Towards Formless Production with Skill-Based Industrial Digital Twins

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***Abstract*—Digital twins enable optimization and flexibility in cyber-physical production systems (CPPSs). However, most implementations still replicate static production structures rather than supporting dynamic adaptability. This paper introduces Formless Production as a paradigm in which production systems emerge dynamically from modular, interoperable skills represented through Skill-Based Digital Twins (SBDTs). In this approach, skills encapsulate the operational knowledge of resources, enabling their flexible orchestration based on system state and context. The paper outlines the conceptual foundations of formless production, illustrates how SBDTs realize this vision, and proposes a roadmap toward software-defined, self-configuring manufacturing systems.**

***Index Terms*—Digital Twin, Skill-Based Manufacturing, Adaptive Production, Cyber-Physical Systems**

I. Introduction

Industrial production systems (IPSs) exist and evolve in an environment of inherent tension. They are required to be efficient and flexible, precise and adaptive, stable and innovative, economically viable and ecologically responsible, all simultaneously [1], [2], [3]. This persistent conflict of objectives, known as the *Polylemma of Production* [4], defines the central challenge of all manufacturing theory: no IPS can be optimized for all targets at once. Every paradigm in production history has represented a distinct compromise along this multidimensional space of objectives. From Taylorism and Lean Production to Reconfigurable and Cyber-Physical Production Systems (CPPSs), each paradigm sought to overcome the trade-offs of its predecessor with regard to the respective historical challenges [5], [6], [7]. Yet, despite continuous technological evolution, fundamental limitations remain and become increasingly critical in today's volatile, uncertain, and interdependent industrial ecosystems. To understand these limitations, one must analyze how IPSs come into being, *i.e.,* how their form and capabilities emerge around industrial value creation from the interplay of their constituent dimensions and elements. IPSs are not merely structural configurations but rather the emergent result of the mutual interpenetration of structural, processual, and human dimensions [8], [9], [10] acting and interacting simultaneously: (1) *Structural*: encompassing physical architectures, layouts, machine and resource constellations; (2) *Processual*: including the realization of value creation, related workflows, methods, and routines; (3) *Human*: comprising knowledge, cognition, roles and culture, and coordination mechanisms.

Together, these interwoven dimensions form what we define as the *Gestalt* of the IPS, the concrete manifestation and characteristic form that allows the IPS to act as an organized whole in its current state. However, this Gestalt defines not only the system's performance but also its boundaries. Once the form emerges, it creates path dependencies and lock-in effects. The very moment any decision is made in production – procuring a machine, defining a production sequence for a product, or introducing a new process – the system begins to accumulate legacy and inertia. While the Gestalt of the system is the fundamental basis for its performance, efficiency, and stability, it also defines the limits of its transformation. Today's IPSs are, therefore, highly structured and stable while operating in an environment that is increasingly unstructured and unstable. Consequently, these systems are structurally optimized yet dynamically paralyzed: They often excel at incremental improvement but struggle to adapt and reconfigure themselves fundamentally when confronted with discontinuous change [11], [12]. Even modern CPPSs, which integrate digital intelligence into production, largely replicate existing forms in virtual space rather than transcending or transforming them.

We introduce our vision of formless production as a production paradigm that seeks to dissolve the Gestalt of IPSs and, thereby, its limitations. Formless production envisions manufacturing as a software-defined, skill-based, and dynamically emergent system. In this paradigm, structural, processual, and human-related knowledge dimensions are no longer rigid but are represented, orchestrated, and recomposed in digital space before being implemented in the hardware domain. The contributions of this paper, hence, are (1) a description of our vision of the formless production as a paradigm; and (2) a concept of skill-based digital twins (DTs) to enable this vision.

The remainder is structured as follows: Sec. II introduces background concepts, Sec. III discusses related research, Sec. IV presents the paradigm, Sec. IV-D details skill-based DTs, Sec. V outlines a research roadmap, and Sec. VI concludes.

