, and prescriptive maintenance) and reactive maintenance [22], but DTs are mainly used in the proactive maintenance strategy for calculating the remaining useful life of the asset and reducing the cost of asset management [23]. In asset failure analysis, Xu et al. [24] proposed a two-phase DT-assisted fault diagnosis method using deep transfer learning to realize fault diagnosis both in the development and maintenance phases.

The system of DTs established along the product-service lifecycle can promote the integration of product and service design processes, manufacturing processes, and general collaborative service business processes

[10,25], providing potential ways for value creation by a platform-based approach. However, there is relatively less DT research on involving human in the DT environment and establishing production network DTs that focus on communication/interactions between DTs [16].

2.2 Digital thread and Digital shadow

Digital thread and digital shadow are two common concepts related to DT. They can be treated as key enablers for DT [26,27]. The relationship of DT, digital thread, and digital shadow is shown in Fig. 1.

Digital thread can create access channels to diverse but interrelated data sets so that the upstream and downstream is consistent and available to all users involved in a product lifecycle [27]. It can maintain data associativity and traceability in a smart manufacturing process. Digital thread is a pre-requisite to true DTs as it enables the evolution of DTs by enabling bidirectional communication between DTs. Currently, the research on digital thread mainly focuses on linking different lifecycle data in a digital thread to support lifecycle decision-making. For example, Kwon et al. [28] proposed an approach to fuse as-designed data represented in STEP (STandard for Exchange of Product model data) and as-inspected data represented in QIF (Quality Information Framework) in a standards-based digital thread based on ontology with knowledge graphs. Implementing digital thread in manufacturing systems plays a significant role in enhancing cross-functional collaboration, enabling efficient change management in manufacturing and service processes, eliminating rework, and reducing lead times [27]. Digital thread makes it possible to deliver the right information to the right place at the right time [28].

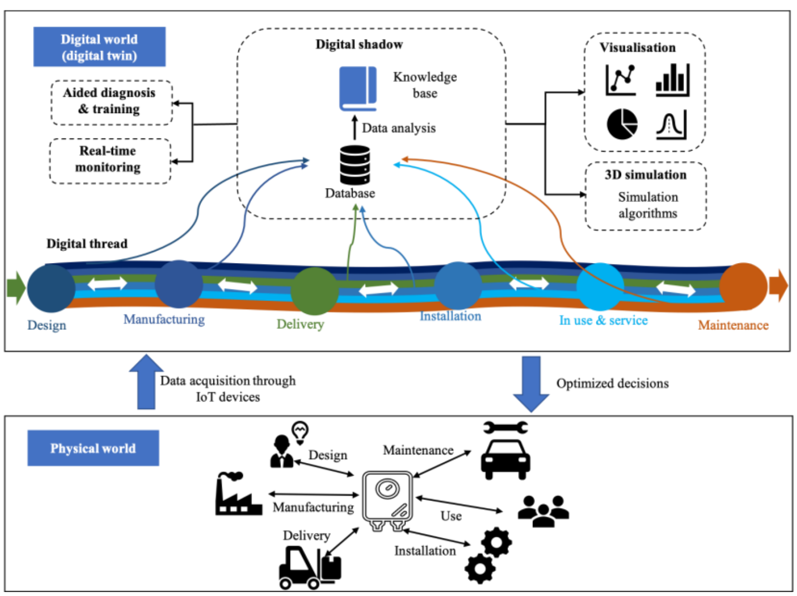


Fig. 1 The relationship of DT, digital thread, and digital shadow.

Digital shadow can be described as 'an always up-to-date information system, which integrates data from all available sensors and IT systems into one virtual representation including seamless interfaces and visualization for all connected services' [26]. It only supports one-way real-time data communication from physical to digital space, reflecting changes in physical objects in corresponding digital models. In practice, digital shadow is mainly implemented at product operation stage to collect product working data [29]. As a core component of DTs, digital shadow enables the management and analysis of real-time data coming from the physical space [30]. In the manufacturing context, the data profiles of any product or component including operation, condition, and process data can be depicted as digital shadows. Digital shadow can achieve a comprehensive structuring of heterogeneous kinds of data available and connect them to their respective semantics and context for later retrieval and interpretation. Digital shadow can be subsets of data from production process according to the specified purpose [31].

In service-oriented digital manufacturing systems, there already exist studies to develop digital shadow for data management and analytics, laying foundation for the development of DT in the future [29]. And digital thread has been adopted to enable connectivity throughout the system's lifecycle and to collect data from the physical twin for updating the corresponding digital representation in the virtual space [32]. However, little existing research has been focused on the communications/interactions between DTs in service process [16]. Implementing service DTs enabled by digital thread and digital shadow can help enterprises deliver experiences and outcomes to customers prescriptively rather than reactively [27].

2.3 Crowdsourcing for service innovation

Crowdsourcing [33] is an innovative business practice of obtaining needed services, ideas, or content or even funds by soliciting contributions from a large group of external people (the 'crowds') or general service providers. It not only actively involves a diverse crowd of users but also involves the management of them via web-based collaborative technologies to elicit their knowledge and skill sets and thus fulfil the pre-identified business goal [34]. In manufacturing industry, crowdsourcing plays an important role in product development, provision of data and information for manufacturing, innovation, crowdsensing, and problem solving [35]. Crowdsourcing has been demonstrated to be beneficial to organizational performance, helping organizations survive and thrive in the ever-changing environment by creating a competitive advantage through constant innovation [36].

To adapt to the prevailing tendency of manufacturing value proposition towards a service-oriented manner, third-party/intermediary digital platforms with co-creation capabilities for crowdsourcing serve as the foundation for delivering XaaS [37]. Previous studies have indicated that adopting a platform approach with modular architecture is very effective in enriching advanced product-service offerings while maintaining cost levels because it allows organizations to achieve flexibility through modularity and allocated responsibility [38]. In the platforms, crowdsourcing is mainly responsible for coordinating service providers to implement the requested service with necessary service resources and crowdsensing user comments/ideas on existing products/services for improvement. The value of generated information in the crowdsourcing process is a key driver of service innovation. For example, typical crowdsourcing platforms such as MyStarbucksIdea and Dell IdeaStorm can preliminarily assess existing ideas by allowing customers and stakeholders to comment on them, so as to acquire a great number of innovative and beneficial ideas or uncover drawbacks of existing products and services [39,40].

However, to the best of our knowledge, there is no report on its integration with a DT platform. Therefore, it is significant to apply crowd-/service-sourcing into coordinating stakeholders and crowd/service providers to work towards an optimal product-service ecosystem along the product lifecycle. When it is integrated with DT in a product-service ecosystem, it will not only enable the manufacturer to have flexible coordination of service providers and manufacturing resources, but also provide an effective way for the manufacturer to engage all stakeholders crossing the product lifecycle and gain feedback information on the product and service system from all of them. The integration of crowdsourcing and DT will maximize the utilization of assets and bring business values to the manufacturer by delivering advanced XaaS provisions such as equipment as a service, product as a service, etc.

3. Service-oriented platform development supported by DT and digital thread

3.1 Industrial background and requirements

Our industrial research partner is a residential/domestic boiler manufacturer. Currently, a domestic boiler, typically a gas boiler, is used widely in huge number of homes for heating purpose. For example, in the UK domestic sector, around 85% percent of energy is used for heating purpose. Typically, a boiler as a product can be owned by a householder or a landlord based on the product-centered business model. Regardless of what the product ownerships are, a boiler itself needs a regular annual maintenance service for reasons including safety check, identifying potential faults, and efficiency. For example, landlords in the UK who rent out their property are legally required to have their gas appliances and flues serviced on an annual basis by a certified Gas Safe heating engineer with a visual inspection and prescribed tests.

