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Towards individualised precast concrete construction-applying concepts of industry 4.0 to industrialised building components

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ABSTRACT

Rising global construction demand calls for greater economic efficiency and ecological sustainability. Precast concrete construction (PCC) can reduce on-site errors and waste by using controlled production environments. However, PCC remains limited by traditional, labour-intensive methods ill-suited to automation and individualised elements. Advances in digital fabrication enable customised concrete modules at scale, but realising this potential requires consistent digital representations that integrate design and production. This paper presents an integrated framework leveraging Industry 4.0 concepts to overcome these limitations, specifically employing the Asset Administration Shell (AAS) to implement modular Digital Twins (DTs). Drawing on perspectives from multiple disciplines, this research outlines design and optimisation methods that demonstrate the potential for highly differentiated, precise concrete modules from various digital production processes. Based on a conceptual multi-storey building as a case study, this work explores advances in the design and production of precast concrete modules to highlight the diverse requirements and use cases for DTs in PCC. Three DT case studies are developed, which support design, production, and quality control. These include the simulation-based geometric modularisation of building elements to support early design phases, the monitoring and structuring of production data for analytical insights, and the management of geometric deviations of individual building modules, assessed in relation to their cumulative effect on the overall structural assembly. The results demonstrate the feasibility and effectiveness of integrating the DT concept via the AAS to manage complexity across design and production phases of individualised precast structures, paving the way for more sustainable and efficient construction practices in concrete.

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1. Introduction

Future construction must address the rising demand for new structures driven by population growth [1] and the replacement of aging buildings [2], while simultaneously reducing its environmental impact. The Architecture, Engineering, and Construction (AEC) sector accounts for 40% of global energy use and 25% of CO_2 emissions [3], with concrete production alone contributing 8%. Although concrete is versatile and durable, its on-site processing and reliance on costly, often single-use formwork hinder resource efficiency [4]. Shifting from manual on-site construction to automated prefabrication offers a pathway to meet future needs with lower material and energy consumption [5,6].

Despite advantages such as weather independence during the production of individual modules, precast construction has struggled with declining public acceptance since the 1970s, which can be attributed to a lack of architectural diversity resulting from the monotony of serial production [7,8]. Although automated to a higher degree than other construction sectors, Precast Concrete Construction (PCC) still lags behind industries like automotive manufacturing [9]. The shift from mass production to mass customisation [10] offers a promising direction, enabling cost-effective fabrication of diverse, individualised building elements [11]. Recent advances in digital fabrication, such as robotic extrusion, spraying, and CNC-based formwork production allow precise, automated shaping of concrete elements [12,13]. Automation also enables the integration of direct feedback from quality control to optimise production workflows [14] and addresses the shortage of skilled labour in construction [15]. However, realising this potential requires the development of integrative methods that combine design, production, and control systems into cohesive and consistent digital workflows.

To capitalise on the full potential of file-to-factory processes and establish consistent feedback loops from production to quality control and back to design, it is necessary to extend the capabilities of current Computer-aided Design (CAD) and Building Information Modelling (BIM) tools [16]. While BIM enables the standardised semantic representation of building components, providing a solid foundation for digital data in planning and design [17], it lacks the fabrication-level information required for automated production. Additionally, BIM is not capable of managing bi-directional data integration between digital planning and physical production workflows [16,18]. The expansion of existing planning methods should enable seamless data exchange between digital building models, physical building elements, and corresponding Cyber Physical Production System (CPPS), to support integrated planning and production workflows [19].

As BIM reaches its limits in supporting real-time feedback, automation, and integrated production control, a more dynamic digital representation is required, one capable of synchronising virtual and physical assets throughout their lifecycle. This demand has brought the concept of the DT to the forefront of current research and industrial practice [20]. As the industry transforms from a static, closed-data present to a future linked-data paradigm, reviews on DTs from the manufacturing sector emphasise the urgent need to use unified and standardised frameworks to further develop DTs and foster its adaptation within the industry [21,22]. One of the key components for the realisation of Industry 4.0 (I4.0), the AAS, serves as the technical implementation of the DT concept. The AAS is a digital representation of physical entities, such as products, services, or production machines. It facilitates the communication and coordination of various real-world assets without disrupting their inherent functionality [23]. With numerous stakeholders involved across the building life cycle [18], the AAS offers significant potential to mitigate the effects of fragmentation in the AEC industry through standardised, interoperable digital representations of real-world assets and services.

This study presents an integrated approach that combines advanced design-to-fabrication methods for individualised precast concrete components with a modular DT framework that structures and connects information throughout planning and production.

- Contributions in structural design and fabrication: The work consolidates and applies state-of-the-art design and optimisation methods into a coherent design-to-fabrication strategy for a multi-storey precast building. By coordinating architectural, structural, and fabrication constraints across diverse element types, the study demonstrates how geometric differentiation can be achieved in a resource-efficient and industrially scalable manner.
- Contributions in digital integration: Building on these construction-oriented workflows, a DT framework based on the AAS is established to organise design, production, and quality-control information in a modular and interoperable DT structure. Three case studies illustrate how such DT instances can support early-stage design tasks, monitor fabrication-related processes, and evaluate geometric deviations, enabling a consistent flow of information across different stages of the value chain.

These contributions form a transferable methodology that links construction-oriented design innovation with digitally supported production, illustrating how individualised precast concrete construction can benefit from coordinated physical and digital processes operating within a unified system.

The contributions addresses a specific gap in the current state of research. While foundational frameworks for Construction Digital Twins (CDTs) have focused on general semantic interoperability [18] or operation-phase monitoring [24], the synergistic integration of design to production methods into standardised DT frameworks has not been explored yet. Existing production-oriented approaches typically address isolated processes such as additive manufacturing [16], raising the need to develop methods to orchestrate the combination of heterogeneous production methods and respective quality control processes, which are inherent in the current research for the digital production of PCC modules. By deriving the requirements for the presented DT framework from state of the art design and production methods, the research presented is specifically tailored to operationalise the continuous data management required to build the foundation to transform mass customisation in PCC from a theoretical concept into a scalable reality.

Given the challenges of transitioning from traditional, sequential design and manual production to consistent digital design and automated production of precast modules, this research aims to address the following questions:

- Customisation: How can precast concrete modules be designed, planned, and produced for high-volume yet highly differentiated output, while ensuring quality, functionality, and seamless integration with automated manufacturing?
- Orchestration: How can modular DTs be developed to enable standardisation and flexibility in the industrialised production of precast concrete modules, while addressing the dynamic nature of construction assets?
- Integration: How does integrating the AAS across the design, production, and quality control phases enhance the industrialised manufacturing of individualised PCC modules, enabling improved data continuity, process monitoring, and adaptability?

To address these questions, this paper is structured as follows: Following this introduction, Section 2 gives a brief overview of the state-of-the-art on digital design and fabrication methods for PCC. Furthermore, relevant concepts from I4.0, especially regarding DTs in construction, are outlined and compared with well-established BIM processes.

Section 3 outlines the proposed methodology for structuring and integrating domain-specific design, production, and quality control processes in precast concrete construction through a modular digital twin framework based on the AAS. It is followed by Section 4, which presents specialised design and digital fabrication workflows for individual precast concrete modules, illustrating how diverse, element-specific data generated during planning and production informs the development of an integrative AAS- and DT-based information framework.

Section 5 explores the development of specific AASs through three detailed case studies that demonstrate its application across a wide range of tasks from architectural design workflows to production and quality control. To encapsulate the findings and the presented methodologies, the paper concludes with a discussion in Section 6, reflecting on the key takeaways and providing an outlook on the potential trajectories for the future of PCC.

This comprehensive approach aims to provide an illustrated roadmap for integrating advanced digital frameworks and data models into the evolving landscape of PCC, emphasising the significance of a seamless digital–physical interface in realising Construction 4.0 objectives, such as interoperability, decentralisation, and real-time capability [25]. A key principle to achieve these objectives is modularity. Through the definition of clearly delimited yet interoperable subsystems and respective interfaces, modularity makes complexity manageable. It is important to highlight that modularisation is not limited to the geometric subdivision of building structures according to functional or fabrication requirements, but constitutes a fundamental principle for structuring both processes and products into manageable units [26]. In construction, this duality means that modularisation applies both to the physical building, the organisational processes, and the production systems that materialise it. Historically, the concept evolved from the pursuit of proportional order in architecture, exemplified by Le Corbusier's Modulor, to an interdisciplinary ordering logic for managing complexity through standardised interfaces and systemic coordination [27].

While individual design, optimisation, and production methods have been explored in prior research, the primary contribution of this research lies in their synergistic integration into a cohesive digital framework specifically tailored for individualised PCC. This includes the demonstration of integrative methods connecting design and fabrication processes illustrating the need and potential for DTs in PCC (Section 4) and the development of specific AASs for supporting early design stages, production monitoring, and quality control (Section 5). Together, these contributions address core I4.0 objectives by enabling virtualisation, interoperability, and real-time data integration between the design, planning, and production of PCC structures.

2. State of the art

This section outlines recent developments in design and production methods for PCC. It begins with an overview of methods for Digital Fabrication with Concrete (DfC), which expand production capabilities beyond conventional prefabrication. It is followed by corresponding developments in design methods and the ongoing extension of BIM approaches towards CDTs. Furthermore, this section introduces key concepts from I4.0, and in particular the AAS, which serves as a standardised framework for the development of DTs in the I4.0 context.

2.1. Digital fabrication and design in precast concrete

2.1.1. Digital fabrication with Concrete (DfC)

DfC is an emerging field that significantly extends the range of production methods available for precast concrete [28]. It describes the use of Computer Numerical Control (CNC) machines and robotics to produce building components directly from digital design data, thus minimising the need for manual translation of geometry into form [8,29].

DfC methods are broadly categorised into direct production of concrete elements and digitally fabricated formwork systems [30,31]. In the latter, formwork systems are typically distinguished as temporary or permanent, depending on whether they are removed after curing or remain integrated into the final element. Subtractive [32–34], formative [35], and polymer-based additive processes [36,37] are mostly used for temporary formwork. In contrast, extrusion-based mineral foams [38] and 3D Concrete Printing (3DCP) techniques [39] have been used to fabricate permanent formwork components.

For the direct fabrication of precast elements, additive manufacturing processes dominate [40]. Particle-Bed Binding (PBB) achieves high-resolution components by selectively infusing binder into granular material layers [41]. Fused-deposition Modelling (FDM) employs robotic or gantry-based extrusion systems to build up elements layer by layer [42–44]. Robotic spraying methods allow for highly adaptive and rapid material deposition, expanding the geometric possibilities for prefabricated components [45]. Hybrid strategies, such as robotically guided fabric formwork [46] and robotic slipforming [47], further extend the design space by overcoming the limitations of conventional formwork systems. Fig. 1 gives an overview of the methods described.

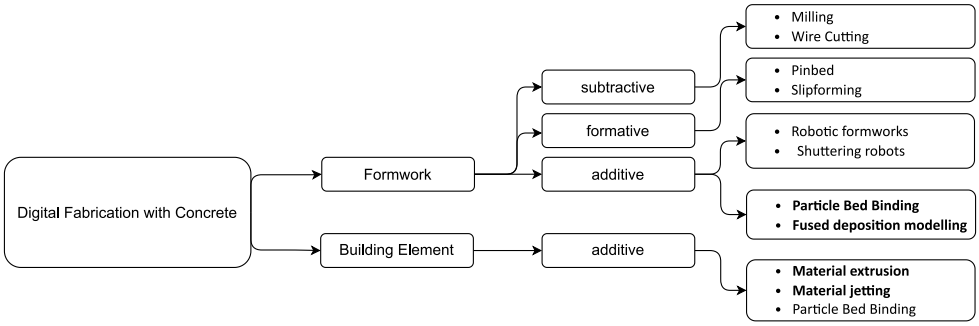


Fig. 1. DfC methods (based on [31]). Methods used in the case study building are highlighted in bold.

Despite the promise of direct additive fabrication, formwork-based approaches remain critical. They enable the integration of conventional reinforcement systems and ensure predictable surface quality, two challenges not yet fully solved in free-form additive concrete production [48]. In parallel, the development of automation strategies for reinforcement production [49,50], as well as embedding reinforcement directly into additive processes [51,52], is gaining momentum. Complementary innovations in concrete mix design [53] and automated batching and mixing [54] further enhance material performance and process reliability.

Across all approaches, DfC fundamentally transforms how precast elements are designed and produced, enabling geometric complexity, individualisation, and material efficiency at an industrial scale. Yet, these benefits can only be fully realised if design methods, material systems, and production processes are tightly integrated [55]. This calls for shared digital languages and standardised data exchange protocols to coordinate stakeholders and systems across the entire production chain.

Accordingly, Section 2.2 introduces I4.0 concepts, which offer the technological foundation for connecting digital design with intelligent, automated production.

2.1.2. Design methods

Current advancements in production processes for PCC necessitate the methodological extension of existing planning and design methods to harness the full potential of digitalised, thus individualised PCC. Design, planning, and production in the manufacturing industries encompass a blend of methodologies tailored to optimise processes, reduce waste, and maximise value [56]. Methods like Lean Manufacturing aim at eliminating waste and uncertainty in production processes through scientific management and therefore prove to be beneficial for the optimisation of production processes in the construction industry [57]. Other methods like Design for Manufacturing and Assembly (DfMA) declare the ease of manufacturing and efficiency in assembly as key aspects to be optimised during the early design process in product development [58]. Following DfMA methods, the main design principles are the standardisation of elements, reduction of possible connections and fasteners, and thereby the minimisation of potential errors in assembly [59]. In traditional precast production methods, mostly relying on the usage of repetitive planar formwork elements and their labour-intensive manual assembly, the application of DfMA principles can lead to overall cost reduction [60]. Furthermore, by reducing the chance for errors, DfMA has the potential to decrease the amount of waste related to production processes in PCC [61]. Advancements in production technologies, such as additive manufacturing, along with optimisation-driven design methods, are enabling more complex yet material-efficient precast elements [62]. While methods such as DfMA and Lean Manufacturing emphasise standardisation and repetition to improve efficiency, they require further adaptation to support the formal and procedural flexibility required by emerging digital production and design methods. New planning methods need to incorporate this expanded design space [63].

Co-Design, a method involving iterative and collaborative design processes, emphasises the integration of fabrication constraints, structural requirements, and design intentions [64]. By doing so, Co-Design methods present themselves as a possible extension for the flexible, fabrication-aware development of prefabricated building systems [65]. Furthermore, iterative feedback mechanisms enhance quality control and sustainability by minimising waste and aligning design with production capabilities [66]. This collaborative approach fosters interdisciplinary design processes [67], essential for managing the complexity of precast construction.

2.2. Industry 4.0

Industry 4.0 (I4.0) represents a shift towards smart, automated, and interconnected production, integrating technologies such as the Internet of Things (IoT), DTs, and Cyber Physical System (CPS) to enhance efficiency, adaptability, and real-time decision-making [68]. A core objective of I4.0 is the seamless integration of physical and digital assets across the entire product lifecycle to enable consistent, adaptive, data-driven workflows in design, production, and operation [69].

At the heart of I4.0, DTs create real-time virtual counterparts of physical assets, improving process transparency, production control, and efficiency. CPSs enable real-time automation by connecting digital models with physical processes, while CPPSs specifically drive industrial applications, supporting automated, adaptive, and self-optimising production [70]. These technologies

enable automation, real-time production monitoring, and smarter logistics, which are key aspects for enhancing efficiency, precision, and resource use in construction.

The concept of Construction 4.0 describes the application of I4.0 technologies, including BIM, DTs, robotics, IoT, and CPPS, to the construction sector, where they are beginning to transform traditional, manual processes [71–73]. For PCC, these advancements play a key role in enabling automated prefabrication, optimised material usage, and quality control. Despite its potential, widespread adoption is limited by high initial investment costs, a lack of standardisation, workforce adaptation challenges, and data security concerns [72,73]. However, as digitalisation advances, I4.0 offers a significant opportunity to bridge digital and physical processes in construction, streamline individualised and industrialised prefabrication, and enhance sustainability at scale.

2.3. Digital twin

The DT is a key component of I4.0, providing a real-time, data-driven virtual representation of a physical asset, system, or process. By integrating sensor data, predictive analytics, and automation, DTs enable continuous process monitoring, optimisation, and decision-making in manufacturing and construction [68,74,75]. Originally developed in the manufacturing sector, DTs have been widely adopted to synchronise physical and digital processes, allowing for real-time adjustments, predictive maintenance, and quality control [76–78].

Unlike static digital models, which represent a system at a fixed point in time, DTs dynamically update based on real-time data from sensors and process feedback. In PCC DTs enable automated tracking of production progress, real-time adjustments to fabrication workflows, and early detection of material or geometric inconsistencies, ensuring that produced building modules meet given design specifications [79]. Furthermore, DTs support supply chain coordination, linking manufacturing schedules with on-site assembly timelines to prevent delays and inefficiencies [80]. Recent work demonstrates how Semantic DTs integrated with dynamic scheduling frameworks can further enhance responsiveness to disruptions in precast production environments [81]. Beyond production, DTs capture detailed as-built data, providing a foundation for lifecycle management and future reuse of precast elements in a circular construction framework [82].

In this regard, the DT acts as a critical enabler of autonomy in manufacturing systems by providing realistic models of processes and their interactions with the real world [76,83], thus potentially enabling a more precise, customisable and therefore sustainable approach to modular construction.

