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# A digital twin-enhanced system for engineering product family design and optimization

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ABSTRACT

Engineering product family design and optimization in complex environments has been a major bottleneck in today's industrial transformation towards smart manufacturing. Digital twin (DT), as a core part of cyber-physical system (CPS), can provide decision support to enhance engineering product lifecycle management workflows via remote monitoring and control, high-fidelity simulation, and solution generation functionalities. Although many studies have proven DT to be highly suited for industry needs, little has been reported on the product family design and optimization capabilities specifically with context awareness, which could be leaving many enterprises ambivalent on its adoption. To fill this gap, a reusable and transparent DT capable of situational recognition and self-correction is essentially required. This paper develops a generic DT architecture reference model to enable the context-aware product family design optimization process in a cost-effective manner. A case study featuring asset re-/configuration within a dynamic environment is further described to demonstrate its in-context decision-aiding capabilities. The authors hope this study can provide valuable insights to both academia and industry in improving their engineering product family management process.

## 1. Introduction

The advancement of information and communication technologies (ICT) enabled many industries to embark on digitalization roadmaps of varying degrees adaptable to shifting consumer demands and expectations [1]. Faced with increasing competition from disruptive start-ups to ambitious corporations expanding into common markets, industry incumbents strive to retain market share by improving asset and workforce efficiency. The adoption of emerging technologies to strengthen strategic advantage of corporations results in significant market transformation and boosts organizational robustness with reduced operation costs [2]. Digital twin (DT) technology has become a prominent trend in autonomous systems with Gartner, a prominent global research and advisory firm, envisioning 75% of organizations to utilize DT within the end of 2020 [3].

DT applications in fields such as aviation, automotive, and even healthcare have enabled a wave of innovative solutions to increase asset efficiency and facilitate workforce upgrades to achieve revenue increase and profitability. First coined by Dr. Grieves in 2002 [4], the DT concept gained popularity as its application was made feasible with the lowered costs of sensors and IoT systems. As the creation of DT systems are generally expensive and time consuming, DT projects tend to revolve around high value assets aimed at specific tasks such as condition monitoring and process quality control [5]. This paper builds on existing DT research and integrates design paradigms to advance context-aware capabilities. By providing a reusable and efficient methodology for product family asset configuration and modelling, it expedites the creation of high-fidelity digital asset replicas for DT applications. A generic DT architecture featuring a three-layered technology stack is also proposed for rapid DT creation to establish a DT system capable of managing disruptions in complex environments. This methodology provides an alternative to typical DT systems and offers a glimpse into a post-Industry 4.0 setting with self-aware cyber-physical assets, helping industries shape future strategic agendas.

Although many studies exploit DT technologies to value add towards engineering product lifecycle management (PLM) stages [6], the majority of DT utilizations are rigid, single purpose applications. This paper proposes a DT-enhanced product family design and optimization system, which enhances multiple PLM stages to facilitate stakeholder co-creation, and generate context-aware solutions. The rest of the paper

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is organized as follows: Section 2 reviews the related works in engineering product family design and the adoption of DT in both the design and usage stages along engineering PLM phases. Section 3 examines the role of ambient information in context-aware DT systems to better facilitate engineering product design and usage based on family design and optimization approaches. Section 4 further develops on the proposed approaches to present a generic DT architecture, highlighting computational and data flow processes to incorporate situational recognition capabilities. Section 5 further supplements the DT architecture by presenting a knowledge graph framework for smart solution generation. Section 6 features a DT-enhanced product family design and optimization use case with a tower crane asset in a dynamic environment. Lastly, Section 7 summarizes the contributions of this study and highlights future directions on potential DT advancements.

## 2. Literature review

DT stems from an initial concept involving the interconnectivity between physical assets and virtual replicas to simulate tough operation conditions and identify vulnerabilities in NASA rocket systems [4]. This inexpensive solution evaluation technique had gained exponential traction over the past decade, resulting in a gradual consolidation of a concrete DT notion. Widely regarded as a high-fidelity virtual replica of the physical asset, DT combines real-time monitoring, simulation, and decision-aiding systems to facilitate product service enhancement [6]. Hereby, related works of product family design and optimization, and DT's adoptions are introduced below.

### 2.1. Product family design and optimization

Mass customization paradigms stemming from product family approaches are used increasingly to satisfy growing customer demands [7]. This design strategy consists of a platform featuring compatible modular components that are configured to create products for varying purposes [8]. The products share common traits and a range of techniques supporting product design are developed from formal logics [9]. To cater to market needs, product family design can be categorized into both *top-down* and *bottom-up* approaches, with the former focusing on strategic product family development while the latter underlines product redesigning [10]. These approaches, when paired with product utilization data and knowledge reuse, are crucial when determining optimal product platforms for next generation solution design [11].

Platform-based product family design hinges on either a *scalable* or *configurable* design method [12]. Scalable method adjusts the dimensions of the product platform to alter its capacity while the configurable method uses a modular-based design to alter asset functionality. Customer-oriented techniques such as quality function deployment (QFD) focuses on user satisfaction, with Luo et al. developing a five-step QFD methodology for scalable product platforms [7]. Ma and Kim use user preferences to design optimal architectures via a market-driven clustering framework [13]. Apart from optimization approaches, AI techniques highlighted by T. Simpson provides automation which can be incorporated into solution design technologies [10]. Zhang et al. modelled product family configurations via knowledge base components that manage product data and consumer demands [14] while Lim et al. presents an ontology model for contextualized decision support [15]. Alternatively, Wei et al. incorporates robust design principles to address customer preferences via a multi-objective particle swarm optimization algorithm [16]. Zheng et al. proposed a personalized product configuration framework which considers both scalable and modular design methods [17].

Product family optimization emphasizes on design reconfigurations and updates existing product platforms to focus on outlay, product quality, and market reactions [18]. Engineering management approaches such as design structure matrix (DSM) and design of experiments (DOE) are combined with AI techniques to form hybrid approaches aimed at establishing an equilibrium between redesign efficiency and commonality [19]. Savarino et al. presented a generic modularization framework for tapping into smart product information gathered throughout the usage stage to achieve reconfiguration design [20]. For smart connected assets, Zheng et al. proposed a DSM-based robust learning approach using generated data to predict engineering design changes [21]. Qiao et al. adopts a hybrid approach, focusing on static DSMs to segregate product architecture for product reconfiguration [22]. Studies on knowledge representation and usage for product family design have been conducted with Giovannini et al. using an anti-logiscist approach [8] while Nanda et al. used ontologies to represent product families for product design iteration [23].

While product family design and optimization are mature concepts with comprehensive studies conducted via data-driven approaches, there is no existing work on product family re-/design approaches that uses visualization capabilities and in-context systems to increase effectiveness.

### 2.2. DT adoption in design and usage stages

Falling under the broad spectrum of CPS, DT provides real-time control and synchronization of engineering processes [24,25]. Categorized primarily into communication, representation, and computation layers, DT technology stacks are formed using combinations of tools ranging from open-source software to microservices [26,27]. With DT emerging as a trending technology, as reflected by the exponential surge in industrial applications, this segment shows how DT systems can be adopted in design and usage stages.

