Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop

Article *in* Journal of Ambient Intelligence and Humanized Computing · March 2019

DOI: 10.1007/s12652-018-0881-5

6 authors, including:

Jiewu Leng
Guangdong University of Technology
139 PUBLICATIONS **7,350** CITATIONS

Hao Zhang
Guangdong University of Technology
31 PUBLICATIONS **1,855** CITATIONS

Douxi Yan
Guangdong University of Technology
12 PUBLICATIONS **1,228** CITATIONS

Qiang Liu
[illegible]
88 PUBLICATIONS **5,418** CITATIONS

Journal of Ambient Intelligence and Humanized Computing
https://doi.org/10.1007/s12652-018-0881-5

ORIGINAL RESEARCH

Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop

Jiewu Leng[1,2] · Hao Zhang[1,2] · Douxi Yan[1,2] · Qiang Liu[1,2] · Xin Chen[1,2] · Ding Zhang[1,2]

Received: 31 January 2018 / Accepted: 24 May 2018

Abstract
With increasing diverse product demands, the manufacturing paradigm has been transformed into a mass-individualized one, among which one bottleneck is to achieve the interoperability between physical world and the digital world of manufacturing system for the intelligent organizing of resources. This paper presents a digital twin-driven manufacturing cyber-physical system (MCPS) for parallel controlling of smart workshop under mass individualization paradigm. By establishing cyber-physical connection via decentralized digital twin models, various manufacturing resources can be formed as dynamic autonomous system to co-create personalized products. Clarification on the MCPS concept, characteristics, architecture, configuration, operating mechanism and key enabling technologies are elaborated, respectively. A demonstrative implementation of the digital twin-driven parallel controlling of board-type product smart manufacturing workshop is also presented. It addresses a bi-level online intelligence in proactive decision making for the organization and operation of manufacturing resources.

Keywords Digital twin · Smart manufacturing · Cyber physical system · Smart workpiece · Mass individualization · Manufacturing cyber-physical system

1 Introduction

Starting form industrial economy, the pursuit of TQC (i.e., time, quality, and cost) is becoming more difficult. Manufacturers seek to offer unique value propositions, shifting from a firm-view to individualized experiences-dominant logic (Vargoa and Luschb 2008). Mass individualization requirements from diverse customers change the role of the manufacturer from a supplier of products to a provider of services (Gao et al. 2011). The mass individualization paradigm (Jiang et al. 2016; Leng et al. 2018; Leng and Jiang 2016) is disrupting the organizing and operating logics deep into the manufacturing stage and process level. Many manufacturers have started integrating services with their manufacturing resources (Cavalieri and Pezzotta 2012). Customer's individualized requirements drive manufacturers to align the manufacturing processes with their participation, which becomes the new source of value creation (Heinrichs 2013). Under this trend, various new national advanced manufacturing strategies such as Industry 4.0 are issued for helping manufacturers to achieve the successful transitions, resulting in the increasing number of newly-designed smart manufacturing workshops, which is the principle part for fulfilling mass individualized demands from customers.

An all-dimensional interconnection in the smart manufacturing workshop is the foundation of the interaction between the manufacturers and customers. Cyber-physical system (CPS) is emerged as the new generation of Internet-of-Things vision to realize this interconnection, via incorporating and reasoning about extracted knowledge hidden in manufacturing activities, with the goal of finally integrating virtual and physical worlds (Gang et al. 2015). This vision provides a potential way for handling the boosting complexity resulted from the mass individualization in smart manufacturing workshop (Leng et al. 2014, 2017). Moreover, it allows the efficient prediction of the effects of product and process as well as operating decisions on the manufacturing

✉ Qiang Liu
liuqiang@gdut.edu.cn

[1] Key Laboratory of Computer Integrated Manufacturing System, Guangdong University of Technology, Guangzhou 510006, Guangdong, China

[2] State Key Laboratory of Precision Electronic Manufacturing Technology and Equipment, Guangdong University of Technology, Guangzhou 510006, Guangdong, China

Published online: 02 June 2018

system behavior without the need for costly and time-expensive physical mock-ups. However, there are two challenges hindering the CPS-based intelligentizing workshop from its implementation as shown in Fig. 1, namely, the twining of cyber-physical and the context-aware self-organizing involved in CPS environment. The first challenge origins from the difficulty of both multi-source context perception in dynamic environment and real-time connection of heterogeneous equipment. The second challenge results from the need of both intelligent decision-making on dynamic data flow and effective processing of diverse data stream. The key is to realize the computation, communication and control features of the physical systems get distributed, in which physical devices mostly act as data sources for the cyber computation modules (Alam and El Saddik 2017).

To tackle the first challenge, the digital twin model is introduced to perceive the current context of the manufacturing system and recommend control actions for the physical environment if required. While advanced sensing and automation infrastructure usage is becoming abundant in manufacturing, integrating of digital twin model with the advanced manufacturing infrastructure is the key part between the physical layer and the cyber application layer of CPS. Considering the CPS vision is mostly focused on the physical layer of embedded systems, this study will elaborate how the embedded systems of the physical layers will be leveraged to provide both real-time and delay-tolerant manufacturing executions to the application layer of the CPS. Moreover, a manufacturing cognitive-loop based on twining feedback is built to improve the quality and performance of the physical manufacturing system.