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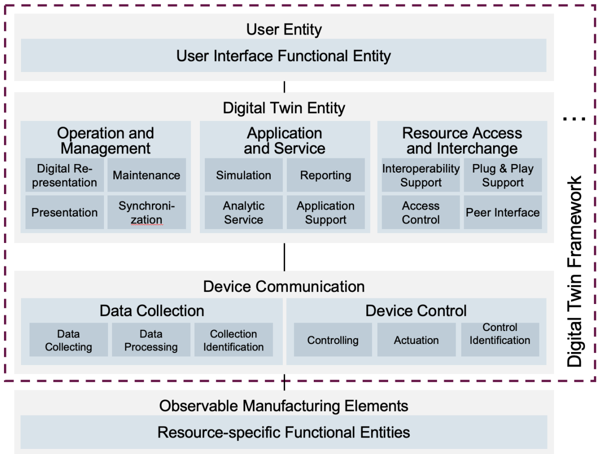

Fig. 1: Functions of DTs according to ISO 23247 [13]

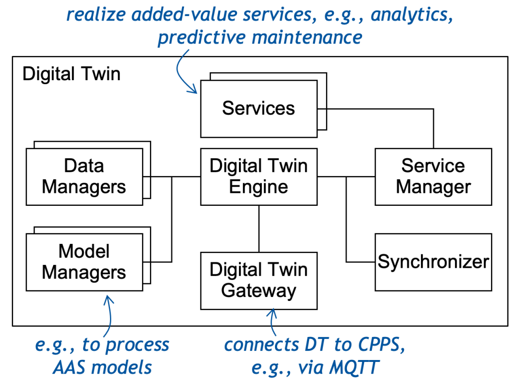

Fig. 2: High-level view on our DT reference architecture [27] based on the 5D model of DTs [28]

II. Background

A. Skill-Based Manufacturing

One foundation of formless production is decoupling production processes from the specific CPPSs realizing them, which aims to make production more flexible and, hence, easier to adapt to changing requirements [14], [15], [16] as well as facilitate the creation of new production functionalities. A popular approach to this decoupling is representing these production functionalities as skills that are realized by production resources [17], [18]. In such a "skill-based manufacturing" [19] or "skill-based production" [20], skills usually carry knowledge *what* can be achieved in a factory but not *how* this is realized [21]. A survey on skills in manufacturing [22] identified common requirements for skills (such as formality, modularity, or executability) and identifies various modeling techniques employed for describing skills, such as OPC UA [23], AutomationML [24], or UML [25]. Often, skills should also be "matchable" [22], i.e., their formalism enables matching production requirements to available skills. Where this is possible, skills can serve as the foundation for automated production planning [26]. Often, however, these skills are represented statically and cannot represent changes to the underlying CPPSs during their lifetime (e.g., through wear-and-tear, environmental changes, or evolution of the CPPS), thus leading to subpar or invalid plans. To mitigate this, we propose making DTs the carriers of such skills.

B. Digital Twins

Research and industry employ DTs to make better use of cyber-physical, biological, and social systems [29], [30]. Therefore, DTs promise reducing development time and costs, improving operations, and deepening our understanding of the represented CPPSs [29]. And while research and industry have devised many reference models of DTs [31], there still is little consensus on what a DT is and what it's implementation needs. Popular definitions either define DTs based on the data flows between the DT and the twinned CPPS [32], coarsely describe abstract modules that they may comprise [28] (data, models, services, interface to the CPPS, and connections between these dimensions), or focus on software architectures of DTs for very specific DT applications. One thing that all DTs according to [32] have in common is that they obtain data from the CPPS, process this, and may use insights gained from this processing to manipulate that system [32]. However, there are many more expectations on what a DT should be able to do as outlined by the functional entities[1] mentioned in ISO 23247 [13] (*cf.* Fig. 1): Here, DTs collect data from observable manufacturing elements, process it and provide it to added-value functions, *e.g.,* for digital representation, analytics, reporting, or simulation. The results are then sent back to control the CPPS.

Ultimately, these findings entail that a DT is a complex software system that receives data from and about the twinned CPPS, uses this data and various kinds of models via services to represent and manipulate that CPPS to provide added-value functions. Consequently, based on these and similar requirements entailed by the DT definitions discussed above, we have conceived a reference architecture for digital twins [27], of which an excerpt is presented in Fig. 2. In this architecture, we refined the 5D model of DTs [28] and devised software components required to realize this model. Our integration of skills with DTs in Sec. IV-D is based on this architecture.

III. Related Work

A central aspect of the *formless production* vision is the virtualization of production knowledge, dissolving rigid forms to enable adaptive, software-defined value creation. Several preceding paradigms share this aspiration by virtualizing control and representation to raise flexibility, interoperability, and intelligence within IPSs. Prominent among these are Software-Defined Manufacturing (DSM), the Reference Architecture Model Industrie 4.0 (RAMI 4.0) with the Asset Administration Shell (AAS), and the Virtual or Digital Factory (DF).