2.4. From BIM to construction digital twins

In the construction industry, the DT is still in an early development phase. However, interest in this area is rapidly increasing, with a growing body of research exploring its potential applications. To date, most research on DTs in construction has focused on the design and engineering phases of the building lifecycle [84]. In this context, BIM has become the prevailing standard of digitally representing assets of the built environment [85].

BIM models typically contain the three-dimensional geometry of building components, along with semantic information such as materials, technical properties, and scheduling data [86,87]. While BIM has improved the coordination and efficiency of design and construction [88], it primarily deals with static data and lacks real-time responsiveness [18,89,90]. In response to these limitations, especially in the context of fabrication, researchers have proposed Fabrication Information Modelling (FIM) as a way to integrate fabrication data into design processes [91]. FIM is based on the open exchange data format Industry Foundation Classes (IFC), the FIM framework integrates seamlessly into the BIM context and enables automated detailing of design information [16]. However, despite its potential to enhance fabrication awareness, FIM approaches often remain project-specific and lack the compatibility with diverse manufacturing systems [92]. In contrast, DTs integrate sensor networks, IoT devices, and automation systems to continuously reflect the state and behaviour of physical assets throughout their lifecycle [18,93,94]. Although BIM models do not inherently qualify as DTs, they often serve as a foundational data source from which DTs can evolve [94,95]. As Deng et al. [96] propose, this transformation can be achieved by integrating simulations, sensor data, and artificial intelligence-based prediction into the static BIM environment, enabling automated feedback loops and dynamic performance control.

Despite their promising capabilities, implementing DTs in construction presents several challenges [94]. The complexity of the underlying technological systems, combined with a lack of industry-wide standards and interoperability, creates significant barriers [97]. Many current approaches remain limited in scope, addressing only isolated use cases [84], while fully integrated and scalable frameworks are still lacking [98,99].

Recent research suggests that modularisation may offer a viable strategy for advancing the development of scalable CDTs [98, 100]. By decomposing complex systems into discrete, manageable digital components, modular DTs can be more easily analysed, optimised, and reused across projects. In particular, container-based information models such as the AAS, or the Information Container for Linked Document Delivery (ICDD), have been proposed as alternatives to traditional monolithic BIM-based approaches [22,101]. These models support semantic interoperability, flexible extension, and lifecycle integration, making them promising candidates for the realisation of next-generation DTs in construction. While the ICDD supports semantic linking of multi-format project data, the AAS is designed for real-time, modular asset representation in CPS, making it a more effective foundation for Construction 4.0 applications in PCC. The following section provides a detailed introduction to the AAS, highlighting its structure, capabilities, and potential role as a modular backbone for scalable, interoperable DTs in precast construction.

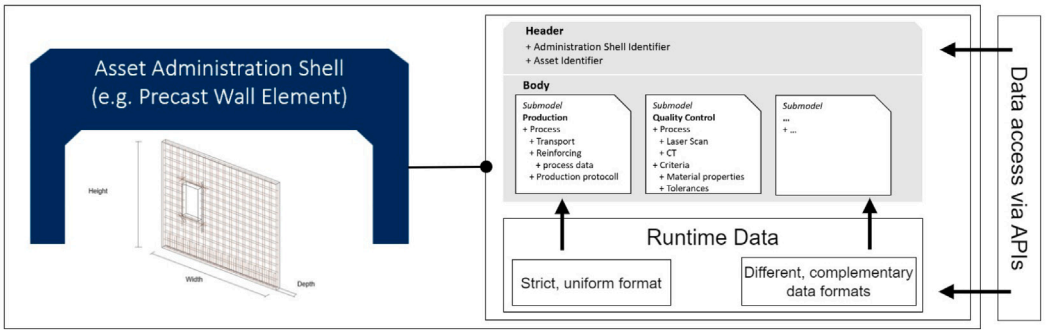


Fig. 2. Schematic representation of an AAS for the implementation of modular DTs for precast concrete modules (based on [103]).

2.5. Asset administration shell

The AAS is the standardised model used in I4.0 to digitally represent and manage assets—both physical and non-physical across all lifecycle stages [102]. As a core enabler of DT functionality, it provides a machine-readable and interoperable structure for describing an asset's properties, behaviours, and services throughout its lifecycle, thus enabling data exchange and coordination across different systems and between various stakeholders. To enable this, the AAS includes interfaces that allow external systems to interact with the asset in real-time. The internal structure of the AAS is built around submodels, each encapsulating a specific aspect of an asset, such as geometry, operating parameters, or lifecycle data, thus enabling modular and extendable representations.

Submodels are defined using submodel templates, which provide standardised structures and formats for consistent data representation. These templates ensure interoperability across different systems and stakeholders. However, for specific application domains, such as PCC, custom submodel templates need to be developed. To further enhance semantic clarity, submodels can reference concept dictionaries and ontologies that define shared vocabularies, using unique Semantic IDs to reference properties and concepts unambiguously. These semantic resources are essential for enabling coherent communication between various actors and systems in an industrial ecosystem [103]. Beyond static descriptions, submodels can also reference asset-related services, such as control routines or maintenance functions, enabling active integration with CPPSs. Fig. 2 illustrates the modular structure of the AAS and its role in supporting DTs of precast concrete modules.

The AAS is based on a technology-neutral, Unified Modelling Language (UML)-derived metamodel that can be serialised into various exchange formats depending on application requirements: XML and JSON for general interoperability, RDF for semantic reasoning, AutomationML for technical data, and OPC UA for machine-to-machine communication. To store or transfer complete AAS structures, the AASX format is used. This container format is based on the Open Packaging Convention (ISO/IEC 29500-2:2012), using ZIP compression with internal XML descriptors. The .aasx format supports long-term storage, version control, and file-based deployment across systems.

A key distinction within the AAS framework is that between AAS types (or templates) and AAS instances. AAS types define standardised structures for particular categories of assets, serving as blueprints. AAS instances, by contrast, represent individual DTs with asset-specific data, created based on these types. This separation enables reuse, standardisation, and efficient data modelling. It also facilitates scalable application of AAS concepts across large, component-based systems such as precast structures.

Finally, AAS implementations can vary based on their interaction capabilities. A *passive AAS* responds to data requests without autonomous behaviour. A *reactive AAS* monitors predefined conditions and triggers actions accordingly. A *proactive AAS* can make decisions and initiate actions independently, supporting higher levels of automation and autonomy in cyber–physical environments [104]. For interoperable information exchange and task negotiation between automation components in I4.0, a special I4.0 language is used as a control system [105]. It is divided into three levels: Vocabulary, message structure, and semantic interaction protocols, where the message structure consists of an identification area and a data area. This language enables dynamic, self-organising, and interoperable value networks in I4.0, ensuring machine-readable data and collaboration between system components.

Existing performance studies report scalability for 10–1000 AAS instances and provide initial latency evidence for registry-based access patterns, demonstrating its performance and applicability to handle large amounts of AAS instances [106,107].

2.6. Knowledge gaps

Despite increasing digitalisation, the construction industry continues to lag behind in the adoption of integrated digital methods [108]. In precast construction, this results in fragmented planning and production workflows, inconsistent use of digital tools, and limited automation across the process chain from early design to on-site assembly [97,109]. Additionally, non-validated or inconsistent data within BIM workflows hampers seamless file-to-factory workflows [85,110].

The design of precast elements remains a key challenge. Traditional methods favour mass production of repetitive modules, while emerging CPPSs open up possibilities for large-scale mass customisation [8]. Architects and planners must balance standardisation

with the need for individualisation to meet functional and programmatic demands [111,112]. Fully digital design processes offer a foundation for continuity from planning to production, but require advanced skills and tools still underdeveloped in the AEC domain [113].

Continuity between digital design and physical production is essential for enabling automation in line with I4.0 principles. However, while BIM serves as the de facto digital standard in planning, it lacks the capacity for cyber–physical integration and real-time feedback [84,114]. This calls for customisable and scalable DTs capable of synchronising with CPPSs and supporting individualised production workflows [115,116].

The AAS offers a promising foundation for implementing DTs in PCC. Yet its adaptation to the specific demands of individualised and modular production remains unresolved, particularly with regard to submodel development, data continuity, and integration with CPSs. These gaps highlight the need for integrative methods that link design, planning, and production through interoperable, semantically rich digital frameworks.

3. Methodology

The core methodological challenge addressed in this research is the integration of diverse, discipline-specific advancements in design, fabrication, and production into a cohesive DT framework for individualised PCC. Thus, the research presented exemplifies a methodology centred around the AAS as an integrative digital backbone for creating and managing DTs in PCC. This framework serves to orchestrate the multidisciplinary planning process, encompassing design and optimisation methods for building elements, their production, and subsequent quality control.

The research employs a mixed-methods design, integrating a case study building to analyse the complexities of multidisciplinary collaboration in digital construction environments and to specify the requirements a construction DT needs to fulfil. The methodological approach enables a structured yet exploratory investigation of the research questions, combining conceptual modelling, case-based demonstration, and computational prototyping to evaluate how AAS-based DTs can support PCC. This approach aims to be representative of a diverse range of building structures. Thus, it requires solutions from several disciplines, ranging from architectural design, structural and mechanical engineering, and construction informatics.

3.1. Requirements for DTs from planning and production processes in PCC

The methodology comprises a general description of the planning process based on an example building structure and a subsequent breakdown into discipline-specific approaches to the design and optimisation of individual building modules and their manufacturing processes. Fig. 3 illustrates the subsequent process steps and information exchange between design and DT implemented via the AAS across different design and production phases. As a metamodel, the AAS abstracts and standardises information flow, structuring diverse data into a unified framework that guides the representation and interaction of DTs across the planning and production phases.

An exemplary building structure is selected from a set of design variants that span a wide range of architectural typologies, highlighting the potential of digital planning and production methods to expand design possibilities in PCC.

As a case study, the design illustrated in Fig. 3(a) combines a standardised grid layout for slabs and columns with a bespoke, form-found geometry for a wide-spanning roof (36.6 m × 12.9 m). While the overall building geometry serves primarily as a conceptual platform to demonstrate the downstream modularisation workflows, the individual elements are defined with specific physical constraints to ensure transferability.

Boundary conditions for the physical and computational models are derived from established engineering standards and element-specific structural requirements: the floor slabs are analysed under self-weight and a live load of 3 kN/m^2 with support conditions defined by the column grid (Section 4.2); the agent-based modularisation is constrained by mass, dimensional, and fabrication limits encoded in the AAS (Section 5.1); heat transfer during curing is bounded by sensor-measured surface and core temperatures with ambient conditions specific to the production environment (Section 5.2); and tolerance requirements follow the national standards DIN EN 13369 and DIN 18202 (Section 5.3). These element-specific boundary conditions are intentionally derived from standardised frameworks and parametrically encoded, ensuring that they can be adapted to different building configurations and production environments.

Consequently, architectural requirements are not imposed as a static global specification, but are encoded as parametric inputs (e.g., maximum element dimensions, available formwork, material grades) within the element-specific workflows detailed in Section 4. This approach allows the proposed digital framework to be decoupled from a single design instance, making it applicable to a wide range of precast typologies.

3.2. Module design and production data: Structuring domain specific information

An interdisciplinary planning process is established, in which domain-specific methods are applied to decompose the case study building design into discrete modules and to optimise these modules according to different criteria, such as material efficiency (Section 4.2), or repetition rates (Section 4.3). For clarity and to best illustrate the diverse requirements arising from different building modules, Section 4 is structured by building element type (e.g., roof, slabs, façade). This structure enables a focused presentation of the specialised approaches required for each module, effectively highlighting the heterogeneity of processes and data that the overarching DT framework must manage. The vastness of different information types, ranging from design to production of various building elements, must be represented in the CDT and thereby serves as a design guideline for setting up respective submodels in the AAS.

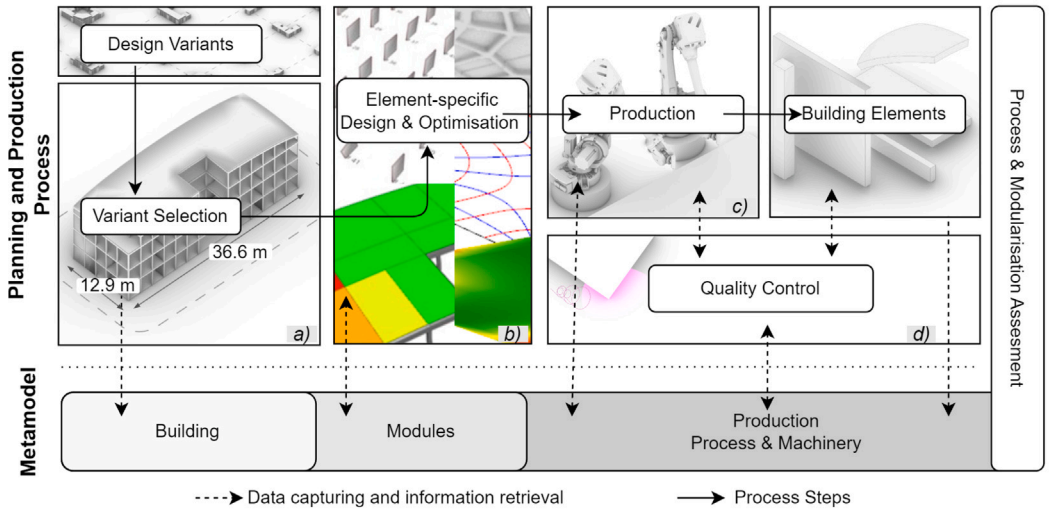


Fig. 3. Schematic representation of the methodological process, illustrating the integration of planning and production phases through continuous data exchange using the AAS. (a) Case study building serves as a conceptual carrier for the methods presented; (b) Element-specific design and optimisation; (c) Production process integration and data exchange with fabrication machinery; (d) Quality control and feedback.

3.3. Information integration and validation: Modular DTs for design, production, and quality control

The above-mentioned steps of design selection, optimisation, production, and quality control are instrumental in collecting building-related data and extracting relevant information to be transferred to the AAS. This incorporates, e.g., the precise geometrical description of building modules, respective production information, and measured deviations between designed and produced building elements.

The research methodology emphasises the critical bidirectional information flow between the AAS as a metamodel and the design, planning, and production processes. This flow is exemplified by the continuous interaction between the AAS and the individual steps from design to production. This dynamic exchange ensures that the DT remains an accurate reflection of its real-world counterpart.

The case studies presented in Section 5 demonstrate how diverse DTs can be created on the basis of the AAS for different requirements along all lifecycle phases of a building element. Thus, they serve to demonstrate the feasibility and utility of the proposed methodology, providing insight into how the AAS framework facilitates the integration and practical use of information from diverse sources across design, production, and quality control of PCC modules in line with I4.0 principles.

4. Integrated design and production

This section details the application of specific design and production methods to individual elements of the case study building, translating the overall structure into discrete building modules. Fig. 3(a.) shows the selected design variant, and Fig. 4 shows a portion of the modularised structure emerging from the methods detailed in the preceding section. In line with the methodological structure presented in Section 3, the following subsections are structured by building element type (roof, slabs, columns/beams, facade, shear walls). This approach allows for a clear presentation of the specific methods developed for each module, reflecting the diverse requirements inherent in building construction and the collaborative nature of this research. More importantly, each detailed workflow effectively illustrates the complex and heterogeneous data (e.g., non-standard geometries, specific fabrication protocols, material properties, process constraints) generated during the design and production of individualised PCC elements. Understanding this data generation is crucial, as it defines the requirements for the integrative AAS and DT information framework evaluated in Section 5.

4.1. Agent-based modelling for the fabrication-aware modularisation of a freeform roof structure

The roof structure design demonstrates a consistent digital workflow that combines Particle Spring System (PSS) for form finding with Agent-based Modelling (ABM) for geometric modularisation. The outcome of this sequence is the efficient, goal-oriented discretisation of the monolithic double-curved geometry roof geometry into individual, discretised roof modules.

Crucially, this method inverts the traditional ‘module-first’ logic, where architectural design possibilities are constrained by a repeating unit. Instead, the method developed preserves architectural freedom by discretising a design geometry into a set of unique, yet manufacturable, modules, thereby overcoming the monotony that has historically often been associated to precast construction.