To facilitate the servitization, our research partner has made the boiler product smart with embedded SIM (Subscriber Identity Module) card so that it can transmit real-time product status data back. However, there is still a long way to implement manufacturing digital servitization. On this digital transformation journey, the core is an approach centered on the DT that is used for collecting data from product design, manufacturing, operations, maintenance, operating environments, and user experience and utilize these data to create a corresponding model of each specific asset.

From two workshops, it is found that there are two key challenges our research partner faces in digital servitization. The first challenge is the lack of product operation data (including product performance, maintenance, user interaction and experience information, etc.) for advanced service innovation. Our research partner hopes to have a big picture of its product usage throughout the lifecycle and based on that to offer advanced service provisions to increase revenues while enhance user experience. In this process, in addition to product design and as-built manufacturing data that have been owned by the business, product operation data play an important role in uncovering insights on advanced manufacturing services innovation as well. Nevertheless, our partner usually adopts fixed contracts with its business partners for product installation and maintenance in the traditional product-centric business model, leading to the fragmented product operation data belonging to its business partners. In the current scenario, it is important to collect product operation data and this should be the starting point of advanced service innovation. The second challenge is the low efficiency in delivering services. The traditional service delivery ensured by fixed contracts is costly and inflexible. After customers request a service, they usually need to wait for a certain time period before getting serviced, greatly reducing the user experience. Our research partner hopes to find a new way to dynamically coordinate service providers such as installers and maintenance engineers to serve customers in a flexible and timely way. In the servitization process, the ownership of product could change to a product provider such as a manufacturer or jointly with householders or landlords, while the heating services including basic, intermediate, and advanced services [11] need to be provided to the end users such as home residents or tenants by various service providers. The better connectivity is also required at the service level to connect the smart product to its owners such as landlords, end users (residents or tenants) and service providers.

Overall, the servitization goal of our research partner is to develop outcome- and performance-based advanced services such as 'heat as a service' and coordinate service providers to deliver them to customers based on product operation data in product use and maintenance stages by integrating crowdsourcing into DTs. Therefore, we design and prototype the DT platform based on the hybrid DT and digital thread conceptual model for evaluating the feasibility of using a smart product and service DTs to support this business concept.

3.2 The service-oriented hybrid DT and digital thread conceptual model

Based on our industrial application context, we design the service-oriented hybrid DT and digital thread conceptual model (see Fig. 2) for innovating advanced manufacturing services, underpinned by new business models, service-/crowd-sourcing, product, service and user DTs supported by IoT, IoU, and IoS. It not only integrates existing smart products with smart services, but also engages all stakeholders such as customers and service providers along the whole product and service lifecycle.

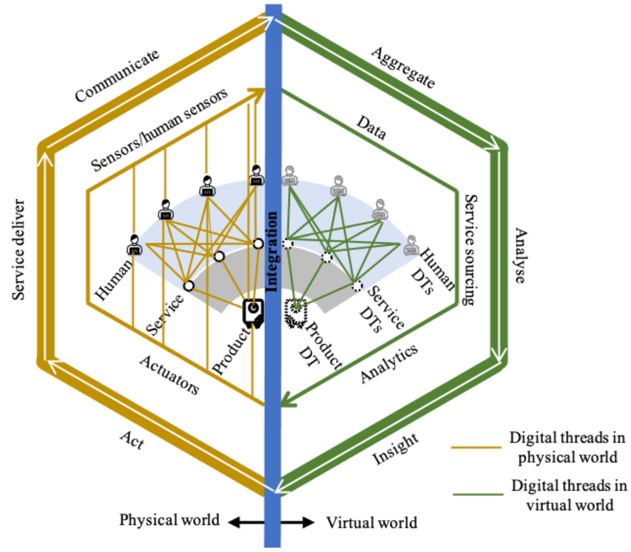
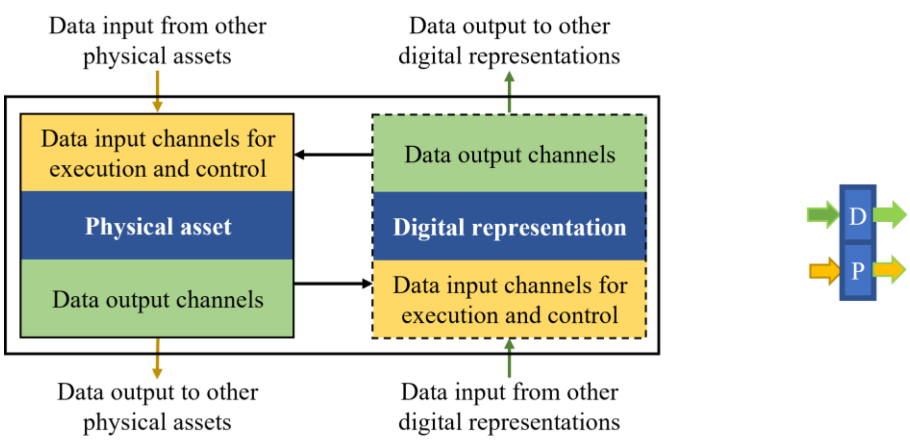


Fig. 2 The service-oriented hybrid DT and digital thread conceptual model.

In Fig. 2, in the physical world side, real world products, services and human participants have their corresponding DTs in the virtual world. A service process could start from either the smart product generated data such as an annual service notice to landlords or householders or customer-generated data such as a repairing or training service request in the physical world. Once these data generated from either physical sensors or human participants (or human sensors) are communicated to its digital counterparts via digital threads, they will be analyzed by the platform for generating proper new service requests (or offers) and creating the corresponding service DTs. For each service under request, crowdsourcing-based service sourcing is adopted to dynamically coordinate service providers to deliver the requested service. It is performed in the virtual space based on the profile of the product, the service requested, and service providers DTs, and as a result, a certain number of competent service providers in the physical world will be invited to act on the crowdsourcing and compete for the service job. As a result of the crowdsourcing, the best suitable ones will be shortlisted for landlords or householders to choose from. Once they select a service provider, a contract containing requester (landlords or householders) address, service date and time, requested service type, selected service provider, etc. will be formed. Finally, the selected service provider will be actuated to deliver the service in the physical space according to the contract, resulting in the physical product status changes as virtual-to-physical twining. In this loop, all data associated with the service and generated by both the boiler and the human users will be recorded and the associated databases will be updated. Thus, when a service is delivered physically, the changes in user-generated data are combined with the product generated data via IoT, IoU and IoS to trigger a physical-to-virtual twinning that updates their corresponding DTs of the product, service, and users. These updated DTs will feed forward to the next round service sourcing and service recommendation for delivering next round services.

To describe a service process at product in use and maintenance stage under the conceptual model (see Fig.