SDM extends principles from software-defined networking and cloud computing into the industrial domain. It separates the control and data planes of IPSs, allowing manufacturing

[1]The standard does not require all of them to be present in each DT.

capabilities to be exposed and orchestrated as programmable software services [33], [34]. SDM enables dynamic resource allocation, edge/cloud collaboration, and Manufacturing-as-a-Service business models [35]. Recent research emphasizes semantic interoperability, distributed orchestration, and AI-driven process adaptation [1], [36]. However, most SDM realizations operate at the control and IT layers, virtualizing communication and configuration rather than production semantics. Processes must already exist in an executable form; thus, SDM optimizes infrastructure more than value creation and lacks an explicit mechanism for self-emergent or context-driven process generation.

RAMI 4.0 provides a three-dimensional reference framework aligning industrial assets along hierarchy levels, lifecycle phases, and architecture layers [8]. Its core element, the AAS, defines a standardized digital representation that encapsulates each asset's identity, data, and communication interfaces [37]. The AAS supports interoperability and the formation of digital twins within initiatives of the Industrial Digital Twin Association (IDTA) [38]. Despite its foundational role, RAMI 4.0 remains a representational architecture: it specifies how assets are described and connected, not how they autonomously interact or compose behaviors. Consequently, it provides structural integration but not behavioral emergence. The value network is modeled as a static hierarchy of assets rather than a dynamic constellation of executable capabilities.

The Virtual Factory paradigm, integrates modeling, simulation, and data analytics to establish a digital counterpart of the physical IPS [39]. In its modern form, the DF, based on DTs, extends this concept through synchronization and closed-loop control, enabling analysis, prediction, and optimization [28], [32]. Overall, the DT is considered as a holistic socio-technical system, combining product lifecycle data, production planning, and virtual commissioning to increase transparency and responsiveness. These developments have made virtualization an indispensable instrument of modern production engineering. Yet, despite their integrative depth, DF implementations generally replicate the structural and procedural form of existing IPSs. They enhance planning and optimization, but rarely recompose or re-imagine the IPS's operational logic. The virtual representation thus mirrors the physical IPS rather than generating new forms of organization or emergent collaboration.

IV. The Vision of Formless Production

Formless production is a paradigm in which industrial value creation is freed from rigid, predefined structures — from its traditional *Gestalt*. In all preceding paradigms, the form of the production system has determined and constrained how value can be created. In contrast, formless production reverses this relationship: *value creation itself becomes the generative principle, rather than a consequence of system formation*. To operationalize such a paradigm, production is conceived from a *pre-Gestalt* state, in which no fixed form of the production system yet exists. The only invariant reference point is the fundamental purpose of industrial production: the task of *creating value at the product itself*. From this origin, system form is not predefined but emerges computationally as the optimal response to the requirements of value creation.

A. Value-Driven System Emergence

How can value creation be planned without predefined systems, processes, or structures? The core idea of the *formless production* paradigm lies in the formalization of platform-independent skills that encode the fundamental capabilities of production processes. In manufacturing, these skills ideally capture the mechanical and thermal impacts on the workpiece and its material. They transform implicit expert knowledge into explicit, machine-processable representations, forming a semantic foundation upon which production planning and execution can be automated. To implement value creation, formless production is first instantiated in a virtual space, where digital product data and platform-independent (manufacturing) processes are jointly aligned. Based on product requirements, contextual constraints, and the current state of the production environment—including the available machines and product portfolio—AI-based planners then orchestrate these skills into executable sequences, virtual machines, factories, and value networks. Through computational reasoning, the resulting *production system is derived, not designed*: its structure, processes, and coordination in the physical world emerge as transient configurations that best fulfill the specified value objectives under the prevailing conditions.

B. Reflexive Adaptation

Consequently, the production system is no longer a persistent artifact but rather a *dynamic state of coherence* between product requirements and available capabilities. The production system becomes a transient computational entity existing simultaneously in two domains: (i) the *informational domain*, where production capabilities are represented as formalized skills and orchestrated by digital intelligence to match the current requirements of value creation, and (ii) the *physical domain*, where these configurations are temporarily materialized and executed. As boundary conditions evolve – from product design and resource state to market demand – the system continuously recomposes and adapts itself. This shift establishes formless production as the first *reflexive production paradigm*: one in which production continuously produces its own form.