Engineering PLM consists of five sequential stages and has been a major cornerstone in improving asset efficiency and management [28]. While many existing DT applications value add towards engineering PLM enhancement, to fit the scope of this study, only past studies impacting asset design and usage stages are examined. In the design stage, DT assists designers in planning and creating new product. Guo et al. presented an integrated design and production DT system using a modular approach for factory design and evaluation [29]. Damjanovic and Wernher designed a DT demonstrator to enhance product design using open source approaches [26]. Zheng et al. demonstrated service innovation concepts on smart wearable designs with Smart PSS and DT [30]. Biancolini et al. performed model analysis and validation with a DT-driven mesh morphing workflow based on radial basis functions [31]. In the usage stage, DT plays a role in next generation product reconfiguration and enhances product efficiency. Liu et al. proposed a DT-driven knowledge reuse and evaluation approach for diesel engine prototyping [32] whereas Iglesias presented a DT-driven JET diverter workflow analysis to enhance operations [33]. For shop-floor improvements, Tao and Zhang evaluated key components crucial for smart-connected factories [34] while Zhuang et al. demonstrated DT capabilities in a satellite assembly case focusing on production management [35]. He et al. presented a DT-driven digitalization approach for plant management to improve the efficiency of a converter station [36]. Ferguson et al. used DT technologies for resource management using Siemens commercial software to evaluate water pump performance [37]. Xu et al. showcased DT-driven predictive maintenance capabilities via deep transfer learning for automotive production [38].

To establish a context-aware DT framework that supports engineering product family design and optimization, studies on existing DT systems are conducted to identify key asset-environment influencers. These studies serve as fundamentals when designing in-context decision support systems. DT-related works related to both asset and shop-floor re-/configuration are categorized into (1) *Geometric assurance.* Schleich et al. presented a skin model shapes concept-driven DT reference model for physical asset design and production [39]. (2) *Value co-creation.* Zheng et al. proposed a data-driven approach which enabled personalized product co-development within a cloud environment [40] and established a DT-enabled smart PSS framework to achieve service innovation [30]. (3) *CPS modelling and simulation.* Arafsha et al. created a DT framework to enhance cyber-physical interactions in assets for real-time and post-processing asset analysis [41]. Coronado et al. presents a low-cost shop-floor DT solution with MES connectivity, displaying productivity and assets' availability [42]. Alam and Saddik proposed a DT architecture reference model integrating system data flow with reconfiguration functionalities [43].

Although these studies reflect DT influence in design and usage stages, none of them considered integrating both stages to support product family design and optimization. Meanwhile, most applications fulfil only a single PLM aspect and their system architectures are not sufficiently robust for use in a dynamic environment. Also, the lack of context-aware capabilities results in rigid DT solutions which are only suitable for a single purpose and incapable of reuse. Hence, the lack of DT-enhanced product family design and optimization indicates a need to develop product family solutions via DT to aid engineering product re-/configurations, thereby improving smart manufacturing processes.

## 3. DT-enhanced solution design and optimization

To fulfil the research gaps mentioned and capitalize on product family approaches to enhance multiple engineering PLM aspects, this section highlights the importance of ambient information in the creation of a context-aware DT and examines the advantages of having context recognition capabilities in engineering products. Supported with design and optimization approaches to aid stakeholders in throughout the design and usage stage, these theoretical elements support smart solution generation ranging from asset configuration to disruption management. Implementation techniques and applications are discussed in the subsequent sections.

### *3.1. Using ambient information to facilitate context awareness*

While existing approaches towards DT establishment typically revolves around asset digitalization, the lack of situational context impedes smart solution generation as disruptive forces are unaccounted for. To advance DT capabilities and boost the effectiveness of product family assets, integration of environment layouts within existing cyber-physical frameworks is essential towards enhancing PLM aspects, especially for design and optimization processes. This ambient information can realize context-aware capabilities within DT systems and facilitate better decision support throughout asset design and usage stages.

To generate smart solutions such as path planning and hazard circumvention, it is imperative that the environment layout model mirrors actual conditions so that reliable ambient information can be obtained. Fig. 1 presents an overview of asset-environment integration for establishing a context-aware DT and highlights key factors influencing DT effectiveness for re-/configurable product design and workflow optimization in dynamic environments. This model uses a product family approach to expedite asset configuration and serves as a guide to examine the various cyber-physical interactions.

Product family configuration uses digital replicas of compatible modular components which reflects accurate manufacturing dimensions and constraints, to facilitate new asset configuration that is best designed to operate within a designated environment layout. Both asset and environment modules are ultimately combined into a virtual replica, enabling stakeholders to design optimal assets for maximum asset functionality during operations. Details on the DT-enhanced asset configuration process are explained in Section 4.

Establishing an environment layout requires the mapping of static structures and inconstant parameters. Static structures refer to fixed and immobile installations which are replicated into 3D models and imported into the DT system. While recent advancement in cloud processing allows the use of point cloud scanning techniques to map 3D environments via LiDAR and high-resolution radar static environments can also be manually designed using software such as plant design management systems (PDMS) and other relevant tools to capture specific zones of interest. Meanwhile, inconstant parameters such as manpower movement and atmospheric conditions are captured with