To tackle the second challenge, a decentralized self-organizing strategy based on the smart workpiece model is established to handle the variety of context (i.e., the physical environment, such as location, time, workpiece status, and available machines), allowing proactive command and control-based interactions with prosumers and smart machines. Based on the proactive ability of one object interacting with another one at a time, the self-organizing between workpieces and machines will enable the on-demand generating of flexible manufacturing services (Wang and Wang 2017; Xu et al. 2017). Further, an online parallel controlling model is proposed and exposed to the digital twin in CPS for holistic decision making. A context-aware holistic parallel control decision scheme is generated from the dynamic management of system metrics via characterizing both smart machine and smart workpieces' situations and goals for adaptive process coordinating in manufacturing CPS. Finally, a bi-level intelligence (i.e., lower-level decentralized self-organizing and upper-level online parallel controlling) is achieved.

The rest of this paper is organized as follows. After a literature review on the cyber-physical system and digital twin in manufacturing workshop in Sects. 2, 3 presents digital twin-driven manufacturing cyber-physical System (MCPS) as a practical solution for parallel controlling of smart workshops. The computation, communication and control properties of the MCPS is presented. Aiming at preparing theoretically grounded solutions for practical purposes, four key enabling technologies for implementing MCPS in smart manufacturing workshop are analyzed in Sect. 4. A prototype in board-type product manufacturing workshop is developed as a demonstrative application in Sect. 5. Finally, the conclusions are presented in Sect. 6.

2 Related works

CPS is emerged as the new generation of Internet-of-Things (Park and Yen 2018). Wang (2010) argued that CPS can achieve intelligence when smart spaces are able to

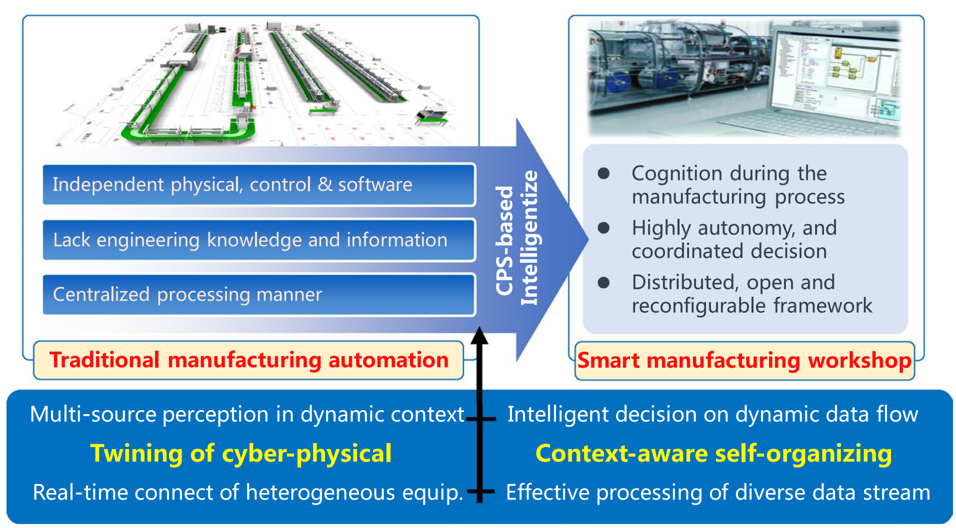


Fig. 1 Major gaps for CPS-based intelligentizing of manufacturing workshop

autonomously observe what's happening inside them, and constructs a model of relationships and interactions with smart space inhabitants and act according to the decisions made. Sheth et al. (2013) proposed the idea of computing for human experience referring to reasoning about knowledge generated by observing interaction activities to improve the user experience in CPS. Hussein et al. (2015) presented a CPS service framework named Dynamic Social Structure of Things, and built a social-based framework of interconnected nodes of people, devices, and services in the airport. CPS provides a potential roadmap for the intelligence in manufacturing workshop (Tao et al. 2017).

Enabled by a growing endeavor for digitalization of manufacturing (e.g., data gathering and processing, and model-based system engineering), the vision of manufacturing CPS are increasingly enriched. Liu et al. (2004) presented a distributed system framework including multiple intelligent agents to collaborate resource and job, improving the production efficiency. Zou et al. (2017) proposed data-driven stochastic manufacturing system model to facilitate real-time production control and decision making in smart manufacturing. Tu et al. (2009) proposed an agent-based distributed production framework adapting to dynamic environment, and used smart device to wirelessly manage shop-floor machines and make local decisions. Wang et al. (2017) integrated RFID with agent technology to make the smart workpieces negotiate directly with the production resources about the details of production procedures. However, little attention has been devoted to the coupling relationship among cyber and physical spaces, and these studies have not yet taken advantages of the obtained information to consistently improving the performance of systems.

With the advent of CPS, the Digital Twin (Boschert and Rosen 2016; Brenner and Hummel 2017; Ferguson et al. 2017; Grieves 2014; Grieves and Vickers 2017) appears as a practical solution to the manufacturing CPS vision. The digital twin vision refers to a comprehensive physical and functional description of a component, product or system (Tuegel et al. 2011), which includes more or less all information which could be useful in the current and subsequent lifecycle phases (Cerrone et al. 2014; Derberg et al. 2017). The virtual "twinning" (i.e., the establishment of relations between physical system and their virtual models) enables the efficient execution of product designing, manufacturing, servicing, and various other activities throughout the product life-cycle (Schleich et al. 2017). These digital twin models not only serve for the design verification and validation (Zhang et al. 2017b), but are also increasingly used as the control of manufacturing system (Tao et al. 2018a, b). Moreover, the evolvements in microchip, sensor and new IT technologies paved the way for the advent of smart workpieces, which synchronize and communicate their operating conditions with system and thus allow to feed the digital twin models with real-time manufacturing data about their status, such as environmental conditions and loads (Zhang et al. 2017a).