2), key assets in the process such as products, services, human actors (including customers, service providers and other stakeholders on the supply chain) have their corresponding DTs (digital representations) in the virtual space. Each of them is identified (or identifiable) by unique identifier and refers to the digital representation/model of a particular asset. A basic DT unit (see Fig. 3) in this paper consists of the physical asset and its digital counterpart. In the DT unit, there are four types of communications: physical-to-physical, physical-to-virtual, virtual-to-physical, and virtual-to-virtual. All these communications are enabled by digital threads represented by arrow lines (the arrow direction indicates data communication direction) with different colors in Fig. 3. The internal communications within the DT unit including physical-to-virtual and virtual-to-physical ones represented by black arrow lines are supported by IoT infrastructures such as sensors and smart devices. The physical asset in a DT unit can only communicate with its digital representation via black arrow line channels and with other physical assets that are connected to it via yellow arrow line channels. Similarly, the digital representation in a DT unit can only communicate with its physical asset and other digital representations connected to it via green arrow line channels. There must exist at least two DTs that are channeled together by digital threads in order to communicate with each other for servicing. As illustrated in Fig. 3(a), a simplest service on the product can be performed automatically by the product itself such as self-diagnostics. The digital threads among physical assets are represented by yellow arrow lines while those among digital representations are green. If we take the communication between the physical asset and its digital twin as default, the simplified representation of a basic DT unit is shown in Fig. 3(b).



(a) Detailed model (b) Simplified representation

Fig. 3 The basic DT unit.

Around a specific physical product in a DT unit, there are many different services such as product installation, annual safety check, operation training, and other maintenance services that are bounded to the physical product (one-to-many relationship). These services have their unique codes/identifiers. The combination of a product identifier and a service code could form an integrated service identifier to indicate the product and the service that are connected. For a product DT, its simplest digital representation could be just an ID

(Identity) for service-oriented applications. Of course, the digital representation can be further improved with 2D (two-dimensional) and 3D (three-dimensional) simulation models when needed.

In the virtual space, DTs are developed in an incremental way in terms of representation detail and interaction complexity. A DT could be just a predefined object with a unique identifier at the very beginning. Then with the collection of more product operation data, the DT can be continuously improved with higher fidelity and ultimately to be a perfect copy/DT to the physical asset. In interaction complexity, DTs including product DT, customer DT, and service provider DTs are independent at the starting point. Then with interactions between the product and customer or service providers happening, service DTs and digital threads are developed incrementally. Service DTs are secondary and associated with initially independent product, customer, and service provider DTs.

Taking a boiler repair service as an example to demonstrate the incremental development process of DTs.

(1) When a physical boiler runs normally at a home, the home user (consumer) can interact with it normally and receive right feedback from the boiler digital representation. The routine interaction process between the boiler and the consumer is shown in Fig. 4 with black, yellow, and green arrow lines representing interactions within the DT unit, between physical assets, and between digital representations, respectively. The closed-loop digital thread in the routine interaction process is marked by red arrow lines connecting the yellow, green and some black arrows lines. For example, the boiler can send its sensor data to its digital representation, and according to the incoming data analysis, the boiler's DT can send a 'healthy' boiler information to the consumer DT. Upon receiving this information, the consumer can continue to use the boiler normally.

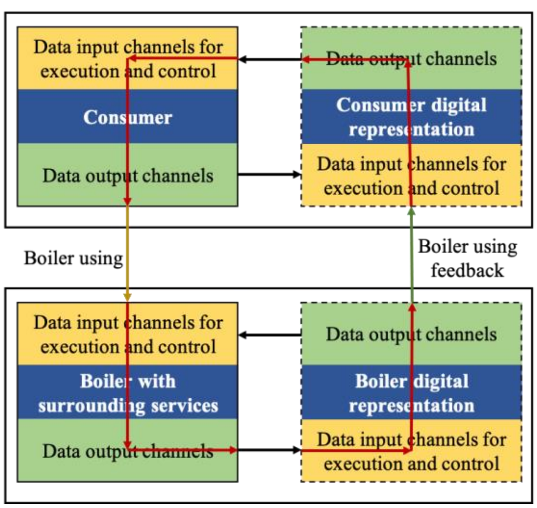


Fig. 4 The routine interaction process between a boiler product and the consumer.

(2) When the physical boiler breaks down, the boiler will send the break-down information to the consumer through its DT and the consumer DT, the home consumer then will request a repair service along the following key process. The key interactions between DT units and the incremental

development of the service DT and digital threads in the process are represented in Fig. 5.

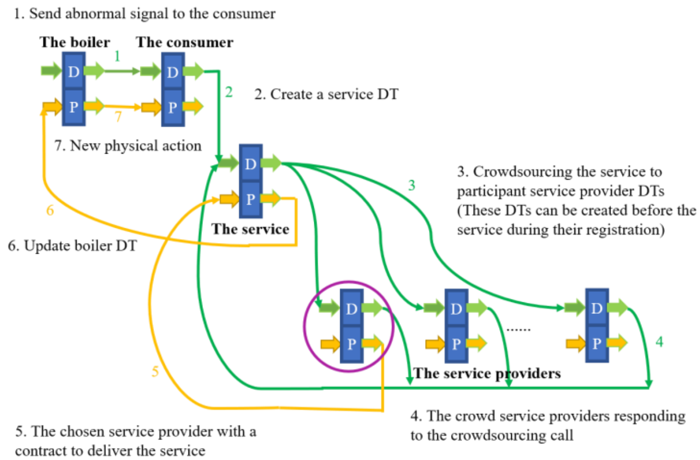


Fig. 5 The interaction process in a typical repair service process.

Step 1: Start with two DTs as shown in Fig. 4, in Fig. 5, the two DTs namely “The boiler” and “The consumer” are represented in their simplified forms. The physical boiler reports the problem to its digital representation and then abnormal feedback will be sent to the smart home consumer via digital thread 1 (in green).

Step 2: With the abnormal feedback, the consumer will make a service request for the corresponding service from the boiler bounded service list with his/her expected service date and time. This request will create a new service DT “The service” connected to the consumer via a new thread 2.

Step 3: The requested service will be crowdsourced to a group of service providers. A group of new service sourcing threads 3 will be created to connect the service in request and the crowd service providers. For each service provider, its DT has already been created when they registered on the platform.

Step 4: At this step, digital threads between digital representation of the service and any service providers that can provide the requested service are developed so that they can confirm their availability at the requested date and time. They will send their responses back to the Service DT via new threads 4.

Step 5: After receiving responses among the available service providers, only the most suitable one based on low-carbon footprint principle or quality priority principle will be chosen to carry on the service job. Let’s assume the first service provider highlighted by a purple circle is selected. The serviceman will provide the requested repairing service in physical world via the interaction 5 (in yellow) and then the communication between the serviceman DT and the service DT can be through a new thread like 4 to complete the service DT with all information involved.

Step 6: After the selected service provider delivers the requested service in the physical space, the physical boiler product will be updated from the repairing service via the interaction 6 (in yellow) and will send real-time status to its digital representation. In this way, the boiler, the consumer, the service, and the service provider DTs are connected in a loop.

Step 7: The service provider is also required to update the formed service in his/her digital representation so that the service completion status can be cross validated, enabling a new physical action 7 (in yellow) such as a 'Restart" to resume the boiler use.

In the service interaction process, the digital thread-based connectivity around the product itself and associated human users will enable the collection of operation data at product in use and maintenance stages. Once the operation data are sufficiently rich, they will be able to drive both updates of existing products/services and development of new products/services from a data-driven product/service design perspective. In this way, the accumulation of operation data and DT updates are happening in turn to support a gradual and incremental digital twinning process along the product/service lifecycle, making the manufacturing system into an ecosystem.

3.3 The Architecture of The DT Platform Prototype

Inspired by the DT Reference Architecture Model [41], the service-oriented hybrid DT and digital thread conceptual model in Fig. 2 can be realized by its four-layered computational architecture as shown in Fig. 6. The four layers are the perception layer, application layer, digital layer, and storage layer.