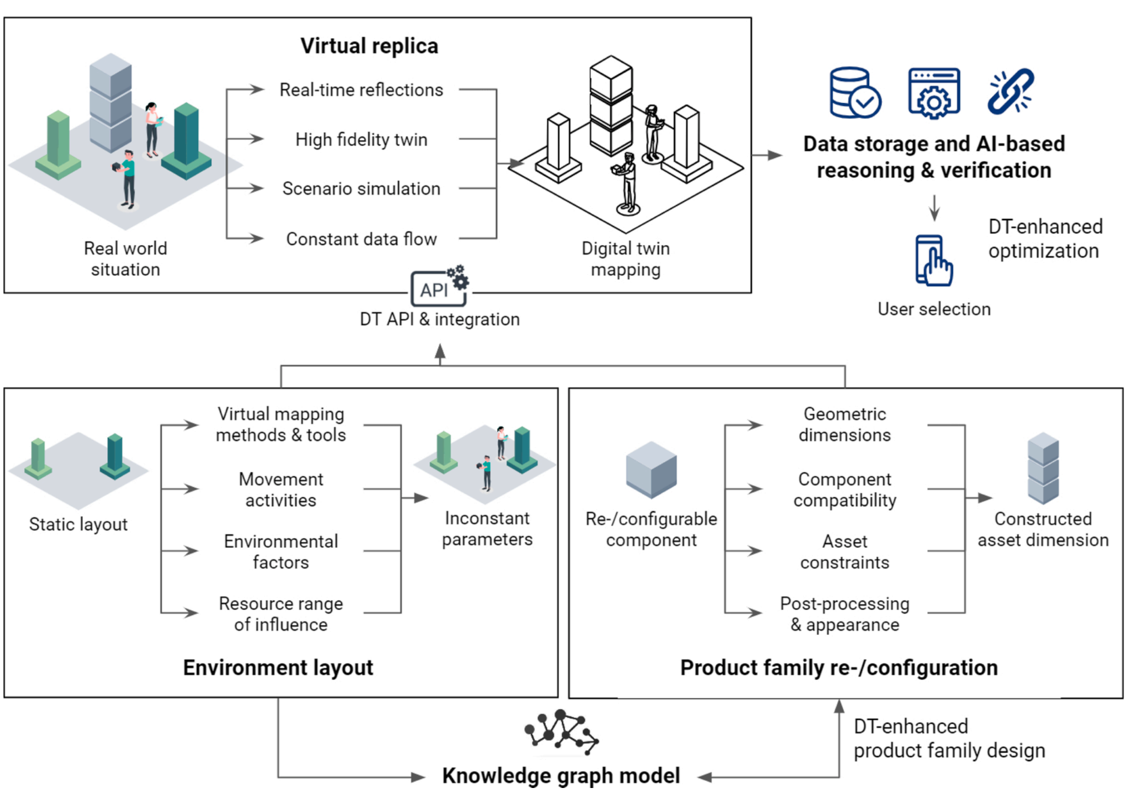


**Fig. 1.** Asset and environmental layout factors for DT creation.

sensors and tracking devices installed at strategic locations. Movement activities such as AGV operations and resource shifts can be tracked via computer vision or RFID tags. These low-cost embedded sensors monitor resource activities, environment factors (E.g. temperature, proximity), and equipment range (machine safety boundaries) to reflect the current circumstance and enable situational recognition capabilities in DT systems. These sensors transmit real-time data via IoT systems using industrial-standard communication protocols such as OPC-UA to ensure reliability and consistency. As the amount of data accumulated increases exponentially over time, cloud and edge computing techniques can be used to process sensor data before storing in databases for further analysis. For detailed monitoring of resource shifts within the environment, GPS and RFID tracking allow for accurate movement data to enable human-machine collaboration or remote facility operations. Establishing knowledge reasoning frameworks such as ontologies within the system allows insights and solutions to be generated via data-driven graph models and pre-defined rules. This allows the DT system to evaluate present or forecasted events and perform self-diagnostic actions before offering smart recommendations.

### *3.2. Design stage - create, plan, and evaluate engineering product configurations*

Ambient information can be used to enhance engineering product design and configuration by providing in-context data throughout the design stage. It expedites the selection process of optimal modular configurations to suit usage context and maximise asset effectiveness. In this stage, DT is used to aid the creation of new products configurations from a range of product family modules and assist stakeholders in identifying optimal installation locations. Due to the numerous constraints brought forth by both project requirements and environment restrictions, configuring modular assets often involves tedious comparison processes between multiple product family combinations. To overcome this hurdle, a benchmarking and interacting mechanism as shown in Fig. 2 is derived to assist designers in the creation of new product family configurations. In the benchmarking mechanism, the use of ambient layouts enables a user-friendly approach for digital product designing while the interacting mechanism takes advantage of the ambient information to enable a higher-level design process. This enables designers to evaluate new product/ service interactions and performance levels within the ecosystem via a smart connected environment. This greatly reduces the reliance on third-party experts that are typically engaged to recommend asset configurations based on project constraints such as resource availability, duration, and cost. This segment explores the use of DT-enhanced product family design to automate asset configuration and installation.

#### *3.2.1. Asset configuration*

The use of DT systems for selecting optimal product family configurations helps avoid the use of costly and time-consuming third-party services while reducing design miscalculations that could result in adverse consequences later during the usage stage. With essential nodes and edges containing information relating to stakeholder requirements, product family CAD models, site layout, and semantic relations embedded within the knowledge graph, a series of compatible configurations can be inferred via reasoning frameworks. The generated results are filtered via basic layout parameter constraints such as safety and dimensional restrictions to ensure that installation process adheres to shop-floor layout protocols. Selected configurations will be sorted via time and cost constraints where duration to transport and install the modular configuration, and various incurred costs such as labour and administrative fees are considered based on the pre-defined requirements. Using the integrated DT simulation, capabilities, manual asset configurations can also be evaluated depending on stakeholder preferences. Recommendation configurations can also be imported into the DT to simulate relevant attributes and functionalities via simulation capabilities.

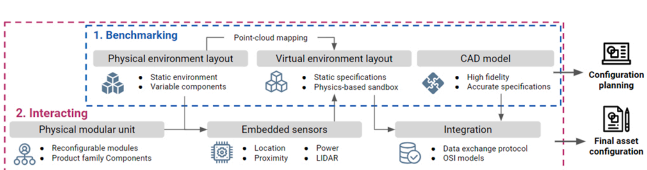


**Fig. 2.** Benchmarking and interacting mechanism for product family configurations.

#### *3.2.2. Asset installation*

After selecting a set of modular configurations, the asset CAD model can be imported into a simulation platform consisting of the environmental layout to assist in identification of optimal installation locations. Since improper planning and evaluation of asset installation will result in a costly and time-consuming relocation, any erroneous decision at this stage will have reverberating repercussions throughout the asset lifecycle. With considerations to capacity and layout requirements such as bottleneck analysis, storage points, resource movement flow, and efficiency, the asset installation can be visualized along with possible repercussions. The use of simulations for layout design is routine with many software such as plant simulation offering 2D simulation capabilities. However, without a 3D enabled environment, these tools may prove ineffective while planning the installation of tall and complex assets such as tower cranes due to insufficient dimensional consideration.

### *3.3. Usage stage - optimize and manage engineering product reconfiguration*

The use of ambient information also serves to maximise asset utilization by increasing workflow efficiency and reducing downtime risks throughout the usage stage via a product family optimization process. This process aids stakeholders to identify optimal product reconfiguration or redesign via the input of large volumes of user data and product status information into a graph-based context-aware system as nodes. As depicted in Fig. 3, product family reconfiguration can occur when the existing configuration falls within a product family scope. Alternatively, product family redesign provides support for parametric optimization or next generation design with new product families. By enhancing engineering product reconfiguration in a systematic and holistic manner, this approach enables stakeholders to manage assets throughout the PLM usage stage in an economical and resource efficient manner. Context recognition capabilities brought forth by DT-enabled technologies can boost operation capacities of product family assets and infer data-driven solutions from knowledge models to manage potential disruptions.

*Process optimization.* Utilization of context-aware DT approaches to achieve process optimization involves assisting the creation of next generation products as well as improving existing operation processes. To aid new product development, much effort is spent on user data and feedback gathering and analysis to generate meaningful insights.

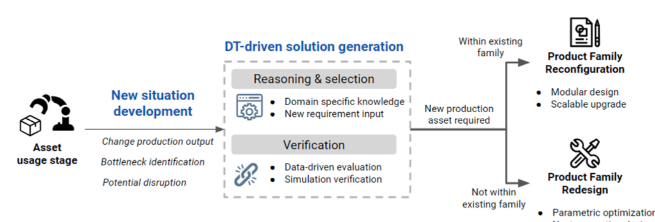


**Fig. 3.** Product family reconfiguration/redesign approach for usage optimization.

Although continuous improvement approaches such as six sigma concepts are capable of statistically identifying key improvement points, these avenues are costly and resource consuming. Relying on low-cost sensors and IoT systems, the proposed DT approach can connect crucial product components with different application scenarios derived from context-aware configurations. This cost-effective approach to realize inverse design methodologies allows stakeholders to better target intended market segments and incorporate business strategies to spur growth.

To enhance asset availability and capacity, many DT applications in the PLM usage stage revolve around product quality assurance and asset condition monitoring to achieve predictive maintenance capabilities. With the inclusion of context awareness, DT is capable of further evaluating asset movements with increased accuracy to generate viable solutions. These data-driven solutions enable operators to plan and visualize asset operations beforehand and remedy safety oversights to prevent accidents. Also, these attributes enable DT-driven assets to function autonomously with minimal human supervision in dynamic environments for manpower reliant tasks.