This paper takes the smart workshop as implementation scenario and proposes a digital twin-driven manufacturing cyber-physical architecture. The digital twin is used for monitoring and parallel controlling of manufacturing system. The goal goes beyond either offline simulation or even periodical scheduling (Zhang et al. 2018), but allows online optimization of physical manufacturing system based on context data.

3 The framework for digital twin-driven manufacturing CPS

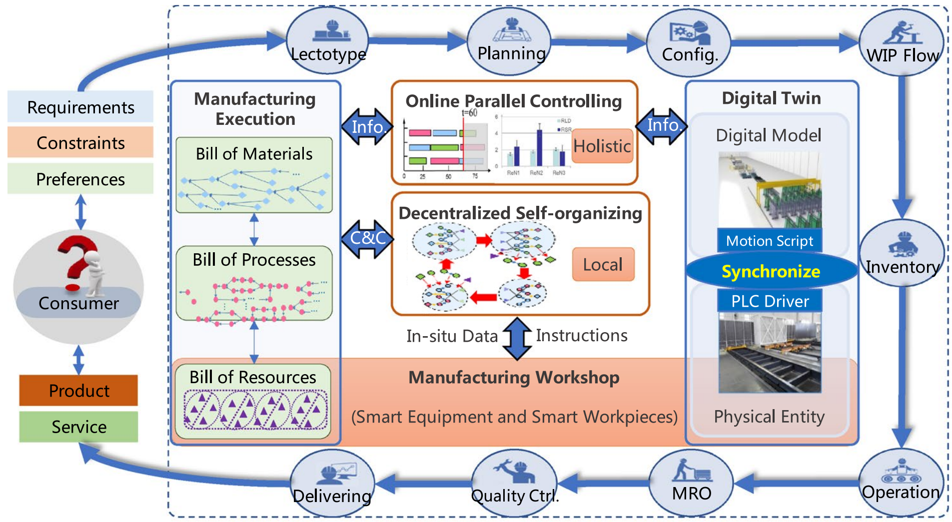
3.1 Digital twin-driven manufacturing CPS architecture

A CPS can be described as a set of physical devices that interact with a virtual cyberspace through a communication network. Each physical device will have its cyber part as a digital representation of the real device, culminating in the digital twin models. So, the digital twin can monitor and control the physical entity, while the physical entity can send data to update and synchronize its virtual model.

A digital twin-driven manufacturing cyber-physical system (MCPS) framework is proposed. As shown in Fig. 2, besides the fundamental Manufacturing Workshop parts, it consists of four parts: the manufacturing execution part mainly translates the upper planning and pushes down executing instructions according to the production order; and it also sends the data received from the lower layer, analyzes execution status, and transmits the results upwards. Three bills (i.e., bill of materials, bill of processes, and bill of resources) are interconnected in this part. The digital twin part is used to establish communication channel between physical equipment and digital model, to perform semi-physical simulation (including physical properties such as friction and gravity) in the model, and to evaluate the metrics about single equipment and execution result of whole manufacturing system. The decentralized self-organizing part is to precisely coordinate the local manufacturing tasks and machines, which is achieved by proactive interacting between smart workpiece model and smart machine model through the PLC-based supervisory control and data acquisition system. The online parallel controlling part acts various holistic optimizing calculation and forms various adjustment schemes, in view of factors such as the optimization mechanism, circumstances of the whole line, and accumulated production recessive disturbance.

This MCPS model is characterized by its bi-level intelligence. In the lower-level, the decentralized self-organizing

Fig. 2 Framework of digital twin-driven manufacturing cyber-physical system



in equipment level not only relieves the communication load on the network by on-tag data, but also avoids the data synchronization between the tag and the centralized database by on-tag indexing of further manufacturing information, and thus can simplify the calculation complexity of upper-level parallel controlling. All production process adjustments are proactively executed and the manufacturing data from cyber space are used to adjust the control parameters and to correct deadlocks. In the upper-level, the overall parallel control solution on the platform can not only be used for quantitative optimization based on contextual computing of digital twin model, but also for counteracting of random disturbance and validation of system robustness.

3.2 Organization and operations rationale

The key part of the proposed MCPS architecture is the digital twin model, which is an exact and real-time cyber copy of a physical manufacturing system that truly represents all of its functionalities. The digital twin is fed with context data about WIP and machine, and used as a basis for manufacturing preparation, on-line optimization, and quick changeover. The digital twin serves as a paradigm shift incorporating manufacturing process into MCPS, as well as connects multiple views and operations in a comprehensive model. Different from the traditional simulation architecture, the digital twin part is used as a validation tool for life-cycle overall optimization solution rather than only visual displaying of simulating random events or documenting the results.

Based on the highly-capable infrastructures through communication technologies, physical manufacturing system collects sensory information from the machines and WIP, and sends them to upper-level online parallel controlling part residing in digital twin computation module. Online parallel controlling module processes these data, notifies the physical system about the findings, and sends control commands to make necessary changes in the physical world or reconfigures system parameters if required. It is an effective iterative process by combining semi-physical simulation technology and rapid on-line optimization method, since on off-line optimization is cumbersome to accommodate for recessive disturbances and dynamic processes changes. Based on the digital twin functionality, optimization programs can be generated in a time efficient way, and smart cyber-manufacturing analysis can give valuable guideline about where to improve.