C. Implications

This paradigm shift entails far-reaching implications for the future of industrial production and for how skills, constraints, and systems must be conceived: (1) IPSs cease to exist as permanent entities; they emerge temporarily and evolve dynamically across structural, processual, and organizational boundaries, dissolving once their purpose is fulfilled. (2) Temporal and capacity constraints are relaxed, as the planning and reconfiguration of entire product portfolios occur continuously and autonomously, adapting to new conditions in near real time. (3) The classical *Polylemma of Production* is systematically mitigated, as efficiency, flexibility, quality, and sustainability can be optimized concurrently within algorithmic planning. (4) Production becomes a *software-defined service*, decoupled from fixed physical infrastructures and executable across globally distributed, dynamically reconfigurable value-creation platforms—or conversely, hyper-localized near the point of use. Formless production therefore marks a *fundamental inversion in the logic of industrial production*. The socio-technical Gestalt of an IPS – traditionally constrained by legacy assets, company-specific processes, and tacit expert knowledge – no longer limits what can be manufactured. Instead, the integral synthesis of all product requirements and boundary conditions dynamically shapes the IPS itself. The system's identity is maintained not through structural permanence, but through *informational continuity and adaptive coherence*in the ongoing pursuit of value creation.

D. Skills as Foundation of Formless Production

The basic ontological unit of formless production is the *skill*, a modular, machine-processable representation of a production capability. Each skill formalizes *what* can be achieved, *how* it can be realized, and under *which contextual constraints*. By abstracting production knowledge from specific machines or platforms, skills provide the semantic foundation for automated reasoning, matching, and orchestration. Through model-driven engineering and formal planning languages such as the Planning Domain Definition Language (PDDL) [40], skills can be composed dynamically into executable production sequences. AI-based planners instantiate these skills on available resources, forming virtual machines, factories, or networks that emerge only for the duration of their purpose. Thus, the system continuously redefines itself through computation, rather than remaining bound to a predesigned structural form.

SKILL-BASED DIGITAL TWINS

The realization of formless production relies on DTs as the operative medium that connects informational representation with physical execution. Within this paradigm, DTs are autonomous, communicative agents representing products, processes, and resources via platform-independent skills. Each DT, therefore, comprises models of the twinned CPPS, its processes, and its environment, e.g., including the CPPS's AAS, its kinematics models, simulation models, SysML models, as well as their inter-model relations and semantics, such that it (a) can properly interpret data obtained from or about the twinned CPPS and (b) provide data and models, linked and enriched with insights obtained from reasoning about them to human and artificial agents.

The realization of formless production requires a mechanism that connects the digital representation of capabilities, the skills with their physical execution, which requires precise information about the systems capable of their execution, including effects of wear-and-tear, environmental influences, or changes to the configuration of the CPPSs. We believe this to be realized by DTs of the CPPSs, which, by definition

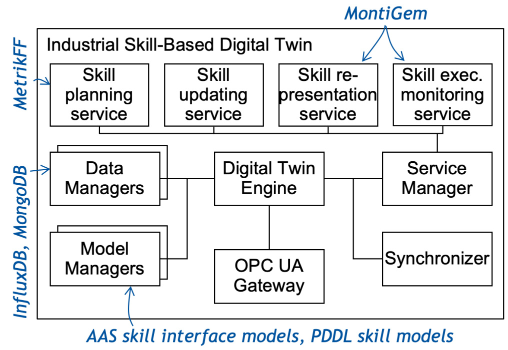

Fig. 3: Reference architecture for Skill-Based DTs

and construction, already comprise much of this information [41]. To leverage this, the DTs must become carriers of the production skills as well. Ultimately, these skill-based DTS become the medium through which the dissolution of Gestalt becomes operational, transforming the static coupling of structure, process, and human activity into a dynamic, data-driven interplay.

For industrial skill-based DTs in manufacturing, we expect representing and using skills via established technologies. Thus, Fig. 3 illustrates a reference architecture for skill-based DTs as a refinement of the general DT reference architecture (cf. Fig. 2) and relates the components to corresponding technologies: (1) Connection to CPPS takes place via OPA UA; (2) Representation and specification of skill requires model managers for the AAS as well as PDDL [26] and whichever models the DT needs to reason about the twinned CPPS; (3) Data is persisted by time-series databases (mostly for monitoring to sensor data and related events) and by unstructured databases (to track changes to models used by the DT); and (4) Services need to include means for representing skills, monitoring their status, updating their specifications, and planning of their use. In this architecture, each skill, as a digital description of a process capability, is associated with its corresponding DT *instance* that comprises multiple integrated models for each skills' parameters, constraints, and performance behavior. The DT continuously synchronizes with its physical or virtual asset, maintaining an up-to-date reflection of its state. By integrating such skill-based DTs into a shared information space, AI-based planners dynamically compose and orchestrate skills into executable production plans. This enables a direct translation from product requirements—expressed in the DT of the product itself—to the orchestration of production skills and resources required to realize them. The DT thus becomes the operative nucleus of formless production. It enables the CPPS to exist simultaneously and continuously updated in the information domain, as a virtual configuration of capabilities, and in the physical domain, as their temporary materialization. Thus, the DT replaces static integration architectures with continuous synchronization and adaptive coordination. Overall, the formless production will leverage DTs in three principal roles:

1) *Representation:* Every relevant production entity, from process capabilities and resources to products, is represented by a DT or sufficient precise model controlled by a DT. Therefore, each DT contains semantic, geometric, and behavioral information that makes its properties interpretable and actionable by human and artificial agents.
2) *Orchestration:* DTs interact autonomously within a federated architecture. Through shared ontologies and standardized communication protocols, they negotiate dependencies, synchronize states, and compose production workflows in accordance with AI-generated plans.
3) *Learning and Adaptation:* Through continuous coupling to physical processes, DTs collect data on performance, quality, and context. This data refines models, optimizes and updates skills and their parametrization, and enables the system to adapt dynamically without predefined or manually re-engineering cycles.

Through skill-based DTs, the Gestalt of the IPS becomes a dynamic state rather than a fixed structure—able to dissolve and re-form as requirements change. Thus, DTs are not merely technical enablers but the informational Gestalt of formless production: they embody system identity not through stable form but through continuous information and coherent interaction. By preserving this informational continuity across changing configurations, DTs keep production coherent, traceable, and purposeful even without a fixed Gestalt.

V. Research Roadmap

To enable our vision of the formless factory through skill-based DTs, certain research activities and results are necessary. This section outlines the nucleus of a research roadmap towards our vision, which includes establishing a *common software architecture for DTs* that can be deployed to all kinds of CPPSs easily and with minimal additional software engineering effort. On one hand, there are many different kinds of software architectures for DTs in research and practice [36], which are generally tailored to very specific applications of DTs and are largely incompatible with one another. On the other hand, there are standards proposing conceptual models of such architectures [13], [42] without concretizing the software architectures required to implement them, hence not significantly easing the realization and deployment of DTs in industry. Similarly, there are various conceptual models of skills, capabilities, and their relations for skill-based manufacturing [43], [44]. Yet a common understanding of such skills, which would be a prerequisite for combining and reusing skills, is missing. Therefore, it is vital to devise a *detailed data model for the specification of skills* with its semantics and standardize it. For the latter, the International Digital Twin Association (IDTA)[2] is advancing the development of AAS [37] as a data modeling framework for describing static and dynamic information about (manufacturing) assets. The AAS supports submmodel templates[3], which are a lightweight mechanism to standardize parts of an AAS data model. Thus, an *AAS submodel template for skills* would greatly facilitate developing, deploying, and distributing skills. For reliable industrial adoption, such a novel model can be extended with adaptable, skill-level protection mechanisms [45]. Finally, the skill-based DTs of the formless factory will be operated by domain experts with little (if any) formal software development expertise. Hence, these DTs must become understandable and configurable without such expertise. Thus, we believe that *low-code DTs* [46], using suitable interfaces for their deployment, configuration, and explainability, are vital for our vision. While some approaches for this exist [47], [48], they are tied to very specific DT applications and hardly applicable generally.

[2]https://industrialdigitaltwin.org/

[3]https://industrialdigitaltwin.org/en/content-hub/submodels

VI. Conclusion

We presented the vision of Formless Production, in which the fixed Gestalt of industrial production systems is dissolved and manufacturing becomes software-defined, skill-based, and dynamically emergent. Central to this paradigm are Skill-Based Digital Twins (SBDTs) that represent, orchestrate, and compose human, processual, and structural knowledge in digital space before realization in the physical domain. Leveraging digital twins as carriers of production skills enables manufacturing systems to overcome long-standing trade-offs between efficiency and flexibility through dynamic virtual reconfiguration and context-aware orchestration of capabilities across all system levels. This paradigm further fosters novel process synergies that transcend conventional technological and organizational boundaries through the seamless recombination of skills across machines, processes, and domains. We conclude that the production systems of the future must be formless: self-configuring, interoperable ecosystems in which manufacturing capabilities evolve continuously through skill-based digital twins.

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