#### 3.3.1. *Disruption management*

Disruptions occur frequent within a dynamic working environment, causing work order delays and other adverse repercussions. The use of a context-aware DT model allows potential setbacks to be forecasted from historical trends and simulated to visualize their effects. These disruptions range from equipment failures to market factors affecting demand which can be detected via real-time sensor and semantic monitoring tools. With DT computation generating simulation-evaluated solutions, measures such as operation rescheduling and business model adaptation provide stakeholders with a robust decision-aiding system to effectively overcome situations. Time and cost emphasis can be established depending on stakeholder priorities with resources being diverted to maximize outcomes. Context-aware DT systems also provide labour intensive operations with more flexibility to face major supply disruptions and in extreme cases, assist operators with shop-floor layout conversions.

The advantages of a context-aware DT system leverages relevant knowledge to optimize existing assets through reconfiguration and redesign processes based on their current status. Realized via ambient data input, this system is is enabled through both benchmark and interactive mechanisms to facilitate product design and evaluation processes in a definitive manner. The following section discusses the integration of product-environment components to acquire context-aware capabilities for a generic three-layered DT architecture with emphasis on key technology modules.

## 4. A generic DT architecture with context-aware capabilities

This section provides a comprehensive analysis on fundamental DT technology drivers, starting with a generic architecture intended for industrial applications. Context-aware functionalities are realized from the integration of both product family modular components and environment layout, with subsequent subsections analysing various data transmission processes, detailing the information flow within the DT system. This architecture adopts the hierarchical data-information-knowledge-wisdom (DIKW) model [44], with huge amounts of asset-model data serving as a fundamental data source. The DIKW model is widely recognized as a generic structure that transforms primary data into meaningful insights for industrial workflow enhancement [45] and has been utilized as a key reference model in establishing DT systems [46]. Designed to aid stakeholders in asset re-/configuration processes, the proposed DT architecture presented in Fig. 4 consists of real-time asset and context monitoring, simulation, and decision support capabilities. Through a three-layered framework, the cyber-physical interaction layer first maps asset on to the digital environments and translates raw data from sensors and actuators into a consistent and reliable information source for storage and retrieval. Next, the data processing and consolidation layer captures essential knowledge via conversion and indexing techniques. Lastly, the knowledge computation and representation layer translate knowledge data into wisdom with smart recommendations for productivity enhancement and disruption management. The subsections below examine each process layer in

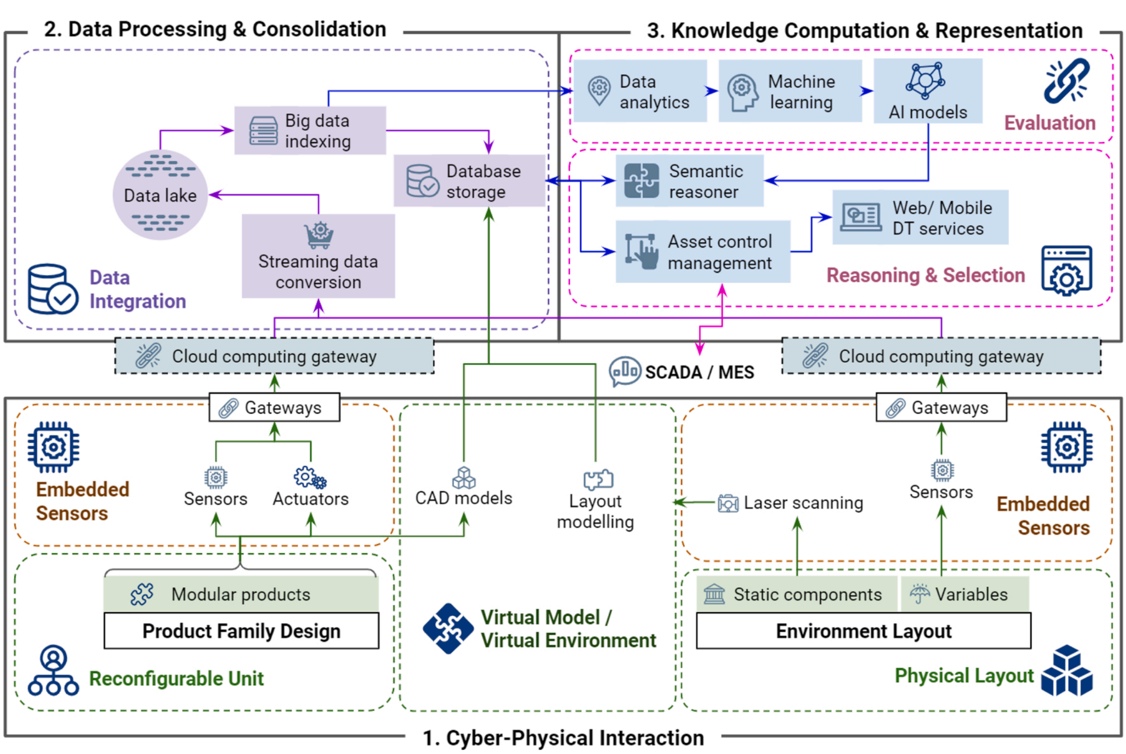


**Fig. 4.** Generic DT architecture for PLM design and usage stages.

detail and discusses the advantages of having a context-aware DT system.

### 4.1. Key components for DT establishment

The three-layered formation provides a comprehensive overview to examine the interactions between different components. Starting with a preferred product family and a pre-defined environment for asset operations, IoT systems and reasoning software provide an integrated data flow from sensor embedded assets to smart solution generation.

#### 4.1.1. Cyber-Physical interaction process

Using high fidelity modelling software such as AutoCAD and SolidWorks, digital replicas of product family components are first created in accordance to manufacturing specifications with functioning moveable components. Embedded sensors relay real-time status of the physical asset and is a fundamental step towards enabling condition monitoring and predictive maintenance. Next, the working environment layout is mapped, capturing accurate static dimensions while sensors and scanners installed at strategic locations provide real-time updates occurring within the layout. As such, a comprehensive view of the environment layout allows 3D visualization for asset control and optimization. To establish cyber-physical synchronization, physical asset status and location data generated from embedded sensors are transmitted via established network architectures such as the service-client model, which has a distributed application structure. Through the selected architectures, the relevant parameters from physical assets are mapped onto their virtual counterparts in real-time, adhering to data exchange protocols that conforms to the open systems interconnection (OSI) models. This industry standardized data transfer process connecting cyber-physical entities is then repeated throughout the DT system, propagating data to subsequent modules which is further examined in section 4.3. Lastly, the incorporation of both asset and environment layout within a simulation platform enables movement tracking and resource monitoring from sensor inputs. This cyber-physical system enables different scenarios to be simulated and is an essential feature in allowing smart solution generation and minimizing the effects of potential disruptions.

#### 4.1.2. Data integration process

Real-time sensor data generated from the asset and environment layout first passes through the cloud computing gateway to the data conversion unit, where meaningful data is filtered out to reduce processing load. The exponential amount of data created would be stored in a data lake, which acts as a repository for structured and unstructured raw data storage. The big data indexing unit manages these data via index referencing, making information transfer feasible when passing to the database storage unit and the evaluation module. The large amount of heterogeneous data accumulated calls for use of NoSQL databases over relational databases, due to their ACID compliance and ability to scale up without compromising performance. The storage of asset information and historical data ensures essential records are preserved for the reasoning and selection module.