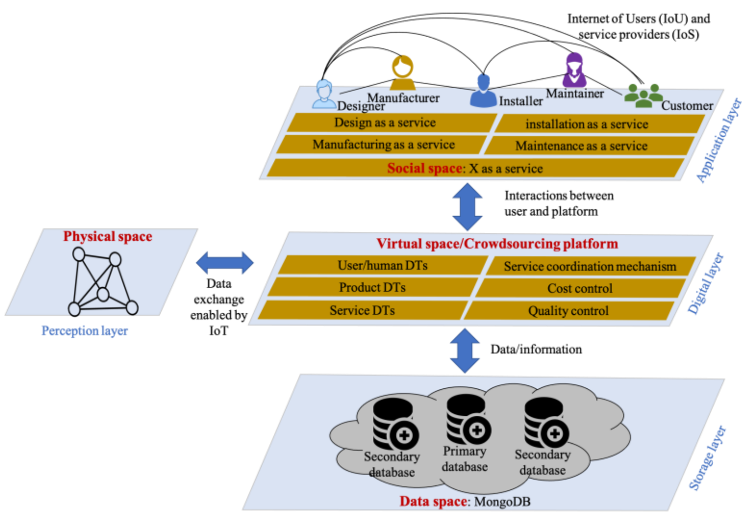


Fig. 6 The overall architecture of the hybrid DT and digital thread platform.

Application layer packages capacities and resources as services to serve stakeholders involved in the product-service ecosystem. Perception layer perceives the real-time status of smart products in physical space enabled by IoT infrastructure. These two layers form the network of humans and products, respectively. The digital layer is the DT-based crowdsourcing platform that not only implements the DTs (virtual models) of users, products, and services but also implements the connections among platform users and between physical product and its virtual counterpart enabled by IoT devices. Key role players involved in the product-service ecosystem including requesters, crowd workers acting as designers, evaluators, installers, and other stakeholders interact with the platform through predefined web-based user portal/interface. When requesters post tasks through their personal portals, the platform will design the tasks and then the platform crowdsources them to crowd workers with expected skills. To improve the capability of data storage in the platform, MongoDB (a NoSQL database that stores data in the form of 'key-value pairs') is used to store the very large amount of raw data with various formats collected from users, products, and services in the storage layer.

In the digital layer, there are mainly three types of DTs, namely user DT, product DT, and service DT. Here a 'user' is a human role player in a product-service system, thus a user DT is the digital representation of a human 'user'. At the concept level, a user DT can be treated as part of human DT [42] while the information to describe a user DT or a Human DT is dependent on applications because human beings are too complicated to be modelled digitally in every aspect at every detail. For example, for smart healthcare application, a human DT [42] may need information related to a specific person's physical and mental development and healthcare, but for a product maintenance service application, we may rather need the user's residential address (or product location) depending on the user's role and the user's service preference and consuming behavior. So, in our application case, based on a user's role type, a human user DT can be instantiated as service provider DT (such as installer DT, or maintainer DT), requester DT (landlord), and customer/end-user DT. In general, a human user DT has three types of information either as input or output information (See Fig. 3) to describe it: (1) the basic attribute information, (2) the user's role-related service qualification information, and (3) the user's service usage data for analytically and incrementally building up various simulation models in the physical-to-virtual digital twinning process. When a user successfully registers on the platform and a user DT can be created simultaneously with some basic attribute information (input): the user's digital ID (the system created), role type, and residential address (for end user and service providers). The role-related service qualification information includes some static data and dynamic data. Taking a service provider DT as an example, the static service qualification information (input) includes formal education qualification, spoken languages for effective communication, professional training qualifications and expertise. The dynamic service qualification information (output) include service accept rate, customer satisfaction score, and service quality score, etc. This dynamic information will be updated once a new service interaction is completed, which are output information based on analytical models. For the user's service usage data, they are rea-time service information (input) required from the human user such as when, where and to whom a service has just been provided, what is the next available time, any comments/rankings on the performed service related to product design, manufacturing, and other stakeholders, etc. Then with the accumulation of data, the service provider DT will be able to build up models (output) by analyzing the service history/usage data to dig out his/her service frequency, fine-tuned expertise, dynamic quality profiles, service preference and service behavior, etc. And then the service provider DT will provide recommendation evidence to the platform when a new service request comes. In our system, some information requires the user to input and some will be created from the system via information cross-referencing mechanism. The others could be output information generated within the DT.

Similarly, when a product/machine is registered on the platform, a product DT will be created as well with three types of information: (1) Basic machine attributes data such as the machine ID, type specification, installation address, status, owner, purchase date, installation date, and warranty period, etc. (2) Machine's real-time performance and status information. After the machine is started, this type of information will be transferred to the digital space continuously via machine embedded sensors, and the status of the corresponding product DT is updated accordingly. (3) Data about services that are provided by service providers to the machine, such as what service the machine has received, when the machine receives the service, and who provides the service, etc. With the increase of the machine's performance and status data and its being serviced data, the product DT will be able to analyze them to learn actual machine usage frequency, the total number of every machine error and its occurrence frequency, the total number of services provided by each service provider and their corresponding service quality comments, etc., thus, to provide prediction models to its next service requirement and issue warning information as breakdown prevention management tool.

Different from the user and product DTs, a service DT is mainly used to describe the relationship between them, consisting of basic attributes data such as the service ID, requested service date and time, service creation date, the machine to be serviced, who made the service request, the service provider's ID and service status, etc. When a service is completed by a service provider, the service quality related data can be generated by the service provider, the service requester and/or the end user. If the machine is smart, the machine 's product DT might be able to self-diagnose the service quality. The service quality information is then to be linked/reflected in the product DT's prediction model, the service provider DT's dynamic service quality profile model and the end-user's service preference and behavior models.

Limited by the data volume on our platform, the analysis models in the user DT and product DT have not been fully implemented because the data analysis accuracy is largely affected by the data volume. But we will implement them in the future when there is enough platform data available.

In the platform, data cross-verification mechanisms are adopted to verify the information sources and reliability. The DT-enabled ecosystem dynamically establishes relationships among ecosystem entities including machines, machine owners (service requesters), service providers, and end users, etc. So, when a machine-based service request comes in, the platform is required to validate the request through two steps. First, it retrieves the machine information with the machine ID from database to check if the service is requested by the right machine owner. Then it retrieves the real-time machine status transmitted by IoT devices to check if the machine status matches the problem in service request. After the service request is validated, the platform will analyze the machine maintenance history to predict service complexity, required qualification skills, estimated service cost, and urgency level for processing the service request. In the platform, the qualification of service providers is a key to ensure the service quality. Therefore, in order to ensure the reliability of service providers, their performance, i.e., accept rate, customer satisfaction score, and service quality score, are only measured by end users that use the machine. Only when the requested service is completed, the corresponding end users can receive the link for evaluating the service quality of the corresponding service provider. In this way, a feasible service solution is enabled.

4. Implementation of service provider coordination mechanism on the DT platform

This section details the coordination of service providers for delivering a requested service. The coordination process includes two steps: service-/crowd-sourcing and service provider recommendation.

4.1 Service-/Crowd-sourcing

Posting a service request is regarded as a start point of the ecosystem evolution. Crowdsourcing integrating with service recommendation is considered as a tool to find the right service providers (crowd workers) with best value for the tasks/services required. Therefore, we formulate the service crowdsourcing problem into a combinatorial optimization one. The goal is to find a small set of service providers from a big crowd pool based on a requested service (task) profile by broadcasting the service request with highest possibility of finding at least one qualified service provider and the minimum unnecessary information burden to the rest of service providers in the pool.