4 Key enabling technologies

4.1 Data driven cyber-physical fusion

The implementation of MCPS requires accessing a large volume of sensors, actuators, appliances, and other manufacturing infrastructure devices with embedded networking processors that can interact with each other, forming a seamless interoperable network. Increased availability of these infrastructures will open up new possibilities for better operating of individualized manufacturing service systems. Simulation and seamless transferring data from one life cycle phase to the subsequent phase is the core of the digital twin vision (Alam and El Saddik 2017). From a system life-cycle management point of view, fusion of all cyber-physical data artefacts into a holistic management system can benefit various digital twin models for querying context data and performing the online optimization, such as manufacturing system robustness.

The data-driven cyber-physical fusion includes three operational levels, sensors level physical fusion, services level cyber fusion, and a deep fusion of manufacturing services fusion. During production, the digital twin is fed with real-time manufacturing context data from both work-in-process (WIP), prosumers, and equipment. Massive ubiquitous data necessitates the effective mining tools to translate into actionable information. Pattern mining, deep learning, and other big data analytics make use of these context data and unveil the complex coupling relationships among WIP, equipment, and operational characteristics that used to be hidden or underlying in the manufacturing process. As shown in Fig. 3, the cyber-physical connected manufacturing system can interact with one another using standard interfaces, analyze context data to predict failures in process level, configure manufacturing services in cyber-physical level, and adapt to prosumer changes in social level.

The MCPS possesses increasingly intelligent interconnections and interoperability, which goes beyond Machine-to-Machine (M2M) interactions or the Internet-of-Things (IoT). It further becomes more scalable with the advanced computing and controlling infrastructures. As shown in Fig. 4, all the physical objects have embedded computing and communication capabilities so that they can perceive the context and coordinate with each other using direct communications to ensure high quality manufacturing services. MCPS consists of two critical metrics: (1) advanced connectivity to collect real-time data of the physical manufacturing system, and (2) intelligent data management, analytics, and computation in the cyber and social space.

4.2 Triple-view cyber-physical synchronization and integration

A digital twin-driven MCPS is resulting from the twinning between the physical world and a virtual model, which is realized by: (1) cyberizing the physical for specifying subsystems with computational abstractions and interfaces, and (2) physicalizing the cyber for expressing abstractions

Fig. 3 Data driven cyber-physical fusion

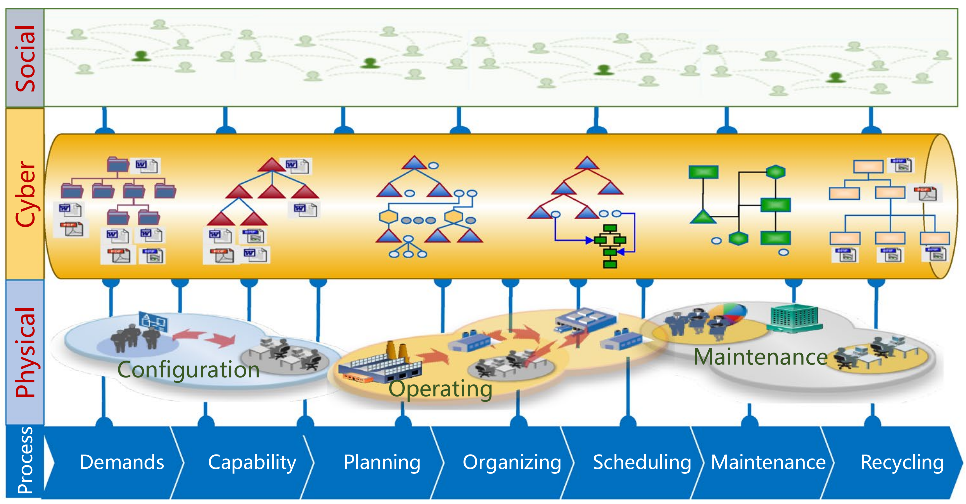
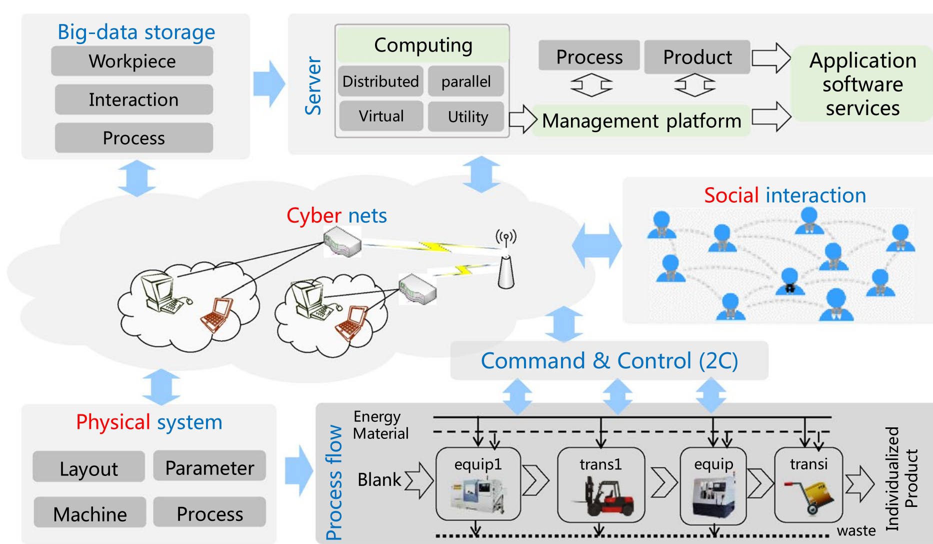


Fig. 4 Horizontal integration of MCPS elements



and interfaces of software/network components to represent manufacturing systems' dynamics in time. The critical challenge of this twining is the real-time monitoring and synchronizing data (Uhlemann et al. 2017).