#### 4.1.3. Knowledge computation and representation

This layer provides asset control and derives meaningful insights regarding asset optimization for smart solution generation. Consisting of two components, the evaluation module extracts information from the big data index to examine asset performance while the reasoning and selection module is connected to the database storage, providing asset control and reasoning capabilities. In the evaluation module, heterogeneous data are first classified and analysed to obtain insights on based asset activities and behaviour in the data analytics unit. Next, the machine learning algorithm uses these training data to recognize historical data patterns and forecast trends on asset conditions. These insights are managed with a predefined set of AI models to provide comprehensive outlooks on various operation aspects such as demand forecasting and predictive maintenance.

The reasoning and selection module implements asset control and generates smart solutions for asset optimization. The semantic reasoner unit provides recommendations inferred from the knowledge graph, which is a network of nodes and edges storing asset and ambient information as well as their connecting relationships. These recommendations serve to optimize operations and minimize forecasted disruptions and are implemented via the asset control management unit. In addition to having smart assistance features, this unit supports asset control remotely through a front-end user interface, thus allowing operators to control multiple assets simultaneously. Disruptions can also be managed via the web/ mobile-based interface, with alerts and suggestions keeping stakeholders informed and ensuring a safe and efficient workflow.

### 4.2. DT computational process model

The computational process forms the crux of the DT structure by utilizing real-time monitoring and simulation capabilities to assist asset operation via two major phases. Firstly, the use of domain specific knowledge to facilitate reasoning and data-driven evaluation frameworks for designing optimal product family configurations. Secondly, the utilization of context-aware DT assets to minimise repercussions of potential disruptions and aid stakeholders in decision making during asset operations.

To examine the role of knowledge graphs in recommendation processes, Fig. 5 presents a process flow model depicting DT-enhanced disruption handling and operator control to facilitate process optimization. When controller inputs and disruption alerts are triggered, the DT system initiates the classification processes to identify the situation type based on predefined parameter thresholds. This information is recorded in the cloud database before passing through the knowledge extraction unit, where it is converted into an event entity within the knowledge graph model. Graph queries derive potential solutions for asset optimization and minimise disruptive repercussions.

The potential solutions are evaluated via a multi-physics model simulation and eliminates options that exceeds predefined safety and financial risk thresholds. Next, the reasoning framework determines the feasibility of these solutions based on parameters such as deadlines, resource, and space constraints that affect shop-floor capabilities. Finally, the choices are categorized according to time and cost factors with other pre-set priority modes and featured via the system interface. The featured recommendations display the required input and parameters affected, thereby providing transparency which is important for stakeholders to make informed decisions. This allows stakeholders to inspect the logic and reasoning behind a recommendation and instil user confidence in the DT-enhanced recommendation system over time. A feedback loop records and prioritizes past user selections to facilitate knowledge reuse for similar situations in future.

The above process utilizes the human-in-the-loop approach, requiring user authorization before any solutions are implemented, allowing the operator to maintain situational control always. However, this poses a challenge as operators managing multiple assets will be overwhelmed by the many bottlenecks arising during shop-floor disruptions. Alternatively, the DT-enhanced model can be turned into a flexible system that facilitates autonomous processing. With a human-on-the-loop approach, the highest rated recommendation will be implemented automatically unless an operator intervenes. This approach is suitable for increasing the efficiency of routine operations and frees up valuable resources during the usage stage.

### 4.3. Communication protocols and APIs

As DT are complex systems requiring data intensive applications, it is essential to facilitate a smooth data flow between physical assets and

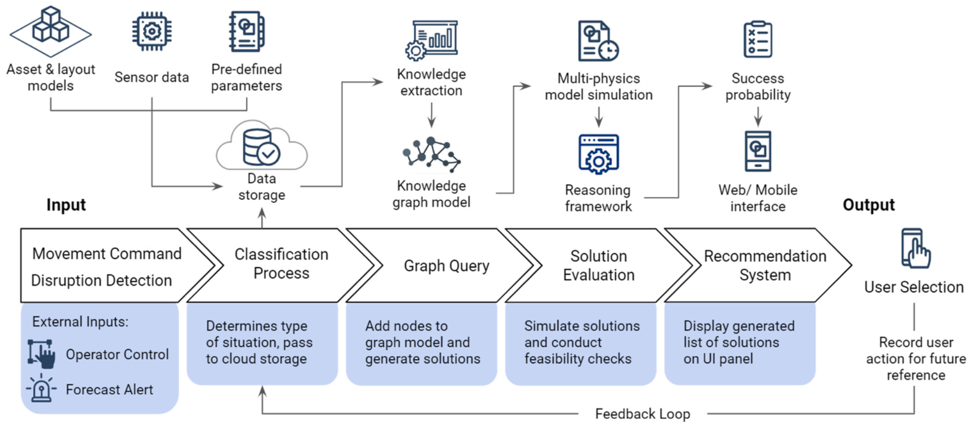


**Fig. 5.** Process flow for computation and knowledge representation.

their virtual replicas. To provide consistent and reliable data transfer, established machine to machine communication protocols such as OPC-UA must be implemented within Industry 4.0 architectural frameworks. One such interdisciplinary framework, the reference architecture model industrie 4.0 (RAMI 4.0) [47], provides an avenue to develop next generation products and incorporates business models, allowing stakeholders to achieve successful transitions towards Industry 4.0.

Starting with the data processing and consolidation layer in Fig. 4, data packets received from the cyber-physical layer are processed and converted into machine-readable format before deposition into the data lake. As a cross-platform industry standard, OPC-UA supports both a binary protocol and SOAP, a web service protocol, hence providing easy access through firewalls with minimal resources. Following the seven-layered OSI model for data transmission acquisition, encrypted information is passed on efficiently between the various DT components. In the event of control operations or disruptions, the signals are forwarded to the physical assets through the OSI layers after conversion to smaller data packets in the same machine-readable format.

To integrate the different DT components and software, APIs containing reference libraries and rules are used, allowing external programs to access information while acting as a control centre for each layer. To establish a context-aware DT, APIs can be divided into three major categories as shown in Fig. 6. The modelling API connects asset models and real-time sensor inputs to the message broker API, where data storage, simulation, and DT computational models provide solution generation capabilities. Lastly, the engagement API connects users to the DT system for asset control and visualization via a mobile/ web-based interface. The next section explores the reorganization of the information model into meaningful insights through a data-driven design approach whereby the different types of documentations are organized via a graph-based approach.