ABM simulates the actions and interactions of autonomous agents to assess their effects on a system as a whole, capturing emergent phenomena arising from individual behaviours and interactions [117]. Form finding with PSSs presents a well-established

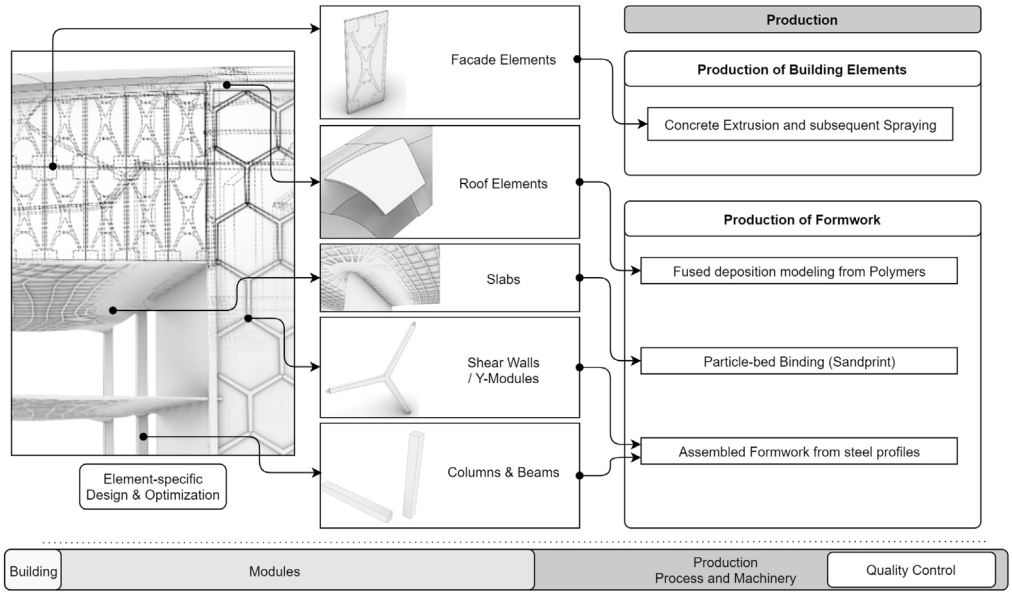


Fig. 4. Overview of building modules and their respective digital fabrication methods. Element-specific production approaches illustrate the diverse design and manufacturing data managed within the DT/AAS framework.

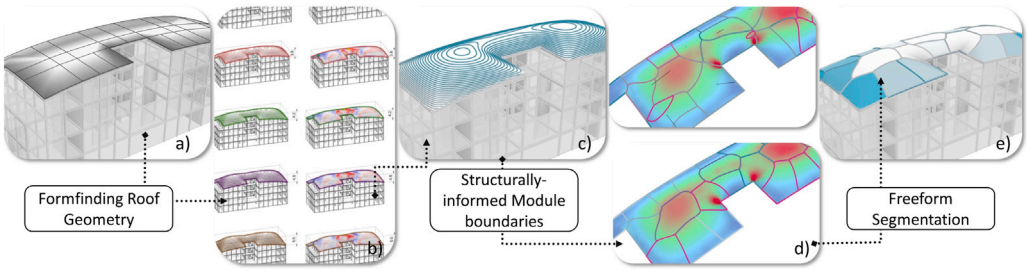


Fig. 5. Initial roof geometry, form finding, and iterative refinement of segmentation.

method for determining optimal geometry under specific constraints [118]. For the case study building, form-optimisation aims at transforming the initial roof geometry into a primarily compression-based structure, as shown in Fig. 5(a–c). The simulation and selection of modularisation variants for this roof structure were achieved through the development of fully CAD-integrated ABM methods. In the context of modularising building structures, ABM allows for the dynamic simulation of various modularisation variants, optimising for fabrication constraints and structural performance while allowing for direct design interaction with the simulation model. This makes it a suitable method to support architectural design processes [119,120]. For the modularisation of the roof, each agent represents a single concrete module. Its boundaries are iteratively updated to meet specified requirements, such as staying within a given range of dimensions, below a certain mass, or avoiding module connections in high-stress areas [121]. The simulation of the modularisation process begins with a given number of agents being initialised on the roof geometry. They subsequently adjust their positions to update the geometry of potential individual modules. If the required size and mass of modules constantly exceeds a given threshold, more agents, i.e., roof modules, are added until all dimensional requirements are met. By dynamically updating module boundaries, the agent model responds to design changes, allowing suitable modularisation variants to be selected. The result is the modularisation of an initially monolithic design geometry into individual building modules. Each module is described as a solid geometry, making it suitable for production in additive processes 5(d–e).

The segmented roof modules serve as the basis for guiding subsequent steps in formwork design and production. The formwork geometry is designed to allow demoulding after concreting, taking into account constraints such as undercuts and the build volume or reach limitations of the specific production equipment, such as an industrial robot, as illustrated in Fig. 6(a–c).

Previous research has highlighted the possibility to use a variety of flowable and fast-hardening, set-on-demand concrete mixtures in combination with 3DPFs [122,123].

Modularisation is guided by a constraint submodel within the roof-level AAS, while each resulting module is instantiated as a separate AAS instance with its own geometric and production-related data. The integration of this agent-based model as an external

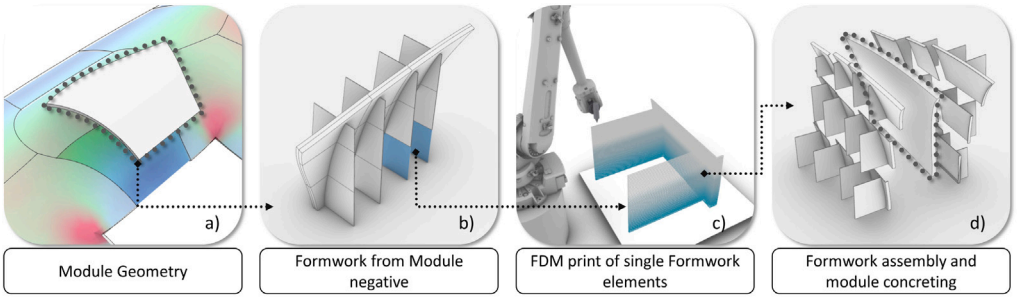


Fig. 6. The geometry of a roof module, its derived formwork, the polymer-based FDM print of single formwork elements, and the formwork assembly and concreting of the module.

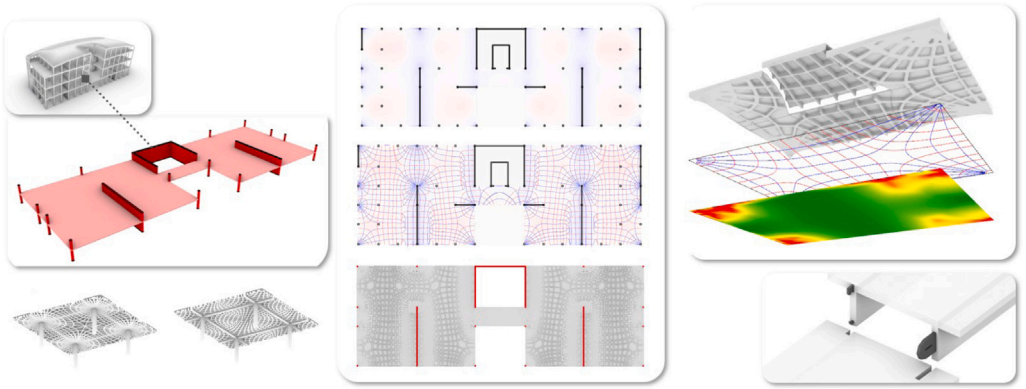


Fig. 7. Design process of the modular floor slab system.

service accessible via the AAS is detailed further in Section 5.1. This integration demonstrates how the complex modularisation process can be incorporated into the planning workflow, effectively offering modularisation as a service callable by the building's DT.

4.2. Topology optimised floor slabs using zero-waste sand formworks

The grid of primary elements (i.e., columns and beams described in 4.3) provides the boundary conditions for design and optimisation of floor slabs. The grid serves as the basis for selecting an appropriate slab typology, such as one-way, flat, or ribbed systems. For this building, a system with isostatic ribs, derived through structural optimisation, was chosen as a highly effective solution for minimising material usage regarding both concrete and reinforcement. Due to varying dimensions and rib patterns, slab modules are difficult to produce using conventional formwork, resulting in high labour and material waste. Thus, the optimised design is materialised through a recyclable formwork system, enabling the production of individual geometries from concrete, including undercuts and bottlenecks, while avoiding waste of formwork material during production [124]. The design process for this modular precast slab system involves several phases, illustrated in Fig. 7. First, the global model of 25 cm thick continuous slab under the self-weight and the live load of 3 kN/m^2 is analysed. Next, the directions of the principal moments determining the direction of the ribs and the magnitudes of the shear forces influencing the thickness of the slab are identified and extracted to serve as input for the rib layout design and dimensioning. Based on a maximum principal moment of 126 kN m/m and a shear force of 77 kN/m, an optimal ribbed slab height of 350 mm is selected. The ribs feature a width of 200 mm to accommodate the required tension and shear reinforcement. Their spacing averages 600 mm, increasing up to 1000 mm at mid-span and converging to zero at the columns to form a solid shear head for improved punching resistance. Replacing the 25 cm flat slab with a 35 cm ribbed system achieves a 40% reduction in concrete volume and up to 25% in reinforcement by eliminating redundant material from tension zones. This optimised depth-to-weight ratio significantly lowers the structure's dead load while maintaining high load-bearing capacity. The slab is then modularised based on production and logistics requirements. Modules are joined together along the rib lines using steel implants capable of transferring bending stresses, thus allowing modularisation to be performed beyond the zero-moment zone. Once the design of the slab geometries is finalised, the individual modules are prepared for production. During this step, the 3D models for formworks, reinforcement trajectories, and implant designs are prepared. The relevant production data, like print paths and machine code, are assigned and saved as attributes that serve as key inputs for the AAS.

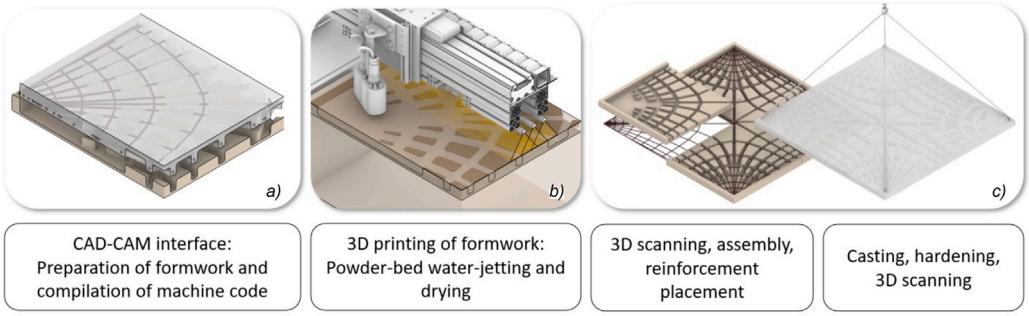


Fig. 8. Design-to-production workflow of ribbed slab modules: preparation, 3D printing, assembly of the formwork, and subsequent casting of the modules.

The subsequent manufacturing process involves printing of the sand formwork using water jetting for binder activation and IR-emitters for drying (Fig. 8b), followed by cleaning, assembly, reinforcement placement, and concrete casting (Fig. 8c). After curing, the slab module is demoulded, and the formwork material is reclaimed for reuse.

Regarding the materials used, previous research has demonstrated the successful use of silica sand and dextrin as a primary formwork material in combination with a self-compacting concrete premix (Sika Grout 551) with a maximum aggregate size of 1 mm [124].

Tolerances on the component edges are compensated using jointing mechanisms. The data generated by this optimisation and fabrication workflow, encompassing complex geometries, structural analysis results, reinforcement specifications, and fabrication requirements extends beyond standard BIM capabilities. A key outcome of this research involved developing and implementing specific AAS submodels to manage the heterogeneous information.

4.3. Columns and beams

The load-bearing structure of the case study building is a skeleton structure, consisting of linear elements (beams and columns). Different methods can be used to optimise skeleton structures. The decisive factor for choosing an optimisation method is the objective of the optimisation process. If, for example, an optimisation of the column concept is required for a specified draft with the most economically possible design of the individual columns or selected groups of columns for a single building, simple iterative calculations or the solution of equation systems are suitable for the determination of the cross-sectional dimensions and the required reinforcement [125,126]. In contrast, the application of a construction kit system, which is composed of modules and predefined individual elements, does not result in an individual optimisation of the single components of a building. In a modular construction kit system, the entire construction process can be considered in the optimisation, taking into account manufacturing, logistics, structural analysis, assembly, as well as conversion and disassembly [127]. A single component is optimised to meet the objectives of the construction kit system in the best possible way. Modularisation often involves multi-objective optimisation, solving a multi-criteria problem. The following explains the optimisation of a beam layout using a combinatorial optimisation algorithm for the development of a construction kit schematically. Fig. 9 shows the optimisation process formulated as a linear programming problem.

In the first phase of the process, an individual building is specified to be constructed with the final construction kit. A graph of the selected floor is generated. The nodes of the graph correspond to the structural joints of the building. The geometric conditions of the components and the forces acting on them represent an essential input variable for the optimisation process. In the second phase of the optimisation process, individual configurations and applications of the randomly generated construction kits are carried out as shown for a section of the graph in Fig. 9. The individual configurations are subsequently evaluated using a function that measures how well each layout meets the defined optimisation goals. The function includes a static calculation for the arranged beam elements.

The beam and column elements selected through the construction kit optimisation are subsequently detailed for fabrication as reinforced precast concrete components using conventional formwork and standard structural concrete mixes, following established precast production practice [128]. This combinatorial optimisation workflow relies on structured information of the component kit, evaluation criteria, and optimisation parameters to drive the selection process. Capturing the resulting element selection and arrangement within the AAS framework, along with the associated decision-making context, is vital for translating these system-level optimisations into reliable decision support mechanisms.

4.4. Hybrid additive fabrication for individualised facade elements

Construction today requires facade systems that balance durability, energy efficiency, architectural adaptability, and sustainability [129]. This section describes the methods used to develop individualisable concrete facade elements. The approach incorporates two different types of additive production processes, concrete spraying and extrusion, for the manufacturing of both serial and custom elements.

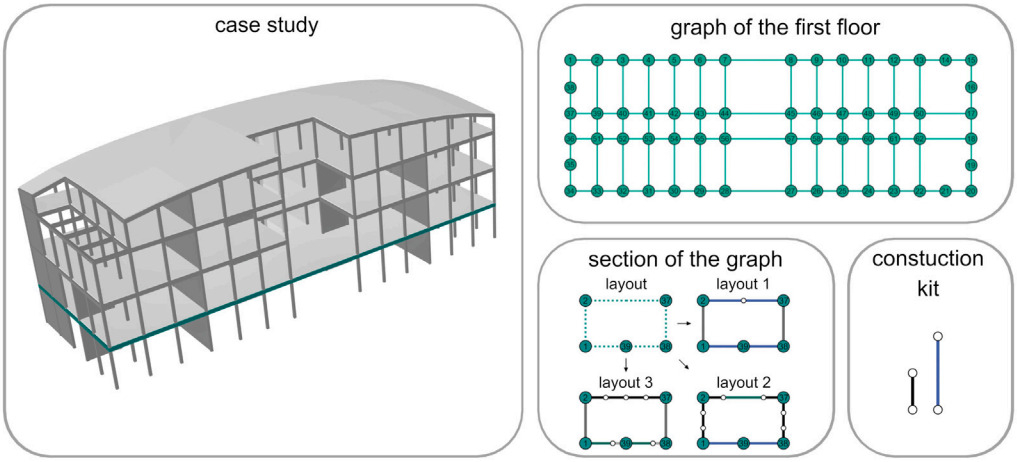


Fig. 9. Beam optimisation formulated as a linear programming problem.

Computational design methods are used to individualise the facade elements while optimising structural performance and reducing material use. Topology optimisation plays a central role in achieving lightweight designs tailored to specific structural and functional requirements. By distributing material only where necessary, the optimisation process generates geometries that reduce weight and embodied carbon while maintaining mechanical integrity [130]. By distributing material only where necessary, the optimisation process generates geometries that reduce weight and embodied carbon while maintaining mechanical integrity. These designs form the geometric foundation for the subsequent fabrication process.

To quantify the material efficiency enabled by this optimisation and fabrication approach, a volumetric analysis was performed on the exemplar panel shown in Fig. 10 (designed for batch sizes >1). By restricting material distribution to essential fastener zones and stiffening ribs, the design volume was reduced from 130,163 cm^3 (for an equivalent solid panel) to 53,512 cm^3 for the optimised version. This corresponds to a material reduction of more than 50%. Considering the lower demands placed on façade panels compared to slabs, this reduction appears to be consistent with the values found in the relevant literature on the topology optimisation of concrete components [131,132]. While it is important to note that the structural capacity of these specific thin-walled geometries requires further experimental validation, these figures highlight the significant potential of the hybrid production spraying and extrusion production method to minimise material consumption compared to traditional formwork-based pouring methods.

Key fabrication parameters influencing the hybrid process, such as material properties (for both spray and extrusion mixes), layer heights, path speeds, and curing conditions, were identified. Understanding these parameters is crucial for planning and control, as they represent important data points for digital process management. Fig. 10 illustrates the production process, from spraying to demoulding, and the various element types, which differ in form and size according to their position within the facade of the example building. For the sprayed and extruded façade elements, a fine-grained high-performance concrete mix was employed, incorporating CEM I cement, sand (0–2 mm), silica fume, dolomite mineral filler, AR-glass fibres, and chemical admixtures to achieve sufficient strength in the malleable state, interlayer bonding between shotcrete and extrusion layers, and long-term durability, as described by Lindner et al. [133]. The process begins with the application of a thin-walled, fibre-reinforced sprayed concrete shell into a mold, followed by the layered extrusion of reinforcement ribs from 3D-printed concrete directly on top of it. Anchoring elements are integrated into the concrete reinforcement ribs while the ribs are still in their green state. These elements provide precise mounting points for the facade elements to be placed onto respective substructures. Demoulding and cleaning complete the process. These methods minimise material waste and allow for the production of a wide range of free-form geometries with high precision. Modular connections are optimised for rapid assembly and disassembly, supporting circular construction principles by enabling future reuse and reconfiguration. The presented production process accommodates varying batch sizes, from single unique elements to larger repeated series, making it particularly suitable for precast construction where flexibility in production scale is essential.