As shown in Fig. 5, a triple-view synchronization among physical equipment, system monitoring, and cyber model enables efficient validating of the manufacturing system performance in a distributed integrating manner. The key of triple-view synchronization is a special software-comprehensible programmable logic controller (PLC) model, which is a hybrid mechanism by incorporating object linking and embedding for process control (OPC) with database, industrial internet-based protocols, and heterogenous equipment-inside application programming interface (API). Especially, the output digital signal and switch variables of simulation should be connected to that of physical manufacturing system. With the binding and mapping among I/O point on the cyber model and I/O address on PLC of equipment, it can guarantee the real-time synchronization.

The proposed digital twin-driven MCPS directly conducts execution logic validation and control in the digital model, quickly locates the malfunction reason, rules out the operating mistakes, and proactively inspects the system whether can meet the practical individualized requirement. How to quickly accommodate the control model to the production demands is the core of MCPS. As shown in Fig. 6, the digital twin-driven manufacturing cognitive-loop quickly translates the individualized demands into the control parameters of the physical manufacturing system, which greatly improves the efficiency from planning to manufacturing. The digital twin has an interface to the inspection database that contains information about individual part as well as statistical distributions for batches of parts.

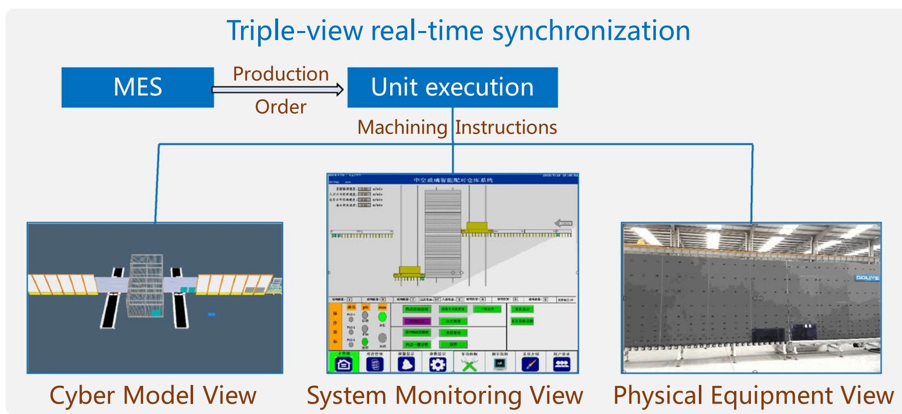


Fig. 5 Triple-view real-time synchronization in equipment-level

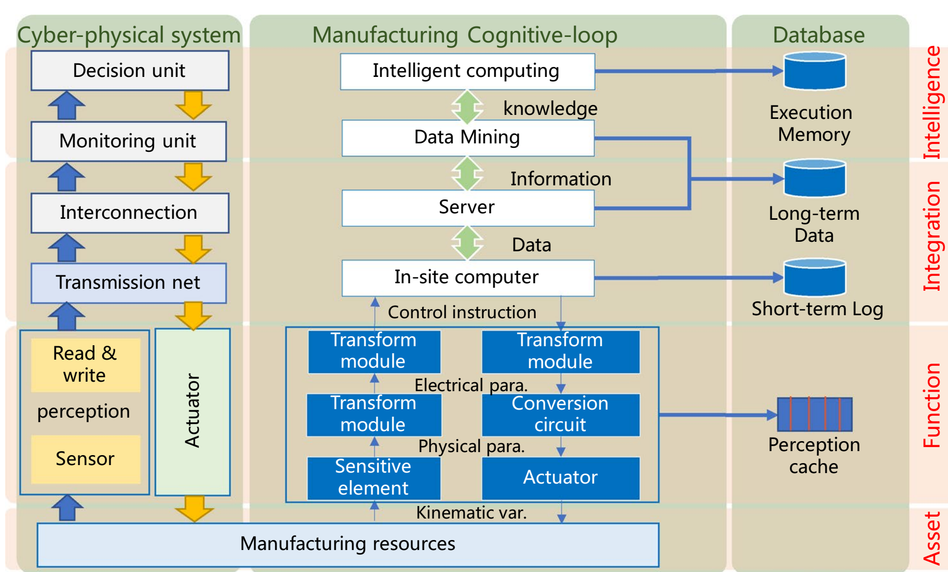


Fig. 6 Vertical manufacturing cognitive-loop from individualized demands to parameters

4.3 Decentralized self-organizing the tasks in the equipment level

Since the hierarchical or centralized control system is cumbersome to accommodate for recessive disturbances and dynamic processes changes (Leng and Jiang 2017a), it is neither flexible nor agile for mass individualization paradigm, in which decentralized self-organizing is a better solution. For a series of individualized requirements and product orders, the sub-processes of the task would be coordinated to multiple machines. Decentralized self-organizing could work effectively when directing the activities of this kind of loosely-coupled network that highly dynamic and autonomy rather than stable structure due to the conflicts of local and overall goals.