## 5. Knowledge graph-driven smart solution generation

Based on the above-mentioned DT architecture, the computational and representation processes are conducted via a graph-based approach to better accommodate the wide variety of data types involved. To better deal with the large volumes of semi-structured and unstructured data, knowledge graphs offers a means to cluster and integrate multi-source data in an efficient manner as compared to conventional SQL databases [48]. These heterogeneous data sources can be unified via semantic-based querying for complex environments to enhance decision support capabilities within a context-aware DT system. To generate smart solutions, it is essential to establish reasoning and selection capabilities built on integrated input data sources such as modular CAD models, specifications, and environmental layout information [46]. This information, including events and abstract concepts, are known as entities that are stored as data nodes within a knowledge graph model which is cross-referenced with stakeholder requirements. The model is capable of interpreting complex relations and handles diverse interactions with ease. Predefined parameters can be set to restrict asset functionality to resemble actual operation practices such as setup time and safety limits. This section highlights the importance of knowledge graph representation for smart solution generation and showcases an

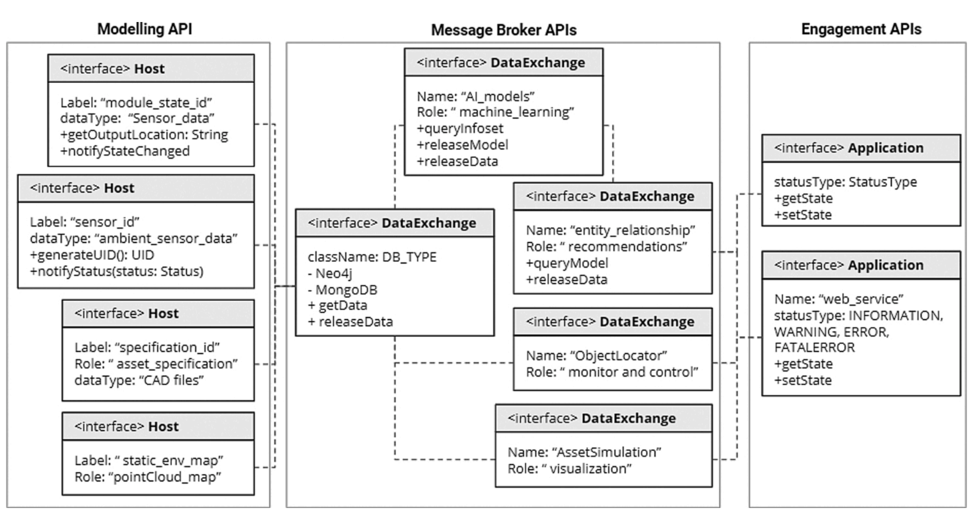


**Fig. 6.** An API framework to facilitate data transition.

ontology schema.

With large amounts of data and information, knowledge graphs can create new inferences for generating recommendations. Consisting of ontologies and real-time data, these semantics-driven models are labelled directed graphs utilizing resource description framework (RDF) models in the form of triples. Triples are binary relations in the form of <*subject, predicate, object*>, where the semantic relationship of *subject* and *object* is denoted by *predicate*. Stacked on existing databases, ontologies handle information acquisition and integration while reasoning frameworks generate solutions and verify process continuity. Information can be queried using SPARQL, an RDF query language, to infer undefined relationships as part of the solution generation process.

Asset modelling is a vital step towards DT creation and the huge amount of effort required to create high-fidelity asset models pose a major obstacle for rapid industry adoption. The lack of knowledge reuse meant that digital replicas must be created from scratch for each asset, making DT solutions unattractive. Adopting product family approaches within ontology schemas enable rapid virtual asset creation and with real-time data input, an efficient and robust knowledge graph is formed. A simplified ontology schema is presented in Fig. 7, illustrating the interactions between asset, environment, and system ontology to achieve knowledge inference. The ontology schema is modelled after a learning pedagogy proposed by David et al. aimed at facilitating a learning environment for asset designing and optimization [49].

The environment ontology enhances context-aware capabilities which aids modular asset design and reuse. Consisting of production layout and project constraints, it connects to the asset ontology and covers resource flow restrictions the modular components can provide. Based on manufacturing specifications of product family components, the asset ontology includes accurate CAD models and their respective bill of materials along with relevant restrictions including cost. The system ontology, when coupled with real-time data input, can extract relevant details, and infer new relations between entities. This enables optimal asset configurations suitable for the predefined layout to be generated and the constant stream of data input further enhances future asset PLM reconfiguration and process optimization. The proposed configurations can be evaluated via simulations as mentioned earlier. Capable of information storage and linking relationships, the graph-based model can achieve context-aware cognitions to fulfil product family design and optimization. When integrated with different AI models embedded in the DT computational layer, predictive capabilities can be enabled for maintenance, usage optimization, asset re-/configuration, and layout planning.

## 6. Case study and discussions

A relevant demonstrative case is presented to showcase the capabilities of a context-aware DT-driven approach to enable product family design and asset optimization. This case study features the design of a modular tower crane asset for hauling activities in an existing oil and gas facility. The asset is modelled after the Liebherr tower crane product family where its compatible modular components allow the DT system to identify optimal configurations. Building on previous work [50], the DT system also uses a dynamic environment layout model to assist operators with path planning operations which recommends the shortest and safest route with disruption management capabilities. Due to the complexity of the initial construction objectives, which involves dual crane lifting, this case study has been simplified to derive the theoretical aspects in a logical manner [51]. Development of the tower crane DT can be outlined in three stages: the creation of digital models for asset and environment, integration into a simulation system, and implementing decision aiding capabilities. The sections below describe the tools and methodologies for DT creation to facilitate product family design and optimization.

### 6.1. DT-enabled asset configuration and installation

The creation, installation, and operation of high-value equipment such as tower cranes require tedious amounts of planning and coordination work whereby miscalculations are likely to incur resource and financial repercussions that last throughout the entire project. In the initial stage, high-fidelity digital replicas of tower crane assets are modelled using 3Ds Max, a CAD modelling tool suited for simulation work. Referenced from manufacturing specification sheets, the modular crane components feature accurate dimensions and are realistically rendered as shown in Fig. 8. To establish the construction environment layout, an existing static layout model was provided by the proprietor through the industrial software PDMS. Alternatively, for environments