Before proceeding further, we start with the following definitions from an overall perspective of the product-service ecosystem based on ordinary crowdsourcing [43].

Definition 1: A product-service ecosystem based on a crowdsourcing platform can be described as a time-related state system with a 5-tuple (M, O, W, C, S).

a) $M = \{m_a | a = 1, 2, \ldots, M_N\}$ is a set of machines on the crowdsourcing platform and M_N is the total number of machines. Assuming that a machine is only used by one end user and owned by an owner at time t, then corresponding end users (such as tenants) set is donated by $C = \{c_b | b = 1, 2, \ldots, M_N\}$ and the owners (such as landlords) set by $O = \{o_x | x = 1, 2, \ldots, O_N\}$, where $O_N \leq M_N$. A new service request could be initiated by a machine m_i's owner $o_x, x \epsilon [1, O_N]$ after receiving the system remainder and problem report from the corresponding end user c_i .

b) $W = \{w_y | y = 1, 2, \ldots, W_M\}$ is a set (pool) of service providers who work on service requests on the crowdsourcing platform and W_M is the total number of service providers.

c) $S = \{s_i | i = 1, 2, \ldots, S_N\}$ is a set of service packages around machines and S_N is the total number of service packages.

In the product-service ecosystem, each key element can be regarded as a live being-B such as a machine, its states at time t can be described as triple (B^{t-}, B^{t}, B^{t+}). B^{t-} represents its history state, B^{t} represents its current state and B^{t+} represents its future state. Exemplar data to describe each state for each element are shown in Table 1. In this ecosystem, B^{t-} is used for service-/crowd-sourcing, B^{t} is used for service provider recommendation, and B^{t+} is used for representing the updated states of beings after contracts end.

Table 1 Being state.

Symbol	**History state B^{t-}**	**Current state B^{t}**	**Future state B^{t+}**
M	Design and manufacturing related data, service history record data, historical performance data, etc.	Machine's current performance data, warning information or codes and/or faculty codes transmitted by IoT devices, etc.	Predictive maintenance or scheduled annual service/check, etc.
O	Location and contact information, the machine ownership history and the machine service management history, etc.	A service request, urgency, current availability, etc.	Appointments for scheduled machine service and planned the ownership change, etc.
C	Location and contact information, the machine usership history and the machine service management history, etc.	A service request, urgency, current availability, etc.	Appointments for scheduled machine service and planned the usership change, etc.
W	Location and contact information, his/her qualifications, professional training and certifications, experience, and quality of the previous services on M, pricing history for the services, etc.	Current location, availability, pricing expectation, etc.	Appointments for delivering services, etc.
S	Service design and associated business models, service quality and associated user experience, service history data, etc.	Service requests to be processed with current resource constraints, etc.	The following up service scheduling, etc.

Definition 2: A service task T_i related to M_i and the inputting request R_i by O_i. With a service analysis tool f, T_i can be defined with five dimensions: complexity (P), required skills (K), estimated service cost (SC), urgency level (SL), and detailed service request description ($):

$$T_i = f(M_i, R_i, O_i) = T_i < P, K, SC, SL, \$ > \quad (1)$$

Based on the previous definition, given a service task T_i around machine M_i, broadcasting T_i on the crowdsourcing platform to a sub-set of W who are qualified to take the service job. For each candidate $W_j (j = 1, 2, \dots, \phi)$, the following constraints must be met. ϕ can be a predefined small number such as 10 for crowdsourcing in order to minimize the unnecessary interruption to most of the members in W.

Constraint 1: potential service provider w_j must have the task requested skills. Denoting the threshold for measuring the minimum value between two skills as ε_1, then the constraint 1 can be formulated as

$$dis1(w_j) = distance(w_j(K), T_i(K)) \geq \varepsilon_1 \tag{2}$$

Constraint 2: the estimated service cost is close to the service provider's historical average price for similar services. Denoting the cost threshold as ε_2, then constraint 2 can be formulated as

$$dis2(w_j) = distance\left(\overline{w_j(Cost)}, T_i(SC)\right) \leq \varepsilon_2 \tag{3}$$

Constraint 3: the potential service providers must be locationally close to machine M_i to have a shorter traveling distance for lower CO_2 footprints from the service. Denoting the distance threshold as ε_3, then constraint 3 can be formulated as

$$dis3(w_j) = distance(w_j(location), M_i(location)) \leq \varepsilon_3 \tag{4}$$

Constraint 4: the performance of the potential service providers must be accepted by the service requester. Assuming that the accepted performance and performance threshold are denoted by θ_p and ε_4, then the constraint 4 can be formulated as

$$dis4(w_j) = distance\left(w_j(performance), \theta_p\right) \leq \varepsilon_4 \tag{5}$$

To measure the performance of a service provider w_j in constraint 4, we quantitively describe it by a 3-tuple (AR, CS, SQ) where AR, CS, and SQ denote acceptance rate, customer satisfaction and service quality, respectively.

a) *Acceptance rate* $AR(w_j)$ of service provider w_i:

$$AR\left(w_j\right) = \frac{Num(T_{accepted}(w_j))}{Num(T_{all}(w_j))} * 100\% \tag{6}$$

where $Num(T_{all}(w_j))$ and $Num(T_{accepted}(w_j))$ denote the overall and accepted number of service tasks taken by w_j.

b) *Customer satisfaction* $(CS(w_j))$. Assuming service provider w_j has taken N service tasks, and the customer satisfaction scores marked by end users are denoted by $CS_i, i \in [1, N]$, then the average customer satisfaction of w_j is calculated by

$$\overline{CS\left(w_j\right)} = \frac{\sum_{i=1}^{N} CS_i(w_j)}{N} \tag{7}$$

c) *Service quality* $(SQ(w_j))$. Assuming service provider w_j has taken N service tasks, and the service quality scores marked by end users are denoted by $SQ_i, i \in [1, N]$, then the average service quality of

w_j is calculated by

$$\overline{SQ(w_J)} = \frac{\sum_{i=1}^{N} SQ_i(w_j)}{N} \tag{8}$$

Then normalize $\overline{CS(w_J)}$ and $\overline{SQ(w_J)}$ through Min-Max Normalization to make them belong to [0, 1], and the normalized customer satisfaction and service quality are denoted by $\overline{CS(w_J)}^* \; and \; \overline{SQ(w_J)}^*$. If the weightings of acceptance rate, customer satisfaction, and service quality are denoted by q_{AR}, q_{CS}, and q_{SQ}, respectively, then the historical performance of w_j is formulated as

$$W_j(performance) = \; AR(w_j) * q_{AR} + \overline{CS(w_J)}^* * q_{CS} + \overline{SQ(w_J)}^* * q_{SQ} \tag{9}$$

Constraint 5: the selected ϕ service providers must have the maximum skills, best performance, and the minimum service cost and distance. Assuming the weighting functions for constraint 1, 2, 3, and 4 are donated by f_1, f_2, f_3 and f_4, respectively. Then the constraint 5 can be formulated as

$$\min \sum_{j=1}^{\emptyset} \frac{dis2(w_j)*f_2 + dis3(w_j)*f_3}{dis1(w_j)*f_1 + dis4(w_j)*f_4}, \emptyset \in [1, W_M] \tag{10}$$

With (2) to (10), ϕ service providers satisfying constraints will be screened out as candidates that will receive the broadcasting of the requested service.