However, an appropriate number of loading task for each machine are supposed to be the trade-offs between the number of tasks and task sizes. If the task number of a machine is too small, then the number of involved machine for processing a workpiece will become too big, resulting in much communication and maintenance costs. On the other hand, oversize task number demands equipment to coordinate with too many workpieces, resulting in performance bottleneck issue.

To enable the machines' decentralized self-organizing collaboration in manufacturing workshop, Fig. 7 build a service self-organizing model to manage the context complexity coming from the diverse interaction between smart workpieces and smart machines. The process is designed as follows: firstly, the context mining (CM) module running on the servers accumulates and applies a set of learned patterns to obtain the explicit individualized requirements from the captured context. Machines are grouped with the aim of direct manufacturing service provisioning and interactions. Secondly, the task composition (TC) module clusters and composites these requirements into task in an optimal granularity. Related services are clustered to available machines to meet individualized requirements. Thirdly, a P2P manufacturing overlay network is dynamically formed using a self-organizing strategy. The self-organization (SO) module component coordinates machines with workpieces to match each task, in which the decision factors are machines' reputation based on maximal sustainability-preferred mechanism. After the available workpieces are identified, the most reputed machines will be elected as its matching performer through multi-criteria trust evaluation.

Several characteristics for smart workpiece is summarizing as: (1) Requires a holistic unique identification in the MCPS; (2) Is capable of interacting with its manufacturing environment; (3) Can retrieve and store context data about itself; and (4) Is capable of participating in or proactively making decisions relevant to its own destiny. In the self-organizing process, the smart workpiece allocates its tasks to the optimal machines through a group intelligence-based mechanism. Based on a unified interface, any smart workpiece and machine interact with each other, and therefore create an individualized information paradigm, which democratizes intelligence and embeds relevant data deep within the network to eliminate the need for extensive optimization via upper-level cyberspace.

4.4 Holistic online parallel controlling of MCPS

Controlling a manufacturing workshop is an iterative improvement process of adjusting the system configuration/operation to changes arising from demanders. Conventional methodologies of continuous improvement of manufacturing

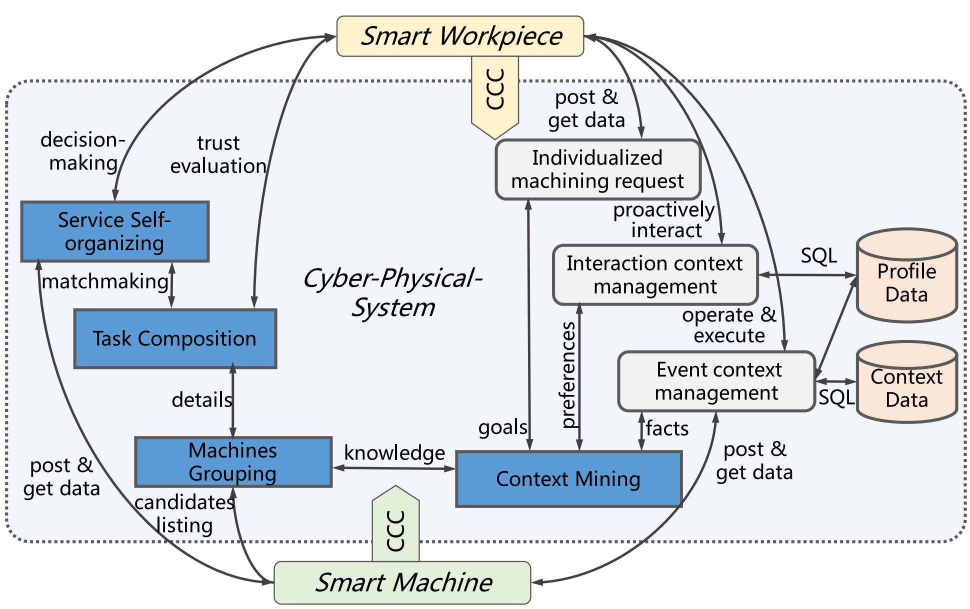


Fig. 7 Decentralized self-organizing the tasks in equipment level

workshop suffer from that less effort has been conducted to connect demand changes with system improvement, due to the lacking detail on quantitative variables to identify specific continuous improvement areas, in which digital twin can link the physical system with its virtual equivalent for mitigating these problematic issues (Cochran et al. 2016).

As shown in Fig. 8, a digital twin-based online parallel controlling model is proposed using fast capturing a large amount of context data to control production and to correct errors. The online parallel controlling model is a set of linked operation evaluation metrics of suitable dimensionality for their intended manufacturing management purpose, and it not only serves monitoring purposes but is also applicable for making predictions about the expected system behavior for manufacturing optimization and improvement. The evaluation metrics of the simplified simulation models evolve from early design stages, while sophisticated simulation models support the maintaining. And the evaluation metrics of operation models are used to decide about scheduling.

The core of holistic online parallel controlling is a dynamic scheduling algorithm based on multi-layer network metrics of manufacturing system, which has been presented in our former study (Leng and Jiang 2017a). Firstly, a complex manufacturing network (CMN) is established. Then, several multi-layer network metrics characterizing systems performance (e.g., resource load degree manufacturing flexibility, manufacturing reliability, manufacturing proportionality, and machine utilization range) of the CMN are dynamically evaluated (please refer to our former study for details). The implications of these metrics lead to a better understanding of the current status and performance of MCPS, and thus are analyzed with respect to time. Finally, using these metrics as heuristic information, a dynamic scheduling algorithm (Leng and Jiang 2017a) integrated with intelligent decoupling algorithm (Zhang et al. 2017b) is used to achieve the continuously-optimized system performance over time. Also, undesirable emergent behaviors and many of those problematic issues are predicted and prevented during production.