4.5. Shear walls — Flow production of Y-modules with rapid heat treatment

Apart from the general structural elements, such as slabs, beams, and columns, the building structure also features stiffening walls or a core, which provide stability. In the case study building, a shear wall is exemplarily replaced by a modular structure inspired by a bionically derived honeycomb. The honeycomb design optimises structural efficiency by reducing material usage without compromising load-bearing performance [134]. Thus, the choice of a modular honeycomb wall topology is driven by its significant potential for resource efficiency. As quantified in recent lifecycle assessments of similar resolved wall structures [135], the transition from monolithic walls to optimised high-performance concrete modules can reduce Global Warming Potential (GWP)

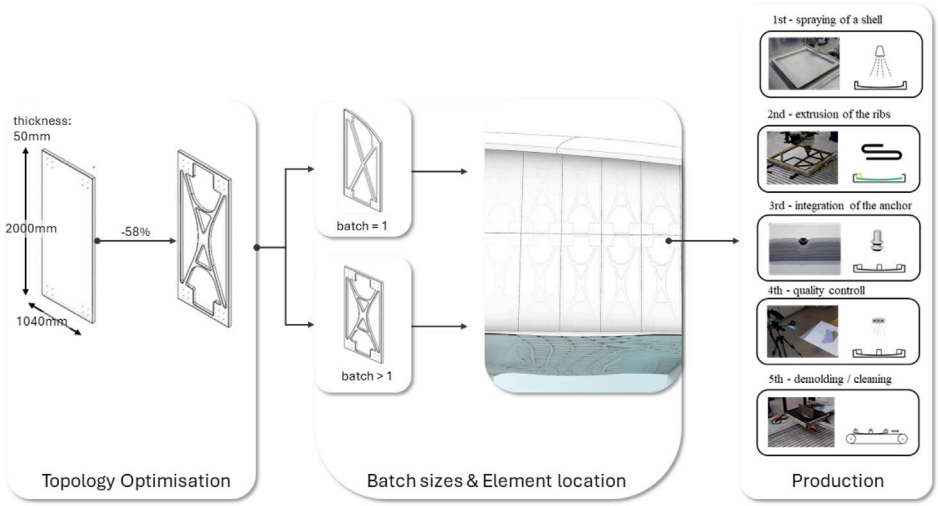


Fig. 10. Material optimisation and hybrid fabrication process for concrete facade elements, showing geometry generation, batch assignment, and the sequential application of sprayed concrete shells and extruded ribs.

by up to 80%. Furthermore, intelligent assembly strategies have been shown to yield an additional 23% reduction in embodied carbon by optimising module placement according to specific load paths.

Due to the general form of the honeycomb, the structure can be mainly modularised into Y-shaped modules. This enables a bottom-up approach to modularisation [136], with the aforementioned Y-modules forming the construction kit for the honeycomb shear wall. By means of a k-means clustering method, six types of modules are derived, forming a construction kit that differs in their cross-sectional dimensions and reinforcement ratios [135]. For the production of Y-modules a standard steel reinforcement and a high-performance concrete enabling slender designs is used. The load bearing capacity for different cross-sections is determined by means of M-N design charts [137].

Modules are placed with the aim of minimising GWP, which is primarily driven by material consumption and assessed individually for each module, while ensuring structural load-bearing capacity. In an optimisation process using metaheuristics [138,139], the internal forces and moments (Fig. 11, left) for each combination of modules are determined and compared with the load-bearing capacity defined by the M-N design charts (centre), and from the possible modules, the one with minimum global warming potential is chosen.

The Y-modules of the shear wall exhibit similar shapes, allowing them to be produced using adaptive formworks in an automated production system for precast concrete components [140]. In flow production, the concrete hardening process becomes a critical factor. For the Y-modules, therefore, a rapid heat treatment, with minimum temperature durations of 2 h at 80 °C and 60% RH is derived [141]. Besides the accelerated strength development of the Nanodur® Compound 5941-based high-performance concrete mix (with basalt aggregate 1/3 and optional micro steel fibres) [142], the heat treatment anticipates significant amounts of the shrinkage deformations. Due to the reduced deformations, the assembly of high-precision structures using bolted connections with standard hole clearance of $\leq$3 mm is possible [143,144]. The monitoring of heat development within the component during production is carried out in real time using heat sensors. Fig. 12 shows a Y-module with the installed sensors and the temperature profile in the centre, which can directly be communicated to the AAS. This enables the monitoring and control of the heating process based on sensor data obtained from the component via its DT [103]. Managing both the discrete optimisation results and the continuous sensor data within the AAS is essential for achieving efficient, quality-controlled flow production and validating the performance. Thus, the AAS implementation is therefore further detailed in Section 5.2.

Section 4 highlighted that individualised precast construction, with its diverse digital design and fabrication methods, produces a heterogeneous and dynamic data landscape spanning various inputs, fabrication processes, and different outputs, considering fabrication, quality control, and sensor values. Effectively managing this complexity requires a robust framework. Consequently, the selected case studies presented in Section 5 demonstrate how the AAS can structure and integrate this varied data, from initial design requirements to final quality assessment.

5. Digital twins for modular concrete construction

The previous section illustrated the design and optimisation of individual modules and the associated production processes applied in the case study building. Having established the design and production workflows, this section demonstrates how DTs implemented through the AAS can be developed to further support and integrate these processes. Three case studies demonstrate the practical application of the DT across key stages of the product life cycle from design and production to quality control.

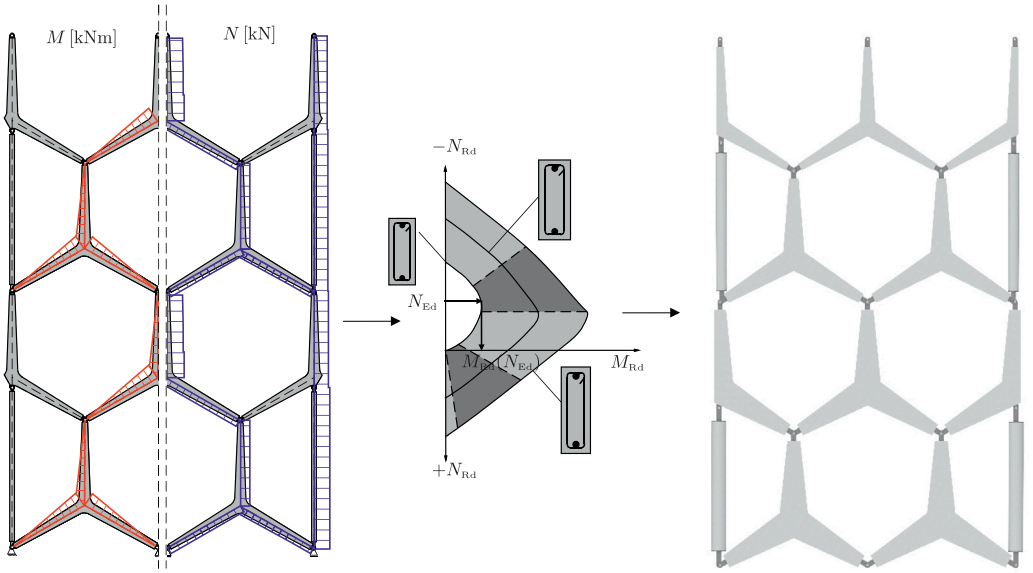


Fig. 11. Iteration step of the optimisation: Internal forces and moments of the structure (left), selection of modules by means of the load-bearing capacity (centre), and visualisation of the optimised honeycomb structure (right).

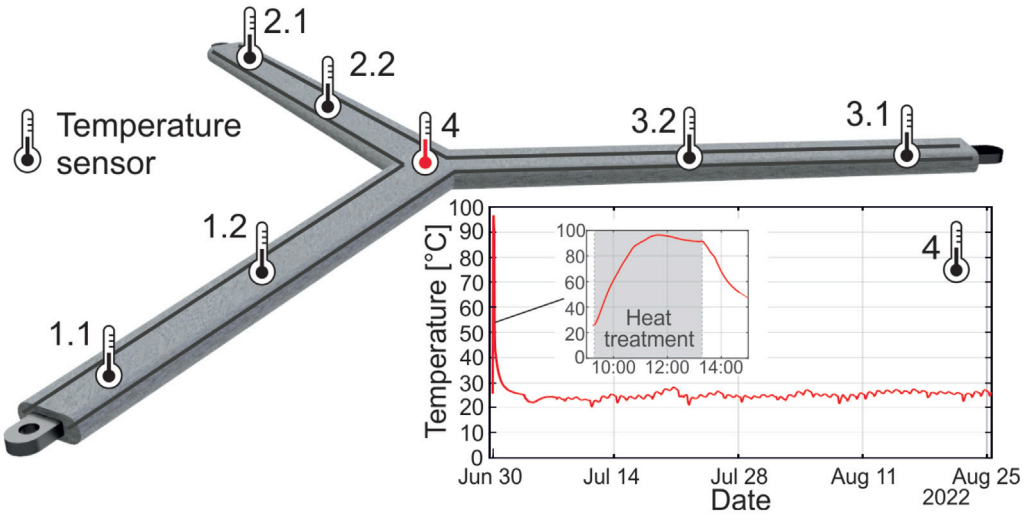


Fig. 12. Y-module with temperature sensors and recorded heat treatment.

The first case study demonstrates how the agent-based modularisation method described in Section 4.1 can be integrated into planning workflows as an automatically callable service, thereby making complex geometric processes accessible to non-experts and supporting and informing early design stages. The second use case focuses on monitoring the production process. Here, monitoring the rapid heat treatment is implemented specifically for the Y-module presented in Section 4.5, which enables targeted process control and optimisation of production parameters. Finally, the third case study focuses on managing production deviations within the context of quality control, enabling the early detection of defects and the efficient implementation of corrective measures.

Beyond the applicability of the AAS across different phases and domains, the selected case studies also exemplify distinct patterns of interaction between the DT and external processes or data sources, and can be categorised in the following way:

- **Case Study 1** demonstrates how an external service can automatically generate DTs by simulating the modularisation of complex building element geometries. Based on initial constraints defined in a custom requirements submodel, the service creates multiple new AAS instances, each representing an individual module.
- **Case Study 2** demonstrates referential Data integration & analytical insight. The AAS serves as a semantic gateway, referencing raw sensor data stored externally while enriching the DT with actionable information.

Table 1
Overview of AAS instances in the case studies presented and their relation to the IFC building model.

Case study	AAS	#	IFC reference	Description
–	Building AAS	1	IfcBuilding	Top-level integration shell maintaining references to all AAS instances, aligned with the IFC spatial containment structure.
1	Roof element AAS	1	IfcRoof	Provides modularisation requirements used by the agent-based modularisation service (ABMaaS).
1	Roof module AAS	22	IfcBuildingElementProxy	One AAS instance per resulting roof module generated by the ABMaaS, referencing module geometry and metadata.
2	Y-module AAS	1	IfcWall	Semantic access point for production monitoring, linking time-series measurement metadata and derived material strength.
3	BeamModule AAS	13	IfcBeam	Module-level deviation and tolerance state for quality control, including OK/NOK status and measured deviation values.
3	StructuralBeamAssembly AAS	1	IfcGroup	System-level aggregation of BeamModule AAS instances, tracking cumulative deviation.

- **Case Study 3** integrates evaluative state updates. The AAS holds key parameters and target values (e.g., tolerances). It integrates measurement data, allowing for an evaluation (e.g., measured vs. required values) that directly updates the state of the relevant module's AAS submodels themselves

Together, the selected case studies demonstrate the frameworks ability to integrate the diverse and dynamic data ecosystems inherent to contemporary PCC and highlight its capability of creating the digital foundation for quantifiable improvements in process efficiency, quality control, and resource management.

The Case Studies validate the system's robustness against real-world constraints by providing functioning software services (Section 5.1), incorporating data from physical prototypes (Section 5.2), and applying industrial quality standards to manage production deviations (Section 5.3).

The resulting DTs must remain consistently anchored within a shared building context to ensure interoperability and alignment with established BIM workflows. In the proposed framework, this anchoring is achieved by integrating the AAS-based digital twins with an IFC-based building model, which provides the authoritative spatial and geometric reference. Table 1 summarises the AASs instantiated in the Case Studies presented. Following the buildingSMART–IDTA best practice, the IFC model remains the authoritative representation for spatial containment and building geometry, while AAS instances represent assets that are explicitly DT-enabled, thereby avoiding redundancy [145]. This results in $N_{\mathrm{AAS}} = 39$ instantiated AAS across the three case studies, 1 Building AAS, 1 Roof Element AAS, 22 Roof Module AAS, 1 Y-module AAS, 13 BeamModule AAS, 1 StructuralBeamAssembly AAS, and the Building AAS as a top-level integration shell that maintains references to the DT-enabled assets.

5.1. Case Study 1: Agent-based modularisation as a service

In I4.0, agents facilitate self-organisation and self-optimisation within CPSs, allowing for efficient resource management, workflow coordination, and seamless communication between I4.0 assets [146]. Thus, ABM is often highlighted as a well-established method to model the interactions of a wide variety of real-world entities and their digital counterparts [147]. As outlined in 4.1, ABM can also be leveraged to manage the complexity of challenging design and planning tasks, thereby facilitating the planning of resource-efficient structures. In the case study presented, the virtual entity of the AAS `Roof Element` assumes the role of an individual designer interacting with the agent model by providing the necessary simulation inputs. Thus, the agent model is embedded as a callable service directly into the communication and creation of new I4.0 components in the form of Roof Modules and their respective AASs.

While ABM has evolved into an established method for solving complex problems across various stages and domains of architectural and engineering planning, the knowledge required to apply ABM remains a barrier to its broader adoption as a modelling and simulation method, particularly outside academic contexts [148]. Although application-specific tools for geometric development environments are being developed [149], the successful modelling of agents, their behaviours, and interactions within associated systems still demands a considerable level of prior knowledge. This includes not only the conceptual foundations necessary to develop targeted, functional models but also the technical implementation, which often requires advanced programming knowledge. Furthermore, depending on the complexity of the task at hand, in-depth knowledge of the underlying geometry models is also required. To overcome these hurdles, in the Case Study presented we demonstrate how the complex task of the modularisation of a freeform roof geometry can be triggered through a specific requirements model within the AAS of the `Roof Element`, allowing for the automatic creation of corresponding AASs for each resulting roof module.

This section examines the synergy between ABM and the AAS, focusing on how AASs act as centralised hubs for data management while enabling external agent-based models to perform specialised planning services, such as the modularisation of free-form roof structures. This integrative framework makes advanced simulation procedures, typically isolated due to the fragmented nature of AEC planning processes [150], more accessible and streamlined for direct design-to-production workflows for precast concrete modules.

Table 2
Correlation between variables (Algorithm 1) and implemented AAS Submodel elements. The schema defines the interface for the external ABM service.

Context	Algorithmic variable	AAS Submodel/Collection	AAS property (idShort)
Input: Constraints & Configuration (Category: PARAMETER)			
Initialisation	Agent Count (A)	Design/Input/ModuleInfo	`ModAgentCount (xs:int)`
Constraints	Max. Weight (C_{mass})	Design/Input/ModuleInfo	`MaxWeight (xs:double)`
	Min. Edge Length (C_{size})	Design/Input/ModuleInfo	`MinEdgeLength (xs:double)`
Geometry	Design Geometry (G)	Design/Input/GeoStructInfo	`GeometricModel (AAS:File)`
Output: Generated module data (Category: INSTANCE)			
Geometry	Module Mesh	Design/Module	`ModuleGeometry (AAS:File)`
Physical	Mass ($a.Mass$)	Design/Module	`ModuleMass (xs:double)`
Dimensions	Bounding Box (X, Y, Z)	Design/Module/BoundingBox	`MaxEdgeLen[X,Y,Z]`
Production	Toolpath Length	Production/Formwork	`PPathLenForm (xs:double)`

5.1.1. Requirements submodel and ABM integration

In this framework, the `Roof Element` AAS provides relevant input parameters that guide the modularisation (e.g., geometric constraints, structural information, and fabrication requirements) from its `Modularisation Constraints Submodel` to the agent model, which is treated as an external service.

The diagram in Fig. 13 illustrates how the AAS manages the flow of data and requests the external modularisation service to automatically trigger the simulation of decomposing the given roof geometry into discrete modules and subsequently create respective AASs for each roof module based on a predefined template that is extended with relevant module information after the modularisation process is run. The operational sequence of the framework involves the extraction of constraints from the `Roof Element` AAS, the passing of these constraints to the agent model for modularisation, and the generation and reintegration of individual module AASs back into the building AAS to ensure a complete digital representation. The following steps outline how the framework facilitates this sequence:

- The specific AAS `Modularisation Constraints Submodel` stores essential data, which is retrieved and passed to the external agent service for processing.
- After the simulation, the resulting modules and respective AASs containing relevant data are integrated back into the `Building` AAS. Each Module AAS instance is based on a `Roof Module` AAS type template. The newly created `Roof Module` AASs relies on predefined templates and is filled with relevant module information.
- Since the number of resulting modules is only known after the successful simulation of the modularisation process, each `Roof Module` AAS is automatically generated as part of the simulation output.