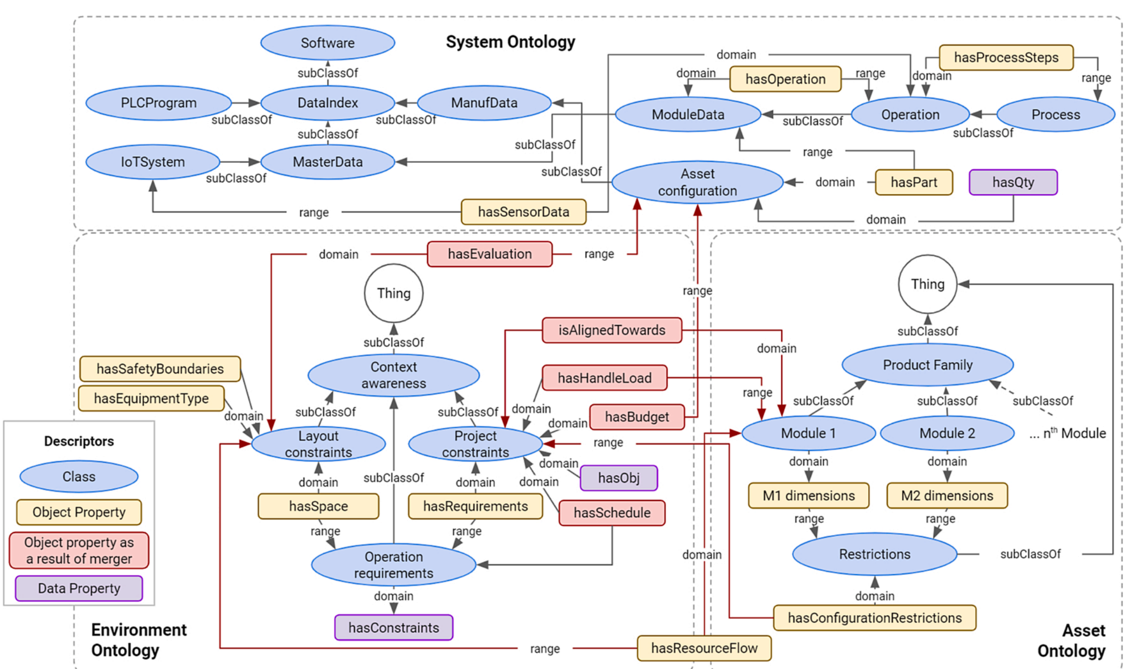


**Fig. 7.** Asset-environment Ontology Schema.

without existing 3D layout models, point cloud techniques can be applied to capture the environment layout for input into the system. The layout, along with the digital asset modules and project specifications are then stored in the knowledge graph as nodes. Project specifications include parameters such as intended lifting tonnage, maximum height, jib range, budget etc, which would filter the number of tower crane configurations.

To aid stakeholders in selecting locations for tower crane installation, the digital asset and environmental layout are integrated within a simulation system which was created using C++ and contains libraries such as MFC and OpenGL. Consisting of modelling, visualization, interaction, and optimization engines, this system implements essential DT capabilities such as real-time monitoring, simulation, and decision-aiding features. Starting with the modelling engine, the digital models are parsed in a hierarchical manner to construct the scene graph. The visualization engine acquires the scene graph and provides 2D and 3D visual outputs to identify optimal locations for crane installation as shown in Fig. 9. Through the user interface, a series of real-time statistics reflects the physical crane status to assist operators during the usage stage. These statistics, identified on the top portions of Fig. 9, include the crane ID, cockpit angle, counterweight, tele sequence, sling length, track length, working radius, distance to load, height map resolution, crane collision check, attached target, attach mode enable operators to supervise crane operations while the path planning algorithm and FPS of the simulator confirms that the context-aware DT system is functioning as expected. Although a wide selection of commercial solutions on digital modelling and simulation are available today, with state-of-the-art techniques and libraries to support DT applications, these tools were not available during the execution of the project. As the custom-made system allows a variety of CAD input format such as 3 ds, Obj, and Ply, alternate tools such as CATIA and CREO can be used to create asset and ambient models. Likewise, improved algorithms can be implemented via REST APIs, thus improving the flexibility of DT systems to suit a variety of industrial applications and provide a robust framework designed to meet specific stakeholder requirements.

### 6.2. DT-driven approach for asset control and optimization

To assist stakeholders in executing lifting processes and managing disruptions, the interaction and optimization engines provide tower crane control and path planning features. Sensors embedded in the tower crane modules and strategic locations on the project site offer collision detection capabilities and other preventive measures. An outline of the data flow between the four engines driving the DT system is shown in Fig. 10 with the interaction and optimization engines exchanging information throughout crane operation.

A tower crane ontology is created using protégé, an open source ontology software that uses OWL-DL syntax for querying. Reasoning plugins such as Pellet can be used for knowledge inference and aid the selection of possible tower crane configurations that suit the project requirements. To meet the project constraints, the resulting configurations should be filtered according to setup time and cost. Manual configurations can also be designed and evaluated for feasibility and comparison. The interaction engine receives input from both sensor networks to display collision alerts and operator commands via the graphical user interface (GUI) for tower crane control. The inputs are passed on to the optimization engine for optimal path generation depending on start/end location parameters for command execution or collision avoidance. For this experiment, a model crane replica is used in place of an actual tower crane to demonstrate the effectiveness of the DT system, with disruption scenarios are enacted on the sensor-embedded crane model. The GUI shown in Fig. 8 allows the typical tower crane controls such as jib rotation, trolley movement and height adjustment. The control inputs are reflected real-time on the model crane and safety distances can be predefined with alerts notifying operators in the event of a breach.

This tower crane DT application aids the design process by providing a detailed visual representation of the environment to facilitate crane configuration selection and deployment. Based on the layout model, the proposed benchmarking mechanism allows better monitoring and stimulation of the design process while the interacting mechanism enables designers to evaluate the effectiveness of potential configurations within the collaborative environment. In the usage stage, operators can establish safety boundaries by altering the predefined parameters within the DT system and supervise lifting operations by relying visual input from the context-aware tower crane in real-time. By utilizing the customized simulation application, potential bottlenecks and crane lifting obstacles can be identified and averted via the product family reconfiguration/ redesign approach driven by the knowledge graph-based decision support system.

### 6.3. Discussion & limitations

This case study demonstrates the relevance of DT technologies in facilitating complex engineering product family design and optimization. While many DT applications rely on real-time asset monitoring, scenario simulation, and decision-aiding systems to generate typical solutions such as predictive maintenance, the lack of situational awareness hinders asset re-/configuration processes. Hence, the ability to respond to real-time developments in both physical and cyber environments is essential for systems to minimise repercussions from a wide array of disruptions ranging from supply chain delays to asset collisions.