5 An implementation with prototype MCPS system

The proposed MCPS model is a massive project. This section presented a Java-based prototype MCPS platform allowing online parallel controlling for mass individualization in a manufacturing workshop, together with an application scenario. By using available manufacturing infrastructures and networking infrastructures in our board-type product manufacturing system lab, this study gives a demonstrative application with a specific case study to validate the proposed idea.

5.1 Architecture of prototype MCPS system

Based on the proposed key enabling technologies, an implementation architecture of demonstrative prototype MCPS is presented in Fig. 9. The essence of MCPS prototype is to provide a bi-level intelligence (i.e., lower-level decentralized self-organizing and upper-level holistic controlling) to build a bridge between smart workpieces and smart machines, thus forming a closed loop of manufacturing service system. The equipment cyber-physical twinning layer is established through secondary development on the command and information channel based on an open source Unity3D engine. The System Network Integration layer feedbacks real-time manufacturing information from the field to the upper-layer execution system. The Manufacturing Execution layer is developed with J2EE SSH programing architecture and transmits the optimization result to upper-layer. The Holistic

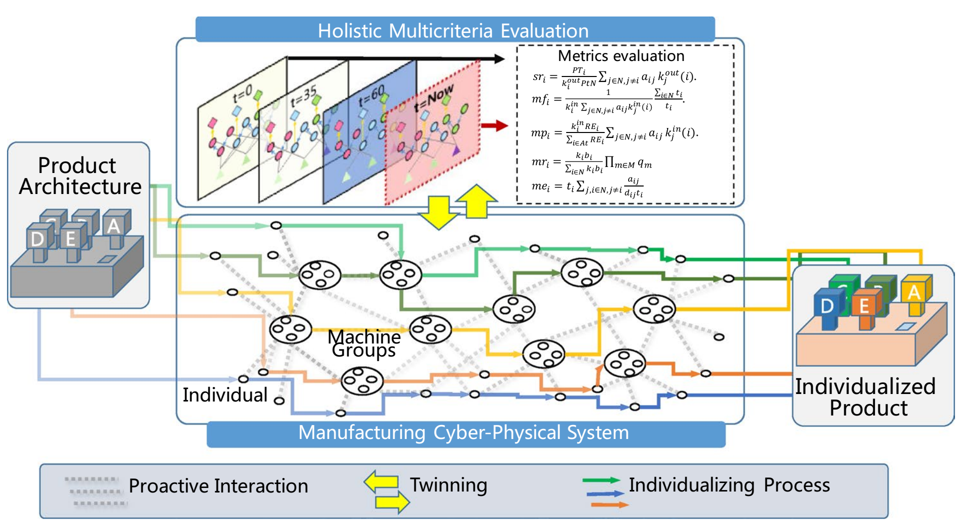


Fig. 8 Holistic online parallel controlling of individualized manufacturing process

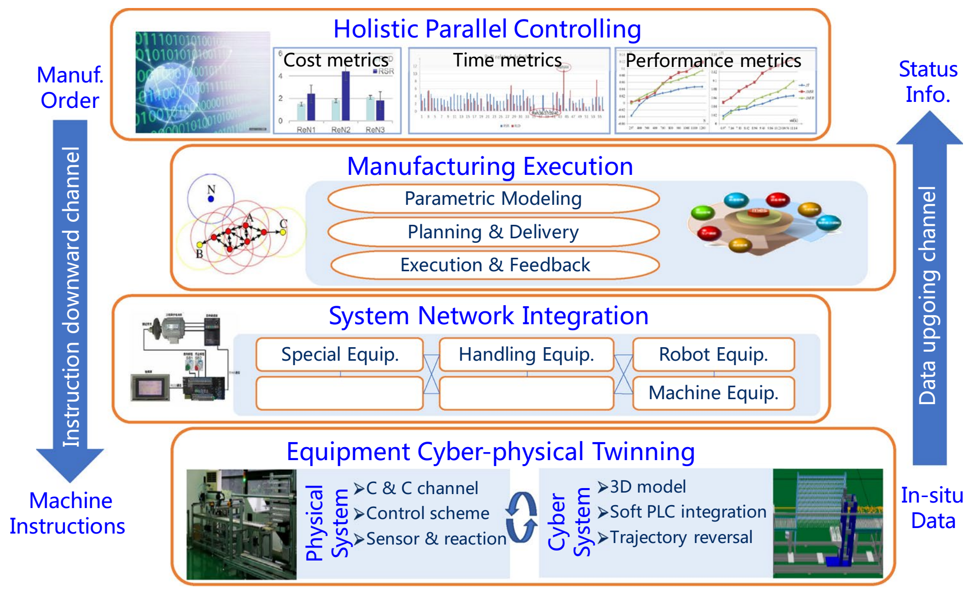


Fig. 9 Architecture of digital twin-driven prototype MCPS

Parallel Control layer executes the optimization kernel and is integrated with intelligent decoupling algorithm (Zhang et al. 2017b).