5.1.2. Framework implementation

For this study, a Flask-based RESTful API [151] interfaces the AAS roof model with the local agent-based simulation. It ensures that input parameters are dynamically retrieved from the AAS, processed by the agent-based simulation environment, and that resulting module data is written back to the newly created AAS templates of `Roof Module` AASs. The agent model reads the Roof Element AAS in Extensible Markup Language (XML) format and processes the data accordingly. The resulting `Roof Modules` AASs are also written in XML format, ensuring consistency and compatibility in data exchange.

To ensure reproducibility and interoperability, the data exchange between the AAS and the external ABM service is formalised through a specific Submodel schema. Table 2 defines the mapping between the algorithmic variables used in the modularisation logic (Algorithm 1) and their corresponding AAS property definitions (idShorts) and data types. The implementation utilises the standard AASX Package Explorer XML serialisation format, ensuring compatibility with specifications defined by the Industrial Digital Twin Association (IDTA). To facilitate adoption and ensure full reproducibility of the data interface, the complete XML definitions for both the Roof Element and Roof Module AAS templates are provided as Supplementary Materials A and B.

The internal logic of the modularisation service, which orchestrates the behaviours of the agent model and therefore the geometries of individual roof modules, is detailed in Algorithm 1. The process begins by voxelising the input design geometry and clustering the resulting voxels into groups. During the clustering phase, every voxel in the grid is assigned to its nearest spine (ReferenceLine), effectively partitioning the continuous design volume into discrete, solid hulls. The positioning and adaptation of these spines is automated by a hierarchical agent system. Each ModuleAgent controls two child VertexAgents (the spine endpoints) and negotiates competing constraints through weighted behaviours:

- Size/Mass Control: Agents shrink or expand by moving VertexAgents into target directions to keep the resulting voxel cluster within set dimensional limits.
- Separation: Repulsive forces prevent module overlap and tiny fragments.
- Optional Alignment: Agents align with principal stress trajectories mapped from FEA data and stored in the voxel environment (if provided), resulting in stress-aware placement of module interfaces.

The convergence of the roof modularisation process at the macro-level is an emergent property of the agent interactions and behaviours at the micro-level. Each `VertexAgent` operates as a spatial entity, resolving local conflicts such as overlaps or edge-length violations through weighted movement vectors. By reacting to given constraints on the 'micro' level of the individual agent, the system converges towards a macroscopically valid and stable modularisation that satisfies the global structural and fabrication requirements defined in the respective AAS `RequirementsSubmodel`.

As detailed in Algorithm 1, the model iterates until equilibrium is reached, which is defined as the state where total agent displacement drops below a convergence threshold (Fig. 14).

Algorithm 1 Agent-based Modularisation Service (ABMaaS)

Require: Input from AAS Roof Element:
CAD Submodel: Design Geometry G
Modularisation Constraints Submodel:
$C_{mass} \leftarrow$ maximum Mass
$C_{size} \leftarrow$ minimum Module Size
$S_{info} \leftarrow$ Structural Information
Ensure: Output: Set of `AAS Roof Module` instances S_{mod}
$V, A \leftarrow$ Initialise(G) ▷ Voxelise geometry & seed agents
while $\Delta_{displacement} >$ Threshold **do**
  $T_{spatial} \leftarrow$ BuildRTree(A); ResetForces(A) ▷ **Pre-Execute**
  for each Agent $a \in A$ **do** ▷ **Execute**
    $N_{loc} \leftarrow$ QueryNeighbors($a, T_{spatial}$)
    if $a.Mass > C_{mass}$ **then**
      $\vec{F}_{vol} \leftarrow$ Shrink
    else if $a.Size < C_{size}$ **then**
      $\vec{F}_{vol} \leftarrow$ Expand
    else
      $\vec{F}_{vol} \leftarrow \vec{0}$
    end if
    $\vec{F}_{net} \leftarrow \vec{F}_{vol} +$ Separation(a, N_{loc}) + StructuralInformation(a, S_{info})
    $a.VertexAgents$.QueueMove($\vec{F}_{net}$)
  end for
  for each Agent $a \in A$ **do** ▷ **Post-Execute**
    $a.VertexAgents$.UpdatePos()
  end for
  for each voxel $v \in V$ **in parallel do** ▷ **Clustering**
    Assign v to closest Agent a (via $a.ReferenceLine$)
  end for
  for each Agent $a \in A$ **do** ▷ **State Eval**
    Update $a.Mass, a.Dimensions, a.Position$
  end for
end while
AAS Generation:
for each Agent $a \in A$ **do**
  $Inst \leftarrow$ CreateInstance(`AAS Roof Module`)
  $Inst.Module \leftarrow$ {id : $a.ID$, Position : $a.Position$, Dimensions : $a.Dimensions$}
  $Inst.Formwork \leftarrow$ GenerateFormworkData(a)
  $S_{mod} \leftarrow S_{mod} \cup Inst$
end for

The `Roof Element` AAS includes a Modularisation Requirements Submodel that plays a crucial role in defining constraints for the modularisation process. This submodel contains key parameters, such as the maximum allowable edge length (`MaxEdgeLength`), minimum edge length (`MinEdgeLength`), and weight limits (`MaxWeight` and `MinWeight`). These parameters are critical for guiding the modularisation of the roof geometry, ensuring that the resulting prefabricated elements meet structural and logistical requirements. By providing a centralised repository for these constraints, the AAS facilitates an automated and compliant modularisation process, enabling efficient integration of physical assets with digital planning workflows.

The `Roof Modules` AAS serves as a reusable template being instantiated for each resulting module generated by the agent-based modularisation simulation. This submodel captures detailed attributes, including the exact geometric description as a polygon mesh (`ModuleGeometry`), weight (`ModuleMass`), and bounding box dimensions (`MaxEdgeLenX`, `MaxEdgeLenY`, `MaxEdgeLenZ`). Furthermore, specific data about the expected production affordances for module formwork is provided, such as contour path length and respective support material needed to produce overhangs in FDM production processes. These parameters are essential for both production planning and evaluating the production affordances of specific modularisation variants. By providing a consistent template, the AAS ensures that all generated modules conform to the defined specifications, thereby facilitating automated integration into digital workflows and maintaining interoperability within the I4.0 ecosystem.

Due to the underlying voxel-based logic detailed in Algorithm 1 the system exhibits high geometric robustness. Unlike boundary-representation (B-Rep) methods, the volumetric approach inherently prevents fatal geometric errors such as self-intersections during the rapid expansion/shrinkage of agents and generation of modularisation variants. On a system integration level, the coupling via RESTful API enables graceful failure handling. Exceptions, such as input parameters violating the Requirements Submodel or a failure to converge within the maximum iteration limit, are captured by the service and returned as standard HTTP error codes. This signals the AAS to halt the instantiation of *Roof Module* assets and flag the process requires manual review, ensuring that only valid, converged geometries are propagated to production.

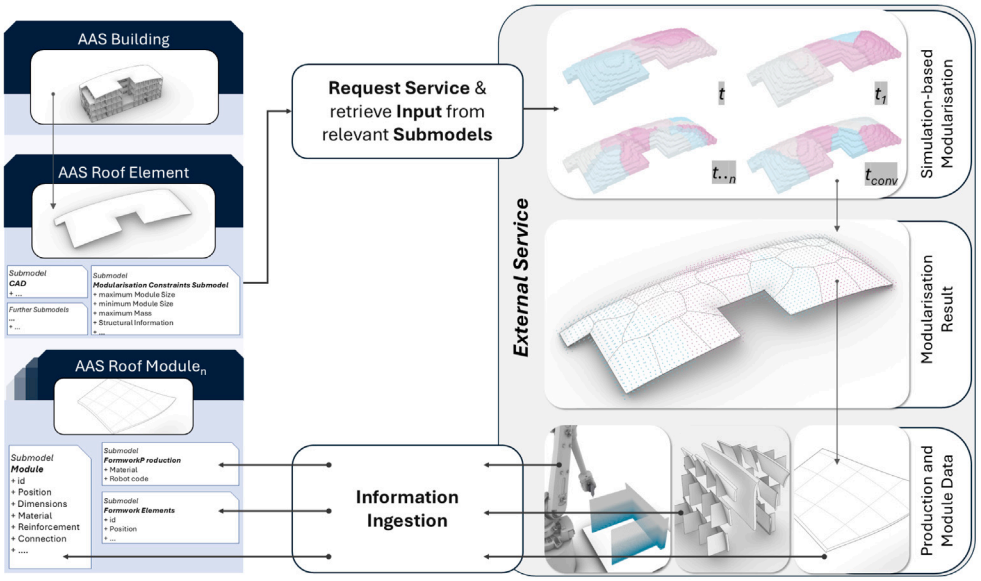


Fig. 13. Automated modularisation using an external agent-based simulation service triggered by the Roof Element AAS. Simulation results are reintegrated as module-specific AAS instances, enabling seamless data flow from design constraints to production data.

5.1.3. Results

While this implementation requires the ABMS environment to be hosted locally and operational, it serves as a functional proof of concept. The integration of Agent-based Modelling as a Service (ABMaaS) within an AAS framework demonstrates the potential for scalable, flexible planning processes where complex simulations can become an integral part of the planning process. By using the AAS as an integration layer, the threshold for implementing complex simulation procedures is significantly lowered, enabling the streamlined integration of complex simulation services, such as modularisation, in digital design, planning, and production processes. This provides a quantifiable acceleration of early-stage design exploration.

To quantify the effectiveness of the developed agent-model, Fig. 14 provides a detailed analysis of the model convergence during the modularisation of the roof geometry. Plot A tracks the bounding box dimensions of the 22 discrete module agents. It demonstrates how modules initially violate fabrication limits but progressively negotiate their geometry to converge strictly within the defined maximum and minimum constraints (indicated by dotted lines). Simultaneously, Plot B illustrates the system's convergence profile on a logarithmic scale. A sharp drop in displacement within the first 25 iterations indicates the rapid resolution of major geometric conflicts, followed by a fine-tuning phase. For reference, this simulation clustered a total of 38,960 voxels. On consumer-grade hardware, each iteration required approximately 0.2 s, with the system reaching stable equilibrium in 197 iterations, which is equivalent to a total runtime of ≈38 s. Convergence is defined as the point where the total geometric displacement falls below the voxel resolution threshold (here set to 0.1 m), ensuring that no significant geometric changes occur between steps.

Regarding benchmarking, it is important to note that a direct quantitative comparison with traditional CAD or BIM workflows is limited by fundamental functional differences. Standard modelling methods rely on manual geometric subdivision and typically lack the inherent capability to optimise module dimensions and structural alignment in real-time. Consequently, achieving a comparable multi-objective solution manually would require a discontinuous iterative loop of modelling, measuring, and checking constraints, spanning hours or days. In contrast, the proposed ABMaaS automates this negotiation, generating validated modularisation variants within seconds. The contribution is therefore characterised by a significant reduction in design cycle time, shifting the modularisation task from a manual drafting process to an interactive computational service.

This rapid feedback enables designers to generate and evaluate multiple modularisation variants based on quantitative production parameters (e.g., module mass, formwork path lengths), facilitating more informed decision-making without creating a bottleneck in the design workflow.

The use of an agent-based model in combination with an AAS provides multiple advantages in the modularisation of architectural elements for precast construction:

- **Data centralisation and reusability:** The AAS centralises all relevant modularisation data (e.g., geometric and logistic constraints), ensuring that it can be reused and updated throughout the lifecycle of the DT. This reduces the need for multiple data sources and ensures that available data and requirements are always up to date.
- **Automated planning services:** By treating the agent model as an external service, the entire digital framework involved in designing, planning, and producing modular elements remains flexible. The AAS can request services from different external models based on the specific planning task required, whether it is modularisation, as demonstrated in this case study, or tasks

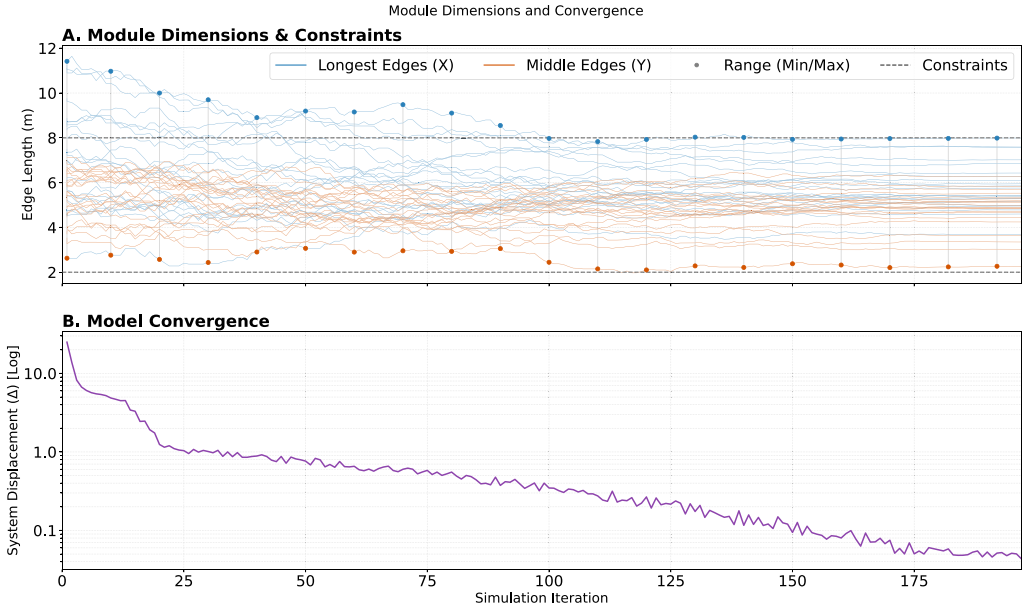


Fig. 14. Quantitative analysis of the agent system's evolution over 197 iterations. A. shows the X and Y dimensions of the 22 individual modules' Bounding Boxes converging towards the given dimensional constraints. B. highlights reduction in overall system displacement. Exit condition for the simulation is triggered, once the overall system displacement falls below a given threshold.

such as structural analysis or production planning. This service-oriented architecture enables greater scalability and integration of specialised simulations.

- **Transition from design to production:** As demonstrated in this case study, the modules resulting from the agent simulation can be directly ingested into the AAS, which serves as the data hub for production-related processes. Fig. 15 shows resulting module geometries and respective raw data is presented in Table 3. This data consistency and the simulation of geometric modularisation processes facilitates the transition from the digital design of roof modules to their physical production through automated fabrication systems.

While the current implementation using Rhino and Grasshopper to run the agent model provides a functional demonstration, future iterations of this framework aim to eliminate the need for locally running geometric development environments. By fully migrating the agent model to a cloud-based service or optimising it for server-side applications like Rhino Compute (with state management), the process can be fully automated and scaled to larger, more complex projects. This would further enhance the ability of the AAS to interact with multiple external services in real-time, fostering consistency in modular design and digital production.

5.2. Case Study 2: Monitoring of production-related parameters

The quality and efficiency of precast concrete production heavily depend on the ability to monitor and control key process parameters. Particularly during the curing phase, external influences such as temperature distribution, humidity, and deformations can significantly impact the dimensional accuracy, structural performance, and assembly readiness of individual modules. Therefore, this case study demonstrates how DTs can be leveraged to accompany these sensitive production stages with data-driven insights and provide actionable feedback to the production process.

The production of a Y-shaped concrete component – part of a modular, load-bearing structure described in Section 4.5 – serves as a demonstrator. Due to its complex geometry, this component is particularly susceptible to uneven curing, thermal-induced stresses, and shrinkage-related deformations. A purely time-based curing approach is insufficient to manage these challenges. Instead, a DT that aggregates real-time sensor data enables adaptive curing control and full transparency regarding the actual curing state of the module.

The DT acts as a dynamic digital representation of the physical module throughout its manufacturing lifecycle. Sensors are embedded into the Y-module to capture temperature profiles at multiple positions (e.g., core, surface, joints), complemented by deformation measurements at structurally critical points. This sensor data is continuously collected, contextualised, and interpreted within the DT, enabling the real-time assessment of tolerances and deviations.

The DT goes beyond passive monitoring, serving as a functional agent in the production workflow:

- **Real-time feedback** enables adaptive control of curing systems (e.g., infrared heating) to maintain optimal temperature thresholds.

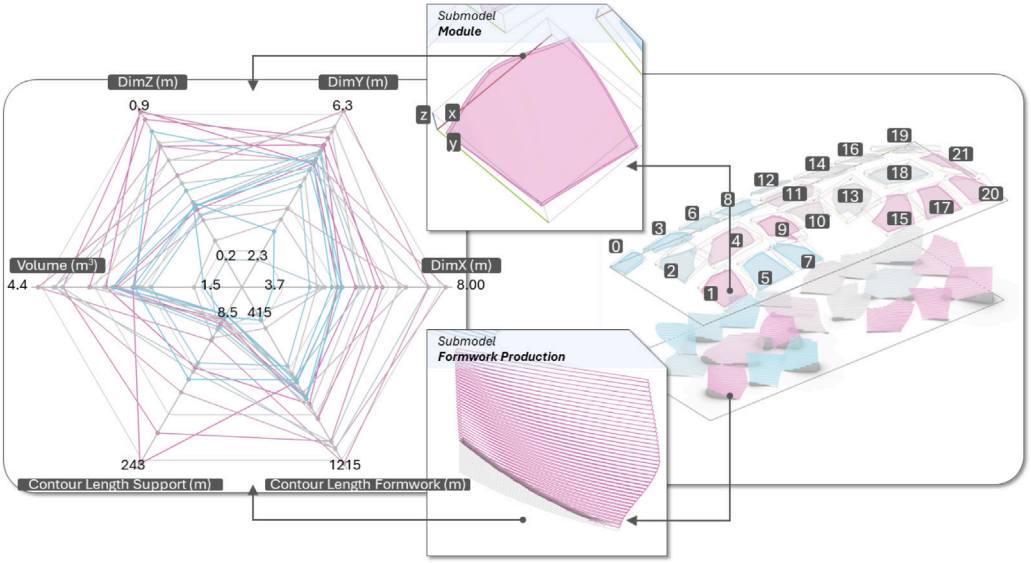


Fig. 15. Resulting module geometries and estimated production parameters for the 22 roof segments created through agent-based modularisation. Key properties, such as dimensions, mass, and contour lengths, are visualised and structured into dedicated AAS submodels for each module.