4.2 Service provider recommendation

Service provider recommendation or personalized task recommendation [43] is an AI agent, one typical application scenario of recommendation algorithms which have been one of the research hotspots for many years to suggest relevant items to users. On a crowdsourcing platform, recommendation principles such as low-footprint, superior quality and whole lifecycle principles are usually adopted [11], and they should be balanced during the recommendation process to provide high-quality services around products to customers/end users while bring maximum benefits to involved actors. For worker recommendation in crowdsourcing context, the jointly considered factors include a worker's capabilities and his/her external assessment of capabilities [43]. Besides these factors, we also consider their availability and location at the expected service time, and their real quote for providing the requested service to calculate their recommendation priorities denoted by $Rank$.

When the ϕ service providers receive the crowdsourcing call, they are required to confirm their availability and provide their quotes for the requested services. Assuming that their availability, locations, and quotes are donated by A, L, and Q, respectively. If w_j is not available at the expected service time, then $Rank(w_j) = 0$, or the rank of w_j should be re-calculated.

When w_j provides his real quote $Q(w_j)$ and current location $L(w_j)$, the $dis2$ and $dis3$ will be updated as

$$dis2'(w_i) = distance(Q(w_j), T_i(SC)) \tag{11}$$

$$dis3'(w_i) = distance(L(w_j), M_i(Location)) \quad (12)$$

Then based on low-cost recommendation principle, the rank of w_j is

$$Rank(w_j) = \frac{dis2'(wi) - dis2_{min}}{dis2_{max} - dis2_{min}} * 100\% \quad (13)$$

Where $dis2_{max}$ and $dis2_{min}$ denotes the maximum and minimum distance the quotes to estimated service cost, respectively.

Based on low-carbon footprint recommendation principle, the rank of w_j is

$$Rank(w_i) = \frac{dis3'(w_j) - dis3_{min}}{dis3_{max} - dis3_{min}} * 100\% \quad (14)$$

Where $dis3_{max}$ and $dis3_{min}$ denotes the maximum and minimum distance the locations to machine location, respectively.

Although the rank of the $\emptyset$ service providers have calculated, which one will be chosen for performing the requested service is determined by the service requester.

When a requested service T_i is finished, the product status and the profile of the selected service provider w_i, primarily the acceptance rate, customer satisfaction score and service quality score will be updated automatically. Denoting the service satisfaction score and service quality score given by the end user as $Score_{CS}$ and $Score_{SQ}$, then the updated customer satisfaction $CS(w_i)^+$ and service quality $SQ(w_i)^+$ are calculated by:

$$CS(w_i)^+ = \frac{\overline{CS(w_i)} * Num(T_{all}(w_i)) + Score_{CS}}{Num(T_{all}(w_i)) + 1} \quad (15)$$

$$SQ(w_i)^+ = \frac{\overline{SQ(w_i)} * Num(T_{all}(w_i)) + Score_{SQ}}{Num(T_{all}(w_i)) + 1} \quad (16)$$

The updated acceptance rate $AR(w_i)^+$ is updated by:

$$AR(w_i)^+ = \begin{cases} \frac{Num(T_{accepted}(w_i))}{Num(T_{all}(w_i)) + 1} * 100\%, T_i \text{ is not accepted.} \\ \frac{Num(T_{accepted}(w_i)) + 1}{Num(T_{all}(w_i)) + 1} * 100\%, T_i \text{ is accepted.} \end{cases} \quad (17)$$

The above constraint variables AR, CS and SQ on service providers are based on their service history data and could be regarded as the service provider's simulated capabilities. The simulation capability for service providers is then used in the service provider recommendation and updated afterwards for next round use. This demonstrates the physical-to-virtual digital twining process in a human service provider) DT and Simulation capabilities for other DTs could be built up in a similar fashion.

5. Case Study Evaluation

The primary goal of the DT platform is to build an ecosystem involving not only the network of smart products but also the network of users and stakeholders. In the case study, ten service concepts [11] have been identified after the boilers have been installed and in use. Taking 'maintenance as a service' (SC2 proposed in [11], shown in Table 2) as an example, we implemented a web application prototype in PyCharm (a Python Integrated Development Environment) based on Django framework to simulate the service process. The client side (user portal) was developed by HTML, Bootstrap, Javascript and JQuery, and the server side was developed in Python with a SQLite3 database. Django was picked due to the following reasons: (1) it follows the model-template-views architectural pattern, and (2) it is a free, open-source, and full-stack web application framework, providing a toolkit of all ready-made components for any web application development. For demonstrating the service process, SQLite3 database has been used for data storage, which would be insufficient to support the interactions among a large number of platform users. However, this issue can be mitigated by switching to more versatile SQL backends with load balancing and segmented databases on separate servers [15]. For a specific boiler in SC2, tenant and landlord act as end user and authorizer, respectively. Servicemen/engineers act as service providers/crowd workers.

Table 2 Key features of SC2 and its corresponding advanced services.

Service concept	Key features	Advanced services under the concept
SC2-Managing access around the annual gas safety check	Opening up communication channels with the tenant and scheduling inspection visits based on engineer locations and availability	(1) Service engineers' training and certification as a service (2) Crowdsourcing or service outsourcing as a service (3) Contract enabled 'warm hours' as a service (4) User Experience as a Service (UXaaS) embedded in the smart service recommendation

Under SC2, annual machine check is one of the typical scenarios formed by these identified advanced services in Table 2. Taking annual machine check service in social housing segment as an example, the DT unit involved in this service process include boiler, landlord, tenant, service providers offering annual machine check service. In order to illustrate the interactions among DTs in the service process, the sequential interaction diagram with information flow in the service digital thread is provided in Fig. 7 where the physical and virtual part in boiler and the selected service provider DT units are separated to respectively represent interactions in physical and virtual space with yellow and green line arrows. The service digital thread has four steps/sub-services: service appointment, crowdsourcing and service recommendation, contract generation, and service evaluation. This service process mainly involves the update of boiler DT and the selected service provider DT. Key interface for boiler DT, crowdsourcing results, and service evaluation are also provided in Fig. 7.

(1) Service Appointment

The annual check date is determined by the installation date of the machine. Before a given period of the expected machine check date, such as two weeks, the machine DT automatically reminds the tenant to request annual machine check with the landlord. When the machine DT notifies the tenant to check the machine, the tenant is required to request the service from the landlord. After the landlord authorizes the service request, the DT-based crowdsourcing platform requests the historical data from the machine DT to diagnose machine problem and calculate the required skills to solve the problem. How to diagnose machine problem and calculate the required skills are out of the scope of this paper. The key output from authorized service request is the requested service type, i.e., machine annual check. When the DT platform validate the service request to be true, a requested service is created which contains the information of the machine that needs service, the information about the requested service, the machine end user, the machine owner (landlord), the expected service date and time, etc.