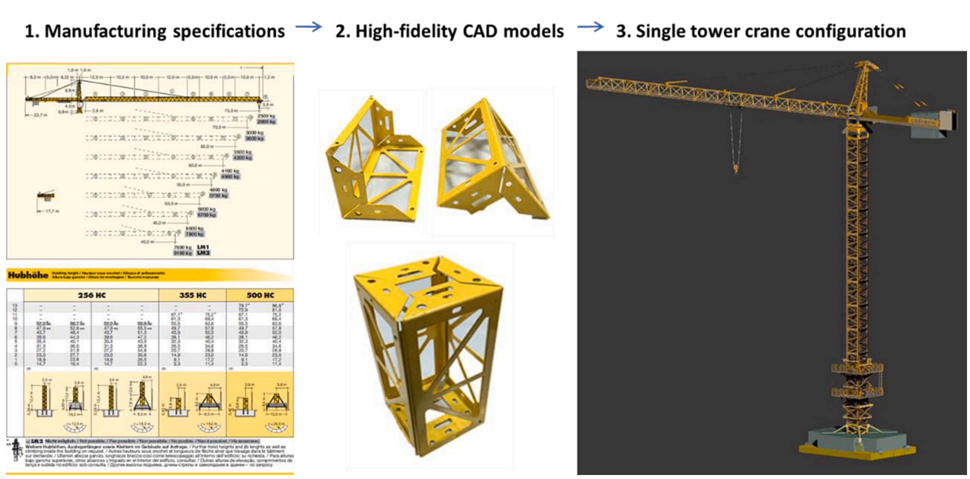


**Fig. 8.** High fidelity asset modelling with realistic rendering.

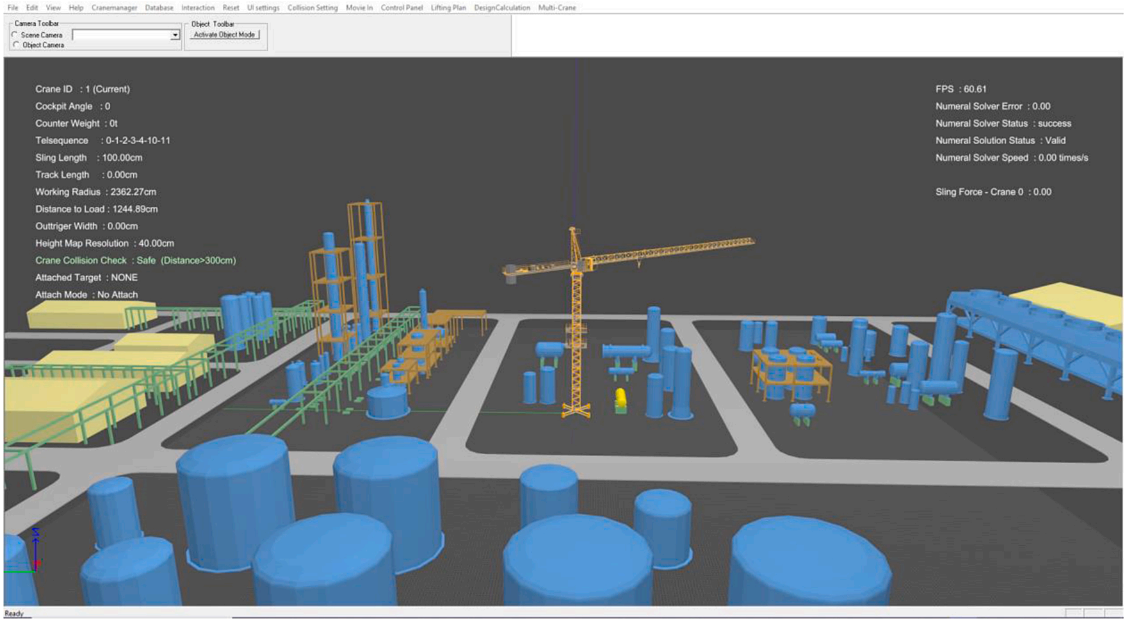


**Fig. 9.** User interface for asset and environment visualization.

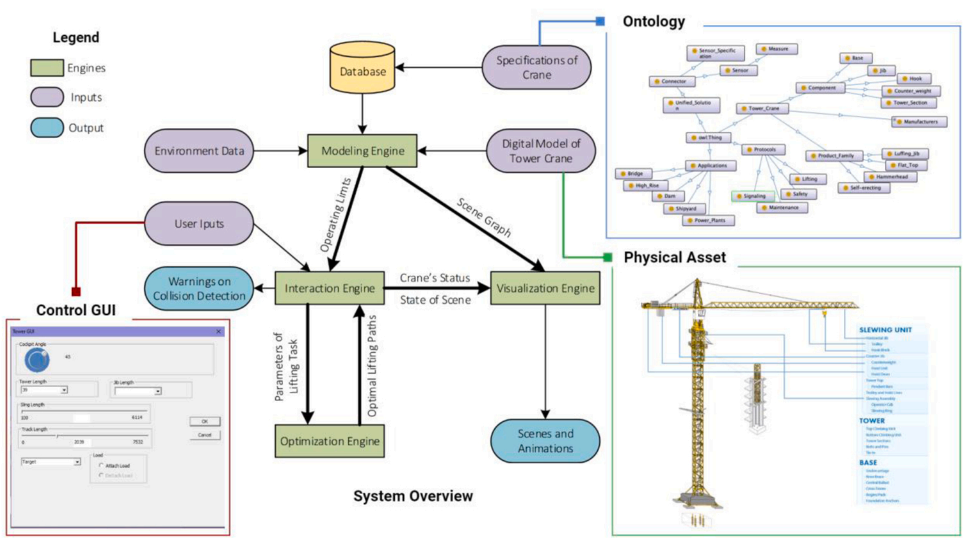


**Fig. 10.** An overview of the tower crane DT system.

Taking advantage of the environment layout model, design processes can be expedited via ambient visualization in a comprehensive and user-friendly manner. Driven by remote sensing, the tower crane asset is capable of adapting lifting paths to suit existing working conditions and support asset optimization via reconfiguration/ redesign approaches. The ambient information supplements the cyber-physical asset to enable context-aware capabilities via product family approaches whereas the generation of smart solutions allows DT-enabled assets to self-adapt based on predicted insights by inferring feasible contingency plans simultaneously. Emphasizing on planning and productivity optimization, the tower crane DT expedites working efficiency during crane configuration and installation planning and assists operators throughout lifting works. Using inverse design concepts, knowledge generated from both design and usage stages contribute to the design of next generation products. Likewise, advanced analytics such as cohort analysis can provide business insights by utilizing user satisfaction and preference data to retain and expand customer bases.

Tower cranes are high-valued assets and are often the bottleneck during construction projects, therefore sharing much resemblance to essential machineries in production facilities. Hence, similar context-aware DT paradigms can be applied to better manage these assets throughout key PLM stages. As high-value bottleneck assets typically require large amounts of resource and supervision for maintenance, safety, scheduling, and operation tasks, DT-enhanced product family solutions can equip assets with smart capabilities that would free up valuable resources and minimize disruptive effects in complex environments. Transparent recommendations derived via knowledge inference enable users to supervise operations while knowledge generated from activities can be adapted and reused for related projects.

Despite those advantages, this study still has some limitations. For instances, it mainly focuses on system functionalities and information flow to enable design and optimization context awareness, where cyber-physical synchronization is omitted in this paper. Nevertheless, one may refer to our previous work [46] for more technical details of the data synchronization. Meanwhile, the case study integrates various systems and physical assets within a lab environment by WiFi communication to achieve smooth data transactions. Hence, it is still far from the real industrial internet applications, where the cutting-edge edge-cloud infrastructure are implemented.

## 7. Conclusion and future work

With market conditions rapidly evolving due to human and environmental factors, industries are increasingly turning towards emerging technologies to simultaneously fulfil growing customer needs and manage market disruptions. Although DT technology provide adaptive solutions to meet these challenges and allow enterprises to gain an edge over their competitors, there is a lack of context awareness to aid operations in dynamic environments. Using a novel benchmarking and interacting mechanism for the design process, designers can explore different asset configurations with the aid of ambient information displayed within dynamic visualization system featuring. Meanwhile a product family reconfiguration/ redesign approach is proposed, allowing the use of context-aware DT systems to enhance workflow efficiency throughout the usage stage. This study showcased a DT-enhanced system for engineering product family design and optimization using a three-layered generic architecture that featured the integration of various technologies such as IoT, knowledge graphs, and other cyber-physical aspects. With the aim of establishing a context-aware DT asset for operations in dynamic environments, a case study featuring a context-aware tower crane DT was constructed using product family approaches, demonstrating crane configuration design and disruption optimization capabilities. The successful DT implementation highlighted a productivity-oriented robust system capable of minimizing operator workload and preventing collisions. Furthermore, this context-aware system can be duplicated and reused for managing relevant projects while the knowledge generated provided essential information for designing next generation products.

Although the simplified system prototype highlighted the feasibility of the proposed context-aware DT reference model with a demonstrative use case, complex functionalities for real construction applications have not been explored. Hence, some potential future research directions are offered, such as: 1) conducting a more sophisticated scenario integrating multiple context-aware assets; 2) development of AI methodologies and algorithms to enhance smart solution generation in context aware systems; and 3) further verification of DT-enhanced applications beyond engineering product re-/configuration in a holistic and sustainable manner (e.g. design for manufacturability).

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jmsy.2020.08.011.

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