Table 3
Modularisation data for the 22 generated roof modules, including bounding box dimensions, module volume, production metrics (formwork contour length estimate/support toolpath length), and topological connections.

ID	Dimensions (X/Y/Z) (mm)	Vol. (m^3)	Contour (m)	Support (m)	Neighbours *(Module IDs)*
0	3688 × 3026 × 498	1.60	445.9	12.4	2, 3
1	5309 × 4835 × 872	3.27	895.1	92.3	2, 4, 5
2	5948 × 5104 × 483	2.73	755.3	8.7	0, 1, 3, 4
3	5397 × 4671 × 485	2.82	779.7	9.7	0, 2, 4, 6
4	8016 × 4897 × 746	4.14	1133.2	130.4	1–3, 5–9
5	5421 × 4978 × 480	3.16	868.4	28.6	1, 4, 7
6	4599 × 4244 × 439	2.50	690.6	84.5	3, 4, 8
7	5156 × 4849 × 812	2.78	765.3	110.3	4, 5, 9
8	5292 × 5192 × 550	3.15	863.2	8.7	4, 6, 9, 11
9	5407 × 5350 × 759	2.81	775.9	242.3	4, 7, 8, 10, 11
10	4979 × 3350 × 329	1.77	488.7	45.4	9, 11, 13
11	7017 × 3637 × 420	3.06	834.2	14.7	8–10, 12–14
12	4957 × 2262 × 244	1.49	415.4	31.2	11, 14
13	5854 × 5702 × 762	3.31	909.6	32.3	10, 11, 14, 15, 18
14	6097 × 5166 × 499	3.54	968.9	19.7	11–13, 16, 18
15	6274 × 5530 × 865	3.56	974.7	16.4	13, 17, 18
16	4782 × 4449 × 443	2.66	734.8	20.2	14, 18, 19
17	5756 × 4869 × 466	3.11	856.8	23.4	15, 18, 20
18	7577 × 4714 × 583	4.17	1137.3	88.7	13–17, 19–21
19	6854 × 5828 × 684	4.02	1101.4	98.2	16, 18, 21
20	6429 × 5280 × 898	4.01	1094.6	194.3	17, 18, 21
21	7589 × 6263 × 617	4.43	1214.8	49.4	18–20

- **Deformation data** allows early detection of potential issues affecting the assembly process and informs adjustments to formwork or handling procedures.
- **Quality assurance** becomes an active process, with data feeding into automated evaluation routines to verify dimensional and structural compliance before stripping or assembly.

This case study extends previous work [103] by moving beyond the monitoring of the heat treatment process to focus on extracting actionable knowledge from sensor data, specifically, assessing concrete strength development to inform production decisions. Rather than treating sensor data as an endpoint for monitoring, this approach emphasises its role as a foundation for deriving process-relevant insights. By doing so, it shifts the perspective from data collection toward knowledge-driven decision support, aligning digital representations with the informational needs of production optimisation.

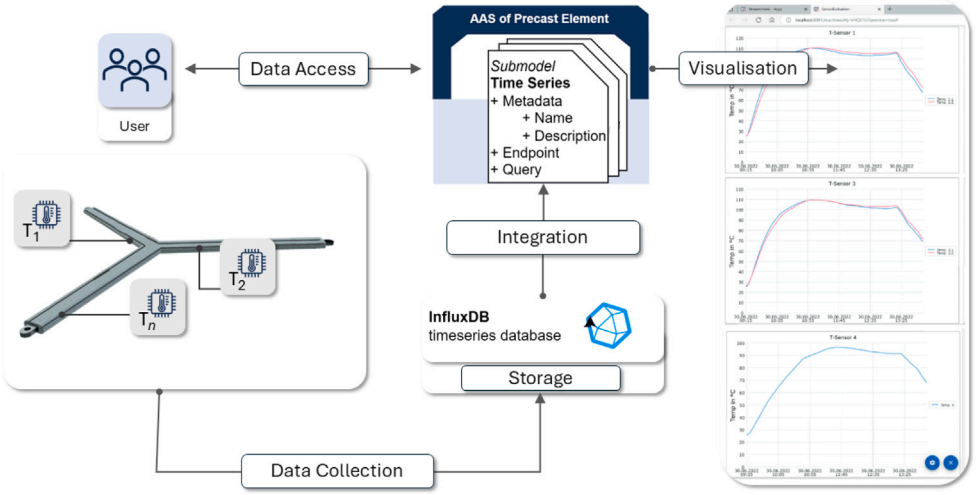


Fig. 16. Semantic integration of sensor data using the AAS and a linked time series database for real-time monitoring and visualisation.

5.2.1. *Digital twin-based monitoring system*

To integrate sensor data into the digital representation of precast modules, we developed a modular system architecture. This setup links physical measurement systems to the DT via a dedicated time series database.

This setup supports scalable, semantically rich access to high-resolution production data and provides a user-oriented interface for visualisation and decision-making. Fig. 16 illustrates the overall architecture of the system.

Temperature sensors ($T_1 \ldots T_n$) are embedded and capture time-resolved data on the internal and surface temperatures, which are collected and forwarded to a central storage component. Unlike previous approaches that stored measurement data directly within the AAS [103], the current implementation separates data storage and semantic metadata. A time series database is used to efficiently handle large sensor datasets. At the same time, the AAS manages only the necessary metadata for accessing this data, such as endpoints, query formats, descriptive attributes, and semantic labels organised in a dedicated `Time Series` submodel. This architecture enables dynamic linking between live and historical sensor data and the DT, without compromising interoperability or performance. Visualisation platforms can retrieve and display data through the AAS-defined interface, allowing users to access key production insights in real time.

Beyond raw data integration, the system also incorporates an interpretation layer that enriches the DT with derived information. In this case, temperature measurements recorded during the curing process are used to estimate the strength development of the concrete element. By linking sensor data with material knowledge, the DT can provide insights into structural readiness, such as whether a module is ready for demoulding or transport. This transforms the DT from a passive data repository into an intelligent agent capable of supporting time-critical decisions. It also illustrates the transition from data (raw temperature values) to information (contextualised readings, such as exceeding curing thresholds), to knowledge (actionable logic, like stopping the heating process), which is a defining feature of advanced DT systems [81].

The AAS thus serves as a digital identifier and semantic anchor point for the component and a gateway to contextualised process data. This decoupled architecture enhances reusability across similar production setups, simplifies integration into existing IT infrastructure, and supports modular expansion toward other sensing modalities, such as strain or humidity.

5.2.2. *Implementation of digital twin system*

The following subsections detail the implementation of the DT system introduced above. First, the integration of time series data is presented, using a standardised submodel within the AAS to semantically reference external sensor data. Then, a dedicated interpretation service is described, which processes temperature data to estimate concrete strength development during curing and feeds this information back into the DT.

Integration of Time Series Data via AAS Submodel

To enable access to high-resolution sensor data collected during the curing of the Y-shaped precast component, the implementation makes use of the standardised `Time Series` Submodel Template as published by the Industrial Digital Twin Association [152]. This submodel offers a structured and semantically interoperable approach to referencing and describing time series data throughout the asset lifecycle. Instead of storing sensor data directly within the AAS, the implementation uses `LinkedSegments` within the submodel to connect to an external time series database. These segments contain metadata, including the measurement endpoint, time range, sampling interval, and query format, which enables third-party services to retrieve temperature profiles dynamically and efficiently. Each sensor is modelled as part of a segment, including fields such as start and end timestamps, record count, sampling interval, and state (e.g., in progress or completed). The submodel's metadata defines its data and information content, specifying

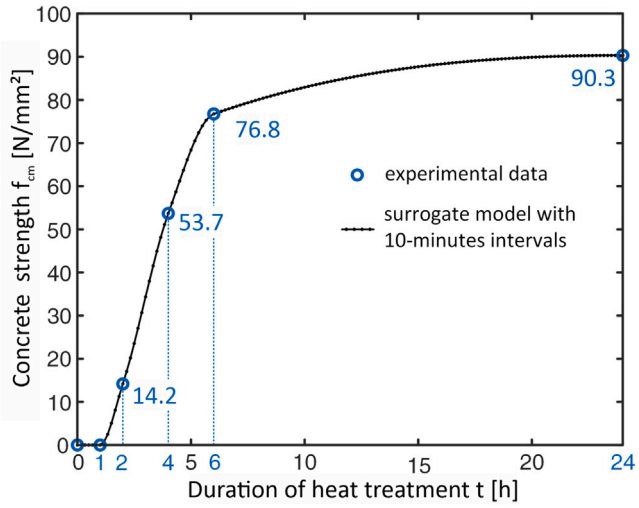


Fig. 17. Concrete strength with respect to the duration of heat treatment.
Source: Experimental data source [142].

attributes such as the time series identifier and a concise description of the observed variable. Additionally, qualifiers—such as `ValueOriginQualifier` or `MeasurementModelQualifier`, attach semantic annotations that characterise the nature and provenance of the values (e.g., whether they are directly measured or derived through computation). This structured semantic representation ensures machine-readable clarity and supports the seamless integration of data streams with visualisation tools, analytical services, and feedback mechanisms within the production environment.

Interpretation Service for Strength Estimation

A Python-based interpretation service was developed to transform the recorded temperature data into meaningful production insights. This service estimates the current compressive strength of the precast concrete element during curing based on its thermal history. The strength development curve used in this context is derived from experimental studies on high-performance concrete under rapid heat treatment [142].

Fig. 17 illustrates the reference data used in the model. Experimental compressive strength measurements were taken at selected heat treatment durations (blue dots). A surrogate model was created using a Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) to enable continuous strength estimation across arbitrary curing durations. The PCHIP surrogate is evaluated at millisecond scale on consumer-grade hardware, specifically chosen to enable real-time decision support during production without dedicated computing infrastructure. This method was chosen for its simplicity and ability to preserve the monotonicity and shape of the original data. The resulting model provides interpolated strength values at 10-minute intervals (black dots), allowing for continuous estimation of time throughout the curing process.

The service queries the AAS `Time Series` submodel via REST to identify temperature profiles, estimate heat treatment duration, and compute compressive strength using the surrogate model.

The computed strength is then written back into the AAS as a new property within a separate interpretation submodel, ensuring that raw data and derived performance indicators are accessible through the same semantic interface.

The service is implemented as a modular Python script that can be deployed within the production environment or triggered remotely. It provides a key functionality in transforming sensor data into actionable knowledge, enabling informed decisions about demolding, handling, or transport.

The PCHIP interpolation was selected specifically for its shape-preserving properties, ensuring that the estimated strength development remains monotonic and does not exhibit the artificial oscillations common in standard spline interpolations. While this surrogate model serves as a deterministic baseline for the prototype, industrial deployment would require the application of a partial safety factor to the threshold value to account for batch variations and model uncertainty. Furthermore, the modular nature of the AAS allows this interpolation service to be replaced by higher-fidelity maturity index models and to be adapted to various concrete formulations or curing regimes, without altering the underlying DT architecture.

5.2.3. Results

Implementing the DT system, particularly the integration of time series data and the strength interpretation service, has demonstrated several tangible benefits in precast concrete production. Most notably, it has enabled real-time transparency over the curing process. Instead of relying on conservative, time-based estimates for demoulding or further processing, production staff can now access up-to-date information on the internal thermal state of the concrete and its estimated strength development. This increased visibility allows for more informed and confident decision-making, particularly in identifying the optimal time for

demoulding without compromising structural integrity. This shift from a fixed schedule to a data-driven trigger enables a quantifiable reduction in production cycle time, as modules can be processed the moment they achieve the required strength rather than waiting for a conservative, predetermined duration. The continuous availability of raw sensor data and interpreted values within the AAS also enhances traceability and documentation, particularly valuable for quality assurance and compliance with construction standards. The system supports a shift from reactive to proactive production control by providing access to contextualised production data.

While the current implementation proves the feasibility and value of the approach, several limitations remain. The interpretation of strength development is based on a simple surrogate model derived from a limited set of experimental data. Although the model provides reasonable estimates, it does not account for variations in mix design, environmental conditions, or non-standard curing profiles. Future implementations could integrate more sophisticated material models or data-driven approaches (e.g., machine learning models trained on historical production data) to improve accuracy and generalisability. Another limitation lies in the static configuration of metadata within the AAS. Currently, sensor endpoints and descriptions must be defined manually in advance. A more dynamic or event-driven architecture could allow the AAS to automatically update its references as new data becomes available or process conditions change. Finally, while the system currently focuses on temperature-based strength estimation, future iterations could expand the scope to include additional parameters such as humidity, deformation, or curing maturity. This would enable a more holistic view of component health and performance during production and could support further automation of quality control processes.

5.3. Case Study 3: Management of production-related geometric deviations of prefabricated concrete modules

Dimensional deviations are a common challenge in producing precast concrete modules, particularly when dealing with complex geometries or multiphase curing processes. However, these deviations are often assessed at the level of individual modules and thereby disconnected from the larger structural context they are part of [153]. This often leads to inefficient decisions, such as unnecessary reworking or discarding of modules. Such isolated assessments fail to account for the deviation's actual impact on the global structural system.

This case study examines a method for incorporating production-related geometric deviations into a composite DT that encompasses the individual precast modules and the structural system they contribute to. The goal is to shift from an isolated quality perspective to a holistic, system-level view, where deviations are evaluated based on their functional relevance to the structure as a whole. The DT becomes a tool for context-aware decision-making during production and assembly by embedding measured as-built data into module- and system-level digital representations.

To explore this concept, the case study begins by outlining the role of geometric tolerances in precast concrete production and their influence on module-level and structural performance. Based on these requirements, a two-level DT structure is developed. At the core of the system are DTs for each precast module, each equipped with a dedicated `Deviation` Submodel that captures production-related geometric deviations, associated tolerance specifications, and relevant measurement data. These module DTs contain the deviation-related data and information. A structural DT represents the overall assembly, serving as a lightweight composite that primarily references the individual module twins and includes system-level tolerance constraints or metadata. This approach is demonstrated through a simplified example using a continuous 1D beam composed of multiple precast modules.

5.3.1. Geometric tolerance requirements

Geometric accuracy in prefabricated concrete modules is crucial to ensure the structural integrity and functionality of modular structures. In addition to material-dependent effects such as creep and shrinkage, geometric deviations result primarily from the production process and are commonly treated as stochastic variables in tolerance analysis, with Gaussian models frequently used as a baseline representation of dimensional variability [154].

Geometric tolerance requirements are standardised, e.g., in the national German standard DIN EN 13369 [155] for building modules and DIN 18202 [156] for structures. The module tolerance Δl_{req} of the size l follows to

$$\Delta l_{req} = \pm\left(10 + \frac{l}{1000}\right) \leq 40\ [\mathrm{mm}] \tag{1}$$

The tolerance requirements for structures ΔL, specifically for basic measures, e.g., lengths, are defined as a function of the total size L:

$$\Delta L\ [\mathrm{mm}] = \begin{cases} \pm 10 & \text{for} \quad L \leq 1\ [\mathrm{m}] \\ \pm 12 & \text{for} \quad 1 < L \leq 3\ [\mathrm{m}] \\ \pm 16 & \text{for} \quad 3 < L \leq 6\ [\mathrm{m}] \\ \pm 20 & \text{for} \quad 6 < L \leq 15\ [\mathrm{m}] \\ \pm 24 & \text{for} \quad 15 < L \leq 30\ [\mathrm{m}] \\ \pm 30 & \text{for} \quad L \geq 30\ [\mathrm{m}] \end{cases} \tag{2}$$

For structures consisting of many modules, the standardised module tolerances are often not sufficient, so tolerance requirements must be explicitly determined for the specific use case. Thereby, boundary conditions can arise from joint accuracies for uniform force transmission, hole clearances for screw connections [144] or structural tolerances [157]. For a 1D structure, such as a sequence of linear beam elements, the required module tolerance can be derived from the structural tolerance requirement ΔL and the number

Table 4
Overview of Competency Questions (CQs) for developing the use case geometrical deviation management information model.

n	Competency Question (CQ)	Response datatype
1	How many modules are part of the overall structure and how are they distributed?	Integer
2	Which modules belong to the overall structure, and how are they classified?	List/Array of Objects
3	In which exact positions can the modules be installed, and where is their installation impossible or problematic?	List/Array of Coordinates
4	What tolerances must be adhered to for each module in terms of dimensions, accuracy of fit, and functionality?	List/Array of Objects
5	How large are the actual deviations of the individual modules from the defined target geometry?	List/Array of Objects
6	What are the exact nature, size, and location of the identified deviations?	List/Array of Objects
7	What are the definitions and thresholds for acceptable and unacceptable deviations from the structure, and how are they determined?	Object
8	Does the module have to be excluded from the process due to deviations?	Boolean
9	Which positioning of the modules minimises the overall deviation of the structure most effectively?	List/Array of Coordinates
10	Is reworking of the modules necessary to maintain the specified tolerances, and if so, what type of reworking is required?	Boolean
11	Is reworking the affected modules technically and economically feasible?	Boolean

of modules n. Taking into account the variance propagation of the module deviations [154], the required module tolerance t_{req} is derived by

$$t_{req} = \min \begin{cases} \Delta L(L)/\sqrt{n} \\ \Delta l_{req} \end{cases} \tag{3}$$

t_{req} is additionally limited to the requirements according to Eq. (1).