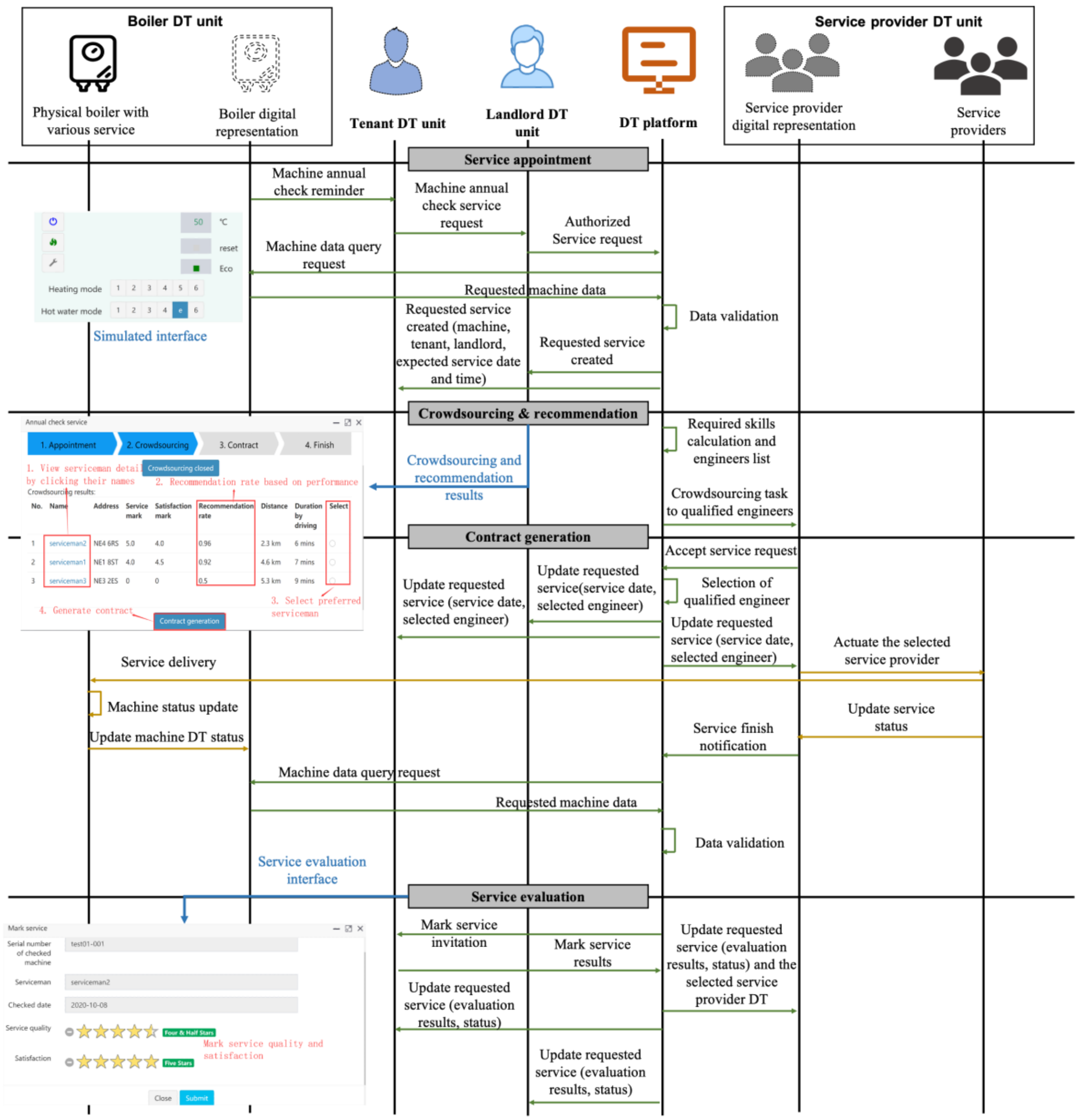


Fig. 7 Sequential interaction process with information flow in annual machine service and interface examples.

(2) Service Crowdsourcing and Recommendation

To recommend a proper service provider/engineer to the requested service, a two-phase recommendation process is adopted:

a. Crowdsourcing and shortlist proper engineer candidates. In the ecosystem, the qualification of an engineer is measured by three simulated capability indicators, namely *AR*, *CS*, and *SQ*. They are initially set as 0, then with the increase of services performed by a specific engineer, his/her performance indicators are calculated by equations (6), (7), and (8), respectively and they will be updated automatically according to equations (15), (16) and (17) when a new service is performed by the engineer. For simplicity, the weighting parameters to AR, SQ, and CS are set to be 0.5, 0.3, and 0.2, respectively. Therefore, the recommendation rate of a specific engineer based on his/her performance can be calculated with equation (9). The performance-based recommendation rate will determine if the engineer can receive the crowdsourcing broadcast or not. Only those with the top 10% recommendation rate are invited as candidates for the requested service, then they can confirm their availability at the requested date and time for the service. And only the top three available engineers will be shortlisted for the requested service. In this step, for each shortlisted engineer, the distance from his/her residential address to the destination (machine address) and the traveling time by car over the distance are also calculated by the platform.
b. Manual selection of the most proper engineer. In the platform, the low-carbon footprint (shortest distance to destination address) principle is adopted to rank shortlisted engineers. Based on that, the requester (landlord in SC2) can view the detailed information about the shortlisted candidates and make his/her decision to choose the most proper engineer for the requested service.

In the crowdsourcing and recommendation step, the landlord and service providers mainly interact with the platform with pre-defined interfaces. They do not have direct communications until the landlord selected an engineer and contracted with him/her. An example of service crowdsourcing and recommendation results is shown in the crowdsourcing & recommendation part in Fig. 7.

(3) Service Contract

When the landlord selects an engineer for the requested service, the service request will be updated automatically, and the platform will notify the tenant, the landlord, and the selected engineer/service provider about the service date and time. Then at the expected date, the engineer will perform the service physically and then tell the service results to the DT platform. After DT platform verifies the service results by cross-checking it with the real-time machine data, the platform will ask the machine end user to mark the service provided by the selected engineer.

(4) Service Evaluation

After the requested service is performed by the engineer, the tenant will be asked to mark or evaluate the service experience and quality. The service evaluation results will be written into service request and the reputation of the engineer (the selected service provider DT) will be updated accordingly. The service evaluation interface is shown in service evaluation part in Fig. 7. The service evaluation results will affect the qualification of the selected engineer for later service requests on the platform.

(5) Simulation capability

Simulation capabilities are essential for DT systems and are useful in product predictive maintenance. They can be built up once enough service history data are available. Otherwise, they can be incrementally built up and refined through a physical-to-virtual twining process over a period when the product is in use and maintenance stage to accumulate service history data. But in this case study, it is hard to fulfil every aspect of a digital twin platform such as the machine (boiler) simulation capability at current stage due to the lack of service history data. Thus, in this paper, our evaluation is focused on using the simulation capability of service providers for coordinating service providers at product in use and maintenance stages.

6. Discussions and Conclusions

Due to the limited data on the proposed DT platform, it is hard to give accurate statistics to show service efficiency improvement and cost savings. But qualitatively speaking, it does have the potential to effectively decrease time cost in coordinating service providers for a specific request by implementing service recommendation algorithms based on multiple conditions (such as service experience, quote, distance, and service quality, etc.) when there are enough service data on the platform. Furthermore, the proposed DT platform has the capability to record the key information in the service process, enabling manufacturers to have the lifecycle information of its products for further product upgrading development.

The system of DTs at product in use and maintenance stages connects manufacturers with their smart products, customers, and stakeholders on the supply chain together, making it possible to collect data from product operation, product application context, and user feedback. In the current highly competitive society, data is the most valuable asset that can uncover many business opportunities. In addition, the collected data at product in use and maintenance stages can provide insights on how to improve existing products. If the system of DTs is extended to the whole product and service lifecycle, it will help manufacturers build a platform-based digital business ecosystem to co-create product-service offerings and values with customers and stakeholders. The ecosystem is generally characterized by modular interfaces for the provision of products and services by different parties [44]. In the platform-based ecosystem, actors use the tools provided by the platform owner (manufacturer) to co-create specialized products or services with/without rewards. Customers and end users can consume these services and provide their feedback for service improvement. The platform owner and actors on the supply side then can incorporate this feedback to upgrade their existing services or develop new services.

The benefits of building such a product-service ecosystem have well identified. For manufacturers, it enables them to co-create product-service offerings and values that better satisfy customers’ needs with customers and stakeholders. Furthermore, the flexible coordination of service providers registered on the platform and the timely processing of service requests can increase the business productivity and efficiency. For service providers and other stakeholders on the supply chain, the platform provides them with a new workplace where they can respond to service requests in a responsive and flexible way with less pressure on travelling for delivering the requested service. For end users, the key benefits brought by the platform are easy-access services and timely response from service providers. From this point of view, the platform-based service ecosystem is a win-win strategy for companies to offer value to all involved actors [45]. It can enable companies to create and capture value from platform-based innovation under dynamic business environment [46].

Therefore, many companies such as Apple, Google, and Microsoft have built their own service ecosystems during the last decades to benefit from value creations from both internal and external innovations [47] and they are on their journeys to digital business ecosystems. In addition, many academic researchers are devoted in investigating platform-based service ecosystems from different perspectives. From a business point of view, Parker et al. [45] analyzed how service platforms help optimize the intellectual property regimes to maximize business growth. From the technical perspective, Hein et al. [44] analyzed the existing service ecosystems in terms of platform ownership, value-creating mechanisms, and complementor autonomy and provided a service ecosystem guideline for companies from four novel avenues, i.e., technical properties and value creation, value capture in ecosystems, complementor interaction with the ecosystem, and make-or-join decision in ecosystems; how service platforms enable value co-creation in the ecosystem by leveraging different boundary resources was also discussed by Hein et al. [47]. The existing research about service ecosystems mainly emphasizes on the ecosystem of actors and how to use their connections to create value. While industrial ecology digitalization requires to build an ecosystem involving both physical products and actors [41].

In the DT-based ecosystem, the development of such a platform that can meet business needs is a key for business success. In this process, the following considerations have to be taken into account:

The effectiveness of the platform-based solution. In this paper, although an industrial case study-based evaluation has been conducted to demonstrate the platform effectiveness in coordinating service providers to deliver requested services, further evaluation on the service coordination efficiency, the time and monetary cost of the platform-based service, and the achievement of inter-organizational collaboration goals (quick connect, quick complexity, and quick disconnect) [48], etc. also need to be progressed. In addition, from the perspective of the manufacturer, the relationship between cost and profit of the platform-based solution also should be considered.

The parallel controlling of the service requests. In the design of DT-based smart manufacturing systems, how to realize the online parallel controlling in the cyber/digital model and feedback the adjustment instructions to the physical system is a key enabling technology, which has been well identified [49–51]. However, in our research, the DT-based service system is mainly applied in product in use and maintenance stages for delivering services to involved users. In this case, we consider that the real-time synchronization between digital model and physical system is less important. For some service concepts identified in [11], such as machine (boiler) safety check and diagnosis of heating problems, the machine is normally turned off (offline service mode) for safety concerns. Then there is no information exchange between the physical machine and its digital model until the machine is turned on again. For some cases, even if the machine is not turned off (online service mode), it is not necessary to feed every action that is adopted by the service provider to the machine back to the corresponding digital model because sensors are not installed in every machine part. For other service concepts that are based on machine historical data, like predictive machine performance and preventative maintenance, analyses are mainly progressed on digital models thus to have an overall understanding of the machine performance and to suggest necessary machine maintenance proactively. At current stage, except providing friendly warnings/reminders to the machine users, it is unlikely to make the machine take actions automatically to those analytical instructions.

The system reconfigurability. The ecosystem is featured by modular interfaces for the provision of products and services by different parties. In the ecosystem, actors use the tools provided by the platform owner (manufacturer) to co-create specialized products or services with/without rewards. Customers and end users can consume these services and provide their feedback for service improvement. The platform owner and actors on the supply side then can incorporate this feedback to upgrade their existing services or develop new services. To satisfy the diverse user service demands, the ecosystem requires not only a flexible system architecture but also a systematic reconfiguring method [52]. The reconfiguration methods could be classified into knowledge-based reasoning methods and artificial intelligence-based optimization methods. In this paper, the knowledge-based method is adopted. In the ecosystem, when a service request is performed (leading to establish a service DT), the pool of suitable service providers will be automatically reconfigured based on the best match to the required service provider's profile and then crowdsourced to, the profile of the corresponding service provider after delivering a service contract will be updated automatically based on the customer's feedback, and the updated profile will determine if the service provider can be selected for next service request.

The system security. In the DT-based system, due to the complicated physical-to-virtual, physical-to-physical, virtual-to-virtual, and virtual-to-physical interactions and enormous product and service data, it is challenging to manage them efficiently and securely from the perspective of data storage, data access, data sharing, and data authenticity [53]. Nevertheless, the security and credit issues in the system are critical in enabling the sustainability of businesses. So far, blockchain is believed to be a new generation of secure information technology in revolutionizing businesses and industries by enhanced security and sustainability in manufacturing systems [54,55]. Leng et al. [56] indicated that blockchain can ensure the system security at the process level, the data level, and the infrastructure level. Currently, the information cross-verification mechanisms already implemented in the DT-based platform is far more enough to ensure the system security and transparency, so we consider integrating the developed system with blockchain to ensure that it cannot be tampered with in the near future.

In conclusion, this paper mainly focuses on involving human users in the DT environment, investigating the interactions between DTs, and integrating crowdsourcing into the DT platform to support dynamic service deliveries. With industrial case study around 'maintenance as a service', we found that the requirement to DTs varies from service to service. For example, for the ten service concepts identified in [11], training the customer to get the gas and heating up and running and diagnosis of heating problems require the digital representation to reflect real-time changes of the physical product when users (tenants and service providers) interact with the product, so a product DT with high fidelity is a must for these two service concepts. But for other service concepts, such as predictive boiler performance, optimizing the thermal performance of the housing stock, provision of 'warm hours', and maximizing organizational operational efficiency, digital shadow is enough for data analysis and visualization. Whatever DT or digital shadow is selected for a service, digital thread must be implemented to enable the communication in the service process.

We consider that this platform-based business solution has the following potentials:

(1) Support increasingly demands on customized products/services and manufacturing capabilities to rapidly respond to market needs at different market segments, greater integration of in-company manufacturing resources/capabilities and outsourced/crowdsourced ones from global and/or local regions is enabled by the crowdsourcing-technology embedded in the digital platform for using in the development process of products, integration of products and services and service delivery.

(2) Ensure better customer or third-party engagement in product design, manufacturing and maintenance, and advanced services requiring very high levels of interactions between the focal firm, customers and suppliers. This is because the digital twin platform can connect not only physical product (device) via IoT, but also services via IoS and various human participants via IoU. Their smart interactions and connections are enabled by the system intelligence with integral support of service crowdsourcing and service recommendation. The service experience also can be captured and feedforward for better service design and delivery.

(3) Support the development of innovative business models around the concept of XaaS such as pay by use and pay by performance with enhanced crowdsourcing models.

(4) Support the prevailing business paradigm of open innovation with data support from end users and end products/services.

(5) Support both lifecycle and low-carbon development principles for product and service systems.

Our future research work will focus on data intelligence and data-driven product/service design and innovation methods and techniques in an ecosystem. With the increase of performed services on the platform, the data on human, product, and service DTs will be accumulated fast. When the data set is large enough, the research investigation will be focused on how to use Big Data Analytics and Artificial Intelligence technology to develop simulation capabilities in various DTs and how to use simulation models embedded in DTs to drive new products and services design and development with enhanced product performance, system productivity, and user experience.

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