The following subsection demonstrates how these requirements can be operationalised and communicated within the DT by defining corresponding submodels in the AAS. These submodels offer a structured approach to representing tolerance specifications, capturing deviation measurements, and supporting decision-making during production and assembly.

5.3.2. Identification and analysis of information requirements

Depending on the use case, submodels require different types of information and functionality. A central step in implementing AAS-based DTs is defining an information model that structures these submodels to ensure standardised, interoperable integration with physical assets. In this case study, a submodel for managing production deviations in precast concrete modules is developed, following the approach of [158]. The first step, aligned with that methodology, is to define information requirements and create a conceptual model as part of the knowledge engineering phase.

The `Deviation Management` submodel provides relevant data for assessing and managing deviations of individual modules within a structural system, ensuring compliance with design specifications, and optimising quality control processes. In particular, it focuses on:

- Comprehensive understanding of modules' composition and spatial configuration within the structural system, ensuring accurate mapping and arrangement of modules.
- Assessment of tolerances, deviations, and quality control, ensuring that modules meet design and functional requirements.
- Decision-making by providing criteria for handling modules that deviate from specifications and evaluating the feasibility of corrective actions, such as reworking or replacement.

In the proposed application scenario, production deviations of precast concrete modules are captured and compared with tolerance values stored in the respective submodel. The tolerance of an individual module is determined in relation to the overall tolerance of the structure, taking into account the applicable standards. The stricter criterion between the two is used as the guiding measure. Based on the results of this comparison, a decision is made about how to proceed with each module. For instance, repositioning the module to a location within the structure with lower precision requirements is a viable option. By aggregating this information, the submodel enables a precise evaluation and management of deviations, ensuring that the modules conform to design specifications and minimising structural misalignments. The detailed insights provided by the submodel support informed decision-making, ultimately enhancing the accuracy, consistency, and overall efficiency of the production process.

Submodels and ontologies are similar in that both aim to structure and model complex knowledge domains [159]. While ontologies focus on the formal representation of concepts and their relationships within a specific domain, submodels play a similar role by representing specific aspects of an I4.0 system or process in the context of I4.0 and DTs. The creation of competence questions is an established procedure for describing the functional requirements of ontologies and is also suitable for capturing the functional requirements of submodels. These questions are formulated in natural language and identify the specific information and processes a model must answer or map in a use case. Competency questions ensure that the submodel accurately captures the necessary domain knowledge and functional requirements of the underlying domain. Table 4 lists the competency questions to define the functional requirements of the submodel.

Based on the identified competency questions, the next step involves deriving a technology-neutral information model that systematically captures the data structures, relationships, and functional aspects required for effective deviation management

(Fig. 18). This abstraction enables the generalisation of domain knowledge independent of specific implementation technologies, ensuring interoperability and reusability within diverse digital ecosystems. The model encapsulates the key entities, such as modules, deviations, tolerances, and positioning constraints, and their interdependencies, as identified through the competency questions. This conceptual representation serves as the foundation for the subsequent modelling step, which includes the definition of AASs and their submodels, as well as the specification of data types and exchange formats required for integration into I4.0-compliant systems (Fig. 19).

Listing 1: Example of linking an IfcBeam to the StructuralBeamAssembly AAS.

```
<IfcBeam>
  <Name>Beam-01</Name>
  <GlobalId>3m7sOFL9n56gxyIMI2o...</GlobalId>
  <Pset_AAS_PSet_Connector>
    <AASReference>
      <Identifier>aas:StructuralBeamAssembly_01</Identifier>
      <ReferenceType>URL</ReferenceType>
      <ReferenceValue>
        https://<aas-host>/aas/StructuralBeamAssembly_01
      </ReferenceValue>
    </AASReference>
  </Pset_AAS_PSet_Connector>
</IfcBeam>
```

Listing 2: Linking a module-level IFC element to a BeamModule AAS capturing local deviation and tolerance state.

```
<IfcBuildingElementProxy>
  <Name>BeamModule-07</Name>
  <GlobalId>1a2b3c4d5e...</GlobalId>
  <Pset_AAS_PSet_Connector>
    <AASReference>
      <Identifier>aas:BeamModule_07</Identifier>
      <ReferenceType>URL</ReferenceType>
      <ReferenceValue>
        https://<aas-host>/aas/BeamModule_07
      </ReferenceValue>
    </AASReference>
  </Pset_AAS_PSet_Connector>
</IfcBuildingElementProxy>
```

To further anchor the deviation management workflow in the context of industry standards and workflows, Listing (1) shows the module- and assembly-level AAS instances and their explicit link to corresponding IFC entities. In line with guidelines by the Industrial Digital Twin Association (IDTA) and buildingSMART recommendations [145], IFC remains authoritative for spatial containment, while dynamic quality-control and deviation states are maintained in the AAS. The linkage is realised by storing a reference to the relevant AAS instance on the corresponding IFC element via a connector property set. Listing 2 shows how individual BeamModule AAS instances can be referenced analogously via module-level IFC elements.

5.3.3. Results

The evaluation is performed using the simplified application of a 1D continuous beam oriented at the lateral system of the building shown in Fig. 9. It is modelled as a three-span beam with effective span lengths of 5.50 m and a total length of $L = 16.8$ m. The beam consists of 13 modules of different sizes, which also have different geometric deviations Δ due to the manufacturing process (Fig. 19). The resulting tolerances t are shown as part of Fig. 20 for all modules.

The deviations Δl are sampled using Latin Hypercube Sampling (LHS) assuming a Gaussian deviation model, where t corresponds to twice the standard deviation. This Gaussian model is employed as a first-order engineering approximation for dimensional variability in precast concrete production, consistent with empirical observations reported in the literature [160,161]. It is important to note that the error propagation model used here (Eq. (3)) represents a deterministic baseline based on Gaussian variance. However, the logic within the *Deviation Submodel* can be upgraded to different stochastic solvers without requiring changes to the underlying data architecture. The choice of a Gaussian deviation model in this case study therefore serves to demonstrate the deviation management logic rather than to prescribe a fixed statistical representation of production variability.

The developed AAS framework allows for two levels of tolerance management. Firstly, each BeamModule AAS assesses its deviation (Δl) against the required module tolerance (t_{req}) and updates its status accordingly. Secondly, and critically for assembled structures, the StructuralBeamAssembly AAS can be configured to iteratively track the cumulative deviation as modules are produced and measured. This provides a dynamic, real-time assessment of the entire assembly's progression toward the overall structural tolerance (Δl), enabling proactive quality control and adjustments during the manufacturing process, rather than relying solely on a final inspection.

With respect to the module size, the required module tolerance t_{req} (Eq. (3)) is derived, resulting in 6.66 mm for all modules. Whether a module needs to be reworked is verified afterwards by comparing the Δl with t_{req}. Table 5 shows the resulting module deviations and Fig. 20 presents the module properties as displayed in the AASX explorer. It reveals that module 7, with a maximum deviation of 7.31 mm is not OK (NOK) and requires reworking or needs to be replaced. However, because the

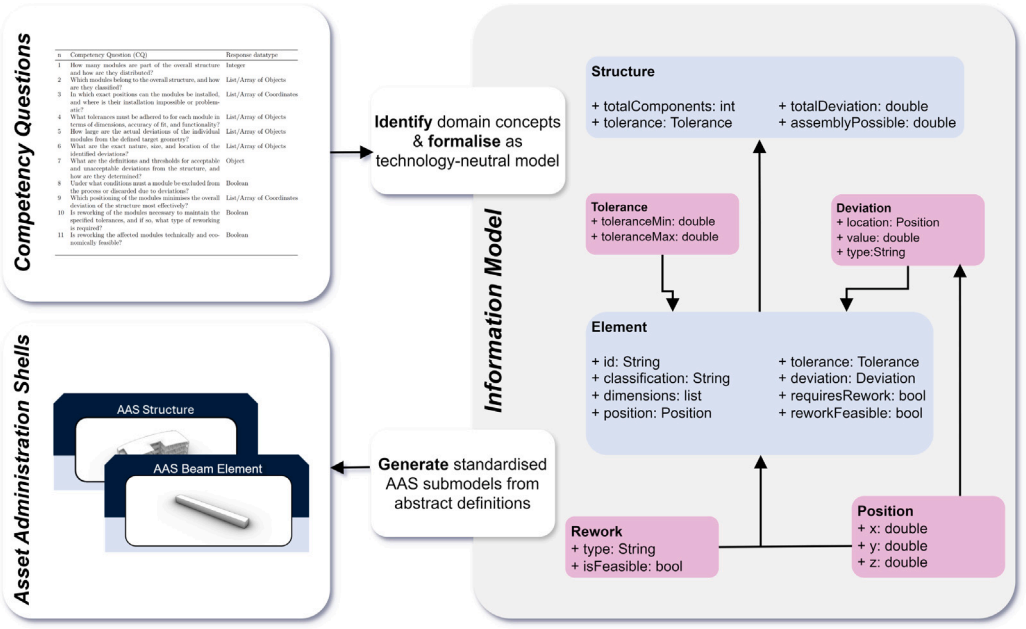


Fig. 18. From competency questions to AAS - Transformation from domain questions to a technology-neutral information model and AASs.

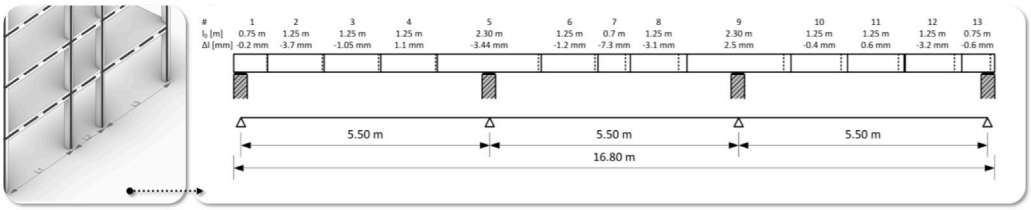


Fig. 19. Occurrence of three span beam elements in the case study building (left), and the modular three span beam with module IDs, lengths, and geometrical deviations after production (right).

Table 5
Modules with measures, deviations and tolerances.

ID	Basic length	Tolerance	Deviation [mm]	Length	Required tolerance		Rework
	l_0 [m]	t [mm]	Δl [mm]	l [m]	Δl_{req} [mm]	t_{req} [mm]	OK/NOK
1	0.75	5.13	−0.19	0.750	10.75	6.66	OK
2	1.25	5.22	−3.65	1.246	11.25	6.66	OK
3	1.25	5.22	−1.05	1.249	11.25	6.66	OK
4	1.25	5.22	1.11	1.251	11.25	6.66	OK
5	2.30	5.40	−3.44	2.297	12.30	6.66	OK
6	1.25	5.22	−1.19	1.249	11.25	6.66	OK
7	0.70	5.12	−7.31	0.695	10.70	6.66	NOK
8	1.25	5.22	−3.07	1.247	11.25	6.66	OK
9	2.30	5.40	2.45	2.302	12.30	6.66	OK
10	1.25	5.22	−0.42	1.250	11.25	6.66	OK
11	1.25	5.22	0.66	1.251	11.25	6.66	OK
12	1.25	5.22	−3.23	1.247	11.25	6.66	OK
13	0.75	5.13	−0.61	0.749	10.75	6.66	OK

StructuralBeamAssembly AAS tracks the cumulative impact, it was determined that the overall structural tolerance of ±24 mm was still complied with.

Case Study 3 demonstrates the AAS's capability in managing production-related geometric deviations. By employing a hierarchical DT structure, where individual BeamModule AASs capture measured deviations and update evaluative states (e.g., 'NOK' or 'OK'), and linking these to the StructuralBeamAssembly AAS that holds overall system tolerances (Fig. 20), the framework moves

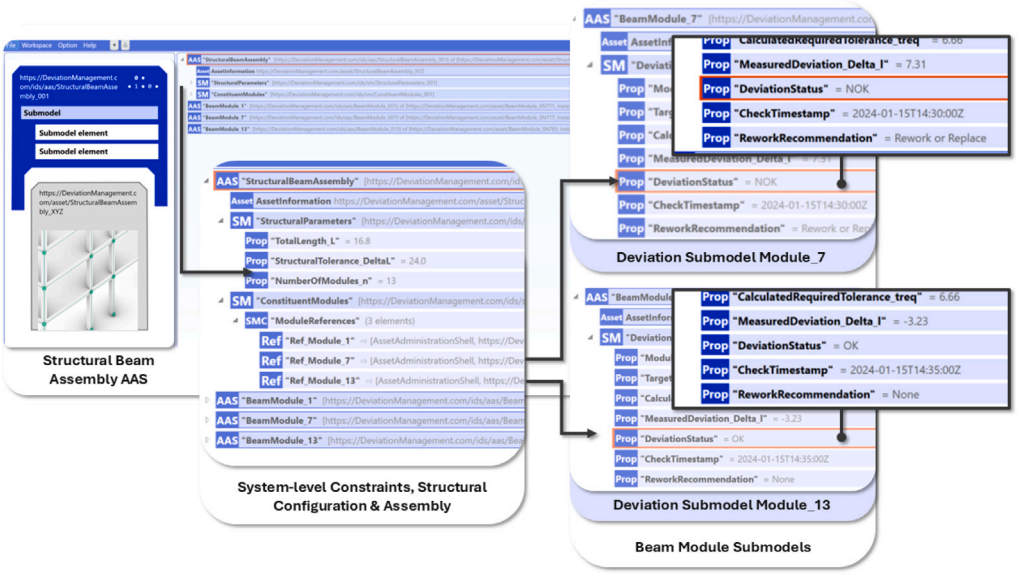


Fig. 20. Structural beam assembly AAS and deviation management submodels developed based on competency questions for context-aware deviation management and displayed using the AASX explorer. The top-level StructuralBeamAssembly AAS holds system constraints (StructuralParameters) and references individual BeamModule AASs (ConstituentModules) containing a DeviationManagement submodel.

beyond isolated component checks towards context-aware, system-level quality assessment. This system-level insight provides a direct, quantifiable benefit: it enhances resource efficiency by preventing the unnecessary cost, material waste, and production delays that would result from reworking or discarding a module that, while individually out-of-spec, is perfectly acceptable within the context of the global structural assembly.

6. Discussion

Shifting Paradigms in PCC

PCC enables fast, controlled production with reduced errors, supporting the growing demand for building structures while reducing on-site waste. Yet, increasing output alone is insufficient to address today's ecological challenges. A fundamental shift is required in how building components are planned and produced. Instead of relying on large, monolithic elements, this research highlights the potential of decomposing structures into smaller, more adaptable modules. As demonstrated by the topology-optimised slabs (Section 4.2) and the honeycomb shear walls (Section 4.5), this approach allows for the materialisation of load-adapted geometries that were previously infeasible or costly to produce using conventional formwork techniques. By utilising highly differentiated, production-optimised modules, it becomes possible to significantly reduce material consumption and employ efficient processes like zero-waste formwork. However, these methods also generate significant data complexity across the design-to-production chain. The heterogeneity arising from these individualised components that range from specific CNC or robotic toolpath instructions for additive manufacturing to unique curing requirements for individual concrete modules generates large volumes of heterogeneous data across design and production and imposes specific requirements on information consistency throughout a structure's lifecycle. Thus, to effectively manage the complexity arising from highly individualised, yet industrialised, PCC components, consistent digital models are necessary. This research demonstrates that DTs, realised through the development of application-specific AASs, enable structured data exchange and automated service integration across design, planning, and production stages. Consequently, the impact of this research lies not only in the digital framework itself, but in its ability to operationalise these advanced design and fabrication methods.

By developing and applying specific DTs using the AAS framework, this study has shown how the AAS can address interface challenges between design, planning, and production phases. The AAS expands existing BIM approaches by harnessing key I4.0 concepts, including:

- **Improved interoperability** between design models and software services, enabling dynamic communication of design requirements to external services, thus improving decision making (Section 5.1).
- **Real-time data updates** and access to up-to-date production data for all relevant stakeholders (Section 5.2).
- **Automated monitoring** of production processes and quality control through the use of specific submodels that evaluate geometric measurements to compute geometric errors and assess their criticality (Section 5.3).

Together, these capabilities position modular DTs as a foundation for cyber–physical production through simulation, process control, and integrated coordination across various life cycle stages of PCC modules. The case studies presented illustrate different forms of interaction and autonomy of the developed AASs and can be classified into different categories according to the current state of research [102]. Case Study 1 (ABMaaS) primarily demonstrates a *passive and reactive AAS*. The Roof Element AAS passively provides initial constraints, and the system reacts by creating new Roof Module AAS instances based on the external ABM service output. Case Study 2 (Monitoring of Production-related Parameters) showcases a more *reactive AAS* with *proactive* potential. The AAS reacts to sensor data, and the interpretation service (estimating strength) updates the AAS. While not fully autonomous, this derived knowledge (e.g., 'ready for demoulding') enables proactive decision-making and can, in future extensions, trigger automated actions. Case Study 3 (Management of Geometric Deviations) also illustrates a *reactive AAS*. The BeamModule AASs are updated with measured deviations and an evaluative state ('OK'/'NOK'). The StructuralBeamAssembly AAS then allows for reactive assessment of overall compliance based on these individual states. While the decision-making process is currently human-driven, structured information can support more proactive and automated quality control workflows. These varying degrees of autonomy demonstrate the AAS's capacity to serve as a dynamic integration layer for advanced computational design and digital production processes within PCC. The drive for resource efficiency necessitates complex, optimised component geometries that traditional, linear and analogue planning processes cannot support.

Boje at al. [18] frame CDTs as a paradigm shift from static information models toward dynamic, lifecycle-spanning representations of built assets. They identify key challenges, including interoperability between heterogeneous systems, fragmentation of data across project phases, and the limited coupling between design intent, fabrication processes, and on-site assembly. The framework presented in this work engages with these challenges by proposing an AAS-based DT architecture that supports modular, selective digital-twin enablement within PCC. While a comprehensive realisation of the CDT maturity model is an industry-wide effort, the research presented demonstrates how selected aspects associated with different maturity levels can be instantiated. In particular, the case studies demonstrate how the AAS can act as an integration layer that links passive monitoring capabilities with evaluative logic and agent-based processes, thereby supporting incremental transitions from monitoring-oriented DTs towards more active, context-aware behaviours and decision-making.

Barriers to Implementation: Infrastructure, Regulations, and Skill

Infrastructure: The progression towards more proactive AAS implementations, where the DT not only represents but also initiates actions based on its state and predefined logic, remains a key area for future development in the construction industry. However, enabling such behaviour in practice requires production environments equipped to receive and act on digital instructions.

While the requisite investment in AAS infrastructure and sensor hardware is generally outweighed by operational savings [162], the specific economic impact and implementation effort remain dependent on the existing level of technological adaptation and digital maturity of each individual stakeholder. The degree of automation and the use of digitally controlled machinery still vary widely in the industrial production of precast concrete elements. While this presents a significant challenge for implementing fully integrated digital planning and production workflows, it also highlights the value of modular DT architectures that can be adapted to different levels of automation and gradually expanded.

Regulations & Approval: The transition from research to industrial application faces significant regulatory hurdles. As Bos et al. report based on a series of realised projects, the lack of a regulatory framework for expedient approval remains a primary bottleneck limiting the structural application of DfC on a wider basis [163]. Similarly, Vasilic et al. identify gaps in standardisation and testing procedures as key barriers hindering adoption [164]. In the German context, processes such as heat treatment are strictly regulated by the DAfStb Guideline "Heat Treatment of Concrete" [165], which mandates precise limits on temperature gradients to prevent micro-cracking. Here, the AAS can serve as a critical compliance tool: by logging sensor data, it can provide the mandatory documentation to prove that the treatment remained within the allowable limits. Furthermore, for novel manufacturing methods where no harmonised standards exist yet, implementation currently relies on project-specific approvals (e.g., Zustimmung im Einzelfall, Germany). The AAS framework supports this rigorous certification process by providing a comprehensive digital pedigree that traces every degree of curing temperature and geometric deviation, thereby offering more transparent data required by certification authorities to evaluate and approve non-standard components.

Skill: Alongside technical infrastructure and the need for regulatory frameworks to adjust, the human capacity to operate and integrate digital methods remains a critical bottleneck. Although a substantial body of research on DfC demonstrates its potential to improve design freedom and resource efficiency, its adoption in industry has been relatively gradual. A major barrier to the broader adoption of advanced production methods lies in the lack of necessary skills among AEC professionals. These skills must be integrated into education and training programs targeting the design, planning, and production of future building structures. Crucially, respective knowledge must not exist in isolation; consistency across tools, workflows, and processes is essential for developing integrative digital methods that enable more efficient and ultimately more sustainable PCC.

Ethics, Liability, and Data Security

The shift toward automated, software-driven production introduces new questions regarding responsibility and risk. As noted by Khodabakhshian, determining liability for wrong predictions, whether they lie with the programmer, data owner, or end-user, creates an "accountability gap" in DT-driven construction [166]. However, by continuously logging the "chain of trust", i.e. recording inputs from sensors, decisions from algorithms, and interventions by humans, modular DTs can provide the possible infrastructure to create a traceable digital pedigree. In the event of a structural defect (e.g., a crack resulting from early demoulding), this data allows stakeholders to explicitly allocate responsibility: differentiating between a sensor malfunction, a flawed algorithmic prediction, or a human decision to override safety warnings. Furthermore, the deployment of such systems in a networked plant environment

raises concerns regarding data privacy and cyber security. Here, the AAS standard (IEC 63278) provides a robust security model based on Attribute-Based Access Control (ABAC) [145]. For example, this ensures that a civil engineer can access geometric data, but proprietary information such as concrete mix designs or sensitive data on worker productivity remains protected, ensuring resilience against unauthorised access to sensitive data.

Limitations and Future Research

While the AAS provides a standardised framework for interoperability, its large-scale deployment in construction, potentially involving thousands of unique AAS instances for individual precast elements, raises practical considerations regarding performance and scalability. Managing real-time data streams from sensors or frequent updates from 3D scans requires efficient data handling strategies beyond simple file repositories. Potential solutions include hierarchical AASs structures (e.g., an AAS for a building floor referencing the AAS of its constituent slabs), optimised query mechanisms, and robust underlying database and network infrastructure.

Several assumptions underlie the models presented. The agent-based modularisation (Section 5.1) discretises continuous roof geometry into a voxel grid, which inherently smooths sub-voxel features; however, the convergence analysis (Fig. 14) confirms that the resulting module geometries stabilise well within given dimensional requirements. The strength estimation model (Section 5.2) relies on a PCHIP surrogate derived from a limited experimental dataset and assumes uniform heat distribution within the module cross-section. In practice, thermal gradients across thick sections may lead to differential curing, particularly for larger or more complex geometries. Industrial deployment would therefore require validated maturity index models accounting for spatial temperature variation, and the application of partial safety factors to the threshold values. The modular AAS architecture explicitly supports the replacement of individual models with alternatives without requiring changes to the overall data architecture.

The case-study implementations presented demonstrate feasibility, but they also have limitations and show potential for future research.

The *ABMaaS* integration (Section 5.1) utilised development-level tools (Flask and XML), rather than industrial-grade protocols. To facilitate ease-of-use, hybrid approaches, such as embedding semantic web technologies, presents a promising avenue for future work.

The *Strength Estimation Model* (Section 5.2) is based on specific experimental data and requires validation for further materials and geometries. A comprehensive evaluation would require testing with larger datasets and more diverse production variations.

The framework proposed in Section 5.2 can potentially be extended to address time-dependent behaviours in later stages of the module production from advanced materials, such as UHPC or alkali-activated concrete mixes, which show significant potential as low-carbon alternative to mixes using Portland cement [167]. As demonstrated in recent studies, these materials exhibit complex time-dependent behaviours that differ significantly from conventional concrete [168,169]. On the topic of heat treatment, Rose et al. demonstrated that the duration of rapid heat treatment significantly influences the short-term creep coefficient, necessitating a process-dependent material model [170]. Through its modular submodel architecture, the developed framework has the potential to accommodate complexity arising from various different domains. Instead of hard-coding simple parameters, a MaterialBehavior submodel can be defined to store complex metadata, such as time-dependent creep functions, shrinkage profiles, or calibrated maturity indices. In addition, the DT system architecture principle can also enable the integration of advanced strength and constitutive models, including rate-dependent or dynamic strength criteria [171]. This ensures that the DT can evolve from a production tool into a lifecycle management asset, capable of evaluating long-term serviceability and fit-up based on the specific rheological history of the module.

The *Deviation Management Submodel* introduced in Section 5.3 provides a structured mechanism to track, aggregate, and propagate deviation-related information across assemblies and lifecycle stages. As shown in recent research on adaptive manufacturing for individual assemblies, employing cross-component process control strategies can successfully determine cause–effect relationships and therefore avoid rejects and rework completely by compensating for tolerances within the assembly logic [172]. Future research and practice could benefit from the integration of more advanced models, e.g., to capture the redistribution of stress paths under assembly imperfections [173], create structured AASs from Lidar-based point cloud segmentation [174], or consider advanced 3D multi scale models for dynamic load-case scenarios [175]. Thus, paving the way for modular DT to form the basis in combining detailed structural insight with lifecycle-oriented data management. Beyond dimensional deviations, recent studies on high-resolution internal imaging and surface defect detection using diffusion-model-based classifiers demonstrate that advanced data-driven imaging techniques can generate actionable quality information, which can be referenced within AAS-based quality management submodels to support non-destructive module inspection and decision-making processes [176,177]. The current model is demonstrated for a linear one-dimensional beam assembly. Future work could address two-dimensional panel assemblies or other further, more complex module connections.

Future research could address the integration of advanced structural models for connection detailing. As demonstrated in recent experimental work on friction-based artificial plastic hinges [178] and composite columns [179,180], contemporary precast systems require sophisticated representations of hysteretic behaviour and load–deformation history. Through specific submodels, higher-fidelity models can be integrated into the AAS, such as advanced multi-objective optimisation algorithms [181,182], stress- and displacement-constrained topology optimisation, or reliability-based methods addressing multi-source uncertainties [183].

Recent process-oriented studies, such as the in-process reinforcement integration for 3D-printed concrete beams presented by [184], demonstrate that digital fabrication methods significantly influence both structural performance and labour organisation. While process benchmarking is beyond the scope of the research presented, the consistent capturing and aggregation of performance- and effort-related indicators across various production runs presents a relevant direction for future research.

These key areas for future research show significant potential to expand the presented AAS framework towards a wider range of materials and later life-cycle phases. Thus, they demonstrate the inherent advantages for dynamic data integration in combination with computational design, cyber–physical production systems and advanced simulation models.

Despite the results shown by ongoing developments both in research and industry, technological challenges remain, and further research is needed to benchmark AAS performance in realistic construction scenarios. These include, but are not limited to:

- **Scalability and orchestration:** Handling thousands of AAS in parallel without performance bottlenecks requires further investigation into containerisation, distributed systems, or cloud coordination.
- **Compatibility:** Interface protocols tailored for established production methods.
- **Security:** Access control mechanisms, such as viewing rights and permissions, to ensure secure and role-based management of real-time communication between different stakeholders in planning and fabrication.
- **Accessibility:** Visualisation of AAS content through targeted development of user-friendly front ends or dashboards.

To further enhance the structuring, coordination, and reasoning about data and processes, further methodological challenges require attention:

- The development of **standardised AAS templates** for recurring building module types.
- **Long-term data stewardship**, ensuring that AASs remain useable for maintenance, refurbishment, and circular-reuse scenarios for building modules.
- Balance usefulness and complexity through **systematic management of AAS granularity.**
- Establishing **validation and certification mechanisms** using the AAS to explicitly assign responsibilities and ensure traceable compliance among stakeholders.

Our results indicate the significant potential the targeted integration of DTs has to improve flexibility and resource efficiency in modular construction. It is therefore a key ingredient in the transition of PCC from a material-intensive, geometrically constrained way of building towards a highly automated, material-aware, and differentiable construction method. Thus, the successful development of DTs for PCC has the capacity to positively impact all three dimensions of sustainability:

- **Environmental:** CDTs support CPPSs, enabling precise, low-error production and optimised, load-adapted designs. Their potential use in Life Cycle Assessments can further reduce the environmental impact of PCC by informing decisions on design, modularisation, and production.
- **Economic:** DTs can potentially streamline production workflows, leading to greater cost efficiency and improved economic viability of resulting building structures.
- **Social:** DTs facilitate the development of adaptable and user-centred designs, thereby potentially improving the quality and usability of built structures from PCC. Additionally, the need for upskilling the workforce in digital methods opens pathways for new, highly skilled employment opportunities in the AEC sector and makes it an attractive career arena for the next generation of digitally-savvy professionals.

This research demonstrates how distinct methods for optimising, modularising, and selecting building elements can be combined to address the urgent necessity for resource efficiency in construction. It shows that tailored digital fabrication methods can satisfy diverse design requirements—from topology-optimised slabs to bionic shear walls, thus making the selected case study representative of the wide spectrum of possibilities in modular PCC. However, operationalising these computational design and production methods requires a robust digital backbone. The findings suggest that the integrated use of the AAS is essential to bridge the gap between these novel design-to-production approaches and industrial reality. By providing a standardised framework for data exchange, the AAS facilitates seamless communication across disciplines. Therefore, it links the intent of interdisciplinary design and planning directly with the reality of the factory floor. This enables architects, engineers, and production professionals to work more effectively together, transforming individualised precast construction into a manageable, scalable industrial process.

7. Conclusion

This work demonstrates that the transition to resource-efficient, individualised PCC relies on the synergistic integration of advanced fabrication methods with a robust, standardised information management framework based on application-specific AASs. By combining computational design and digital production methods with application-specific AASs, the research establishes a framework capable of managing the unprecedented data heterogeneity required for the scalable fabrication of mass-customisable modules.

A mixed methods approach is adopted to achieve the research objective of integrating digital design methods for individualised, yet industrialised PCC with the development of modular DTs utilising the AAS to facilitate sustainability, adaptability, and efficiency in industrialised PCC. The design of an exemplary multi-story building serves as a platform for interdisciplinary research, where various concepts from architectural design, structural and mechanical engineering, and building informatics are developed and integrated. The research demonstrates several key achievements in integrating computational design and digital production methods for PCC and developing respective DT models using the AAS:

- **Managing Heterogeneity from Diverse Design and Production Methods:** The research demonstrates the application of diverse, advanced DfC methods to generate both serial and highly differentiated PCC elements, using a conceptual building as a case study. This breadth of design and fabrication approaches results in heterogeneous data structures, underscoring the need for standardised digital representations of building modules, machines, and services.
- **AAS as an Integration Backbone for Modular DTs in PCC:** The AAS provides a standardised, flexible framework for implementing modular DTs. This research demonstrates how heterogeneous data from diverse design and optimisation methods (e.g., ABM, topology optimisation), advanced fabrication processes (e.g., additive manufacturing), and real-time monitoring (sensors) can be managed through modular DTs, enabling insights into both design and production processes. The use cases demonstrate how the AAS facilitates continuous data exchange and feedback, thereby enhancing the robustness of existing processes for creating and managing digital representations of building projects, such as BIM.
- **PCC-Specific AAS Submodels for Enhanced Functionality:** Tailored AAS submodels were developed to address specific PCC challenges. These include managing modularisation constraints derived from geometrically complex simulations, integrating time-series sensor data for process insights (such as curing estimation), and handling detailed geometric deviation data crucial for assembling digitally fabricated components. Together, these modular submodels demonstrate the versatility of the AAS framework in supporting consistent data handling and system integration across all key phases of design, production, and quality control.
- **Practical Pathways for Developing Construction Digital Twins:** This research demonstrates that AAS-based DTs can be developed incrementally and tailored to specific use cases. By illustrating different levels of autonomy, from passive to reactive and toward proactive behaviours, it provides a scalable methodology for deploying DTs in real construction contexts. The approach highlights how modular, interoperable digital infrastructures can be aligned with the workflows and tools already used by AEC professionals, paving the way for broader adoption.

By successfully demonstrating the integration of modular DTs via the AAS, this research provides a clear and actionable pathway towards operationalising advanced, resource-aware construction methods. By linking design and optimisation methods directly with the reality of the factory floor, these insights serve as a foundation for transforming PCC from a geometrically constrained practice into a flexible, connected, and structurally optimised industry aligned with I4.0 goals.

CRediT authorship contribution statement

David Stieler: Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Simon Kosse:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation, Conceptualization. **Patrick Forman:** Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Conceptualization. **Daria Kovaleva:** Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Conceptualization. **Agemar Manny:** Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Conceptualization. **Tobias Teschemacher:** Writing – review & editing, Methodology. **Jan Stindt:** Writing – review & editing, Writing – original draft, Methodology. **Marco Lindner:** Writing – review & editing, Writing – original draft, Methodology. **Vincent Betker:** Writing – review & editing, Writing – original draft, Software, Conceptualization. **Thorsten Schmidt:** Funding acquisition, Conceptualization. **Detlef Gerhard:** Supervision, Funding acquisition. **Sandra Gelbrich:** Supervision, Funding acquisition. **Kai-Uwe Bletzinger:** Supervision, Funding acquisition. **Lothar Stempniewski:** Supervision, Funding acquisition. **Lucio Blandini:** Supervision, Funding acquisition. **Peter Mark:** Writing – review & editing, Supervision, Resources, Funding acquisition. **Markus König:** Writing – review & editing, Supervision, Resources, Funding acquisition. **Achim Menges:** Writing – review & editing, Supervision, Resources, Funding acquisition.

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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 online at https://doi.org/10.1016/j.jobe.2026.116044.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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