5.2 Manufacturing and networking infrastructures

Figure 10 illustrates the infrastructures of MCPS platform, including manufacturing infrastructures (e.g., machine tools, sensor nodes, and controller) and networking infrastructures (e.g., routers, smart gateways, middleware, and web-applications for Android and PC operating systems). The manufacturing part consists of a demonstrative board-type product automated production line. Each integration of manufacturing infrastructure that includes machine tool, sensors, and controllers will form a smart machine. Each machine has been equipped with CNC-enabled hardware for tracking and controlling machining process flow. Multiple Industrial Internet protocols such as Modbus, Socket, Profibus are integrated to obtain information related to manufacturing progress and status. The networking part of the implementation architectures benefits from the Raspberry mini-computer, offering an effortless deployment by acting as a protocol translation gateway to cope with interface heterogeneity. To accommodate the software heterogeneous complexity of smart machines, the prototype is developed based on a REpresentational State Transfer (REST) (Battle and Benson 2008) architecture with the manufacturing hardware and internet middleware using related networking protocols. The Constrained Application Protocol (CoAP) in the network infrastructure is the key

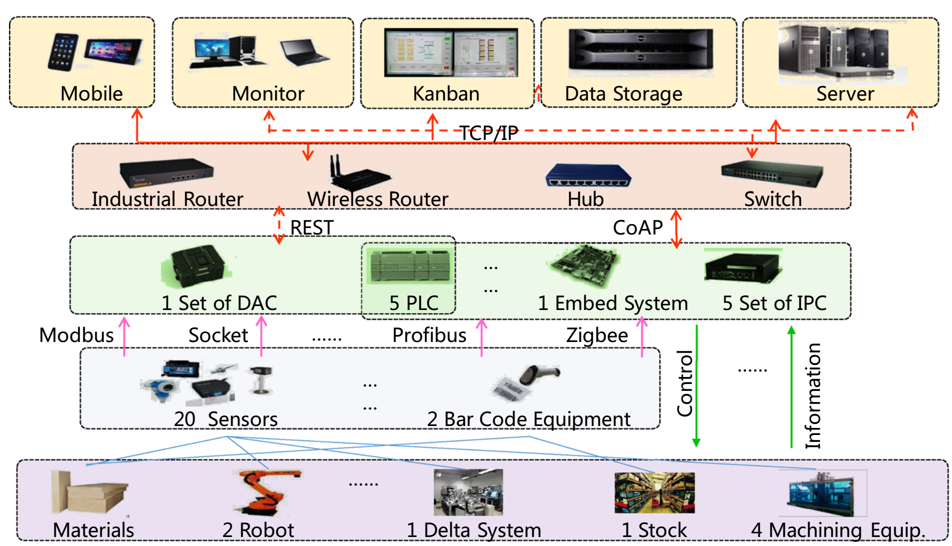


Fig. 10 Manufacturing and Networking infrastructures of prototype MCPS

to integrate smart machines and smart workpieces into the decentralized system.

5.3 An illustrative operation procedures of board-type product MCPS

Figure 11. correspondingly shows an illustrative operation procedures of board-type product MCPS. The implementation effort could be divided into four phases.

During the first phase, each individualized manufacturing order is characterized and captured by four types of parameters, including basic information (e.g., order mount, delivery date, material), geometric features, form and location tolerance, and other individualized requirements. Based on a series of predefined reference models, a series of computational digital twin models are created, verified, and used to make the semi-physical simulation. The interpreted demands are correlated into the system configuration parameters, control scheme parameters, and the execution algorithm primary parameters of MCPS, forming a plan corresponding to the manufacturing order. The efficiency of the plan is static optimized. Once the execution is verified and improved by the semi-physical simulation model, it can be fed into the physical manufacturing system.

During the second phase, the plan is deployed to the MCPS, after which real-time digital twining is considered to scan and analyze data of WIP and system, enabling the engineers and operators to master the status of manufacturing systems. By enabling the peer-to-peer connections between smart entities and online parallel controlling at any time and in anywhere, mass individualization is democratized through the MCPS platform.

In the third phase, the MCPS under holistic parallel controlling is a change process of network topology and node attributes along with time, initiated from the configurations on given manufacturing orders. Each evolution of MPCS is triggered by three conditions: (1) production event, (2) manufacturing orders or configuration changes, and (3) dynamic scheduling results on MPCS. MPCS are in a dynamic balance between network growth (i.e., add new nodes or new edges into network when there exists configuration changes or scheduling results) and network pruning (i.e., delete existing nodes or edges in network when a job is finished). Adjustments to compensate for predefined-objective deviations in the manufacturing process can be made with respect to statistical metrics to optimize the process batch wise, or for individuals.

In the fourth phase, once the accumulated recessive disturbances go beyond predefined limits or system failure happens, simulation-based solutions are realized for optimized operations. Due to a very fast scanning and optimization routines, minimizing the makespan range and balancing the resource utilization could be quickly done to reduce deviation. The comparison between digital twin-driven MCPS with traditional mode has been partly addressed in our former study (Leng and Jiang 2017a; Zhang et al. 2017b). For the reason of space constraint, we will address the intensive quantitative comparison in another study.

5.4 Discussions

Benefited from the first two key enabling technologies, the engineers can quickly complete the equipment configuration and operation, avoiding costly and long-term decisions. Higher degree of accuracy can be achieved and impacts of process and product mix uncertainties (Shardaa and Banerjee 2013) can be considered. Benefited from the last two key enabling technologies, the digital twin-driven MCPS platform can optimize dynamic execution mechanism. The performance of the whole MCPS can be virtually analyzed and feedback to the physical system. Once a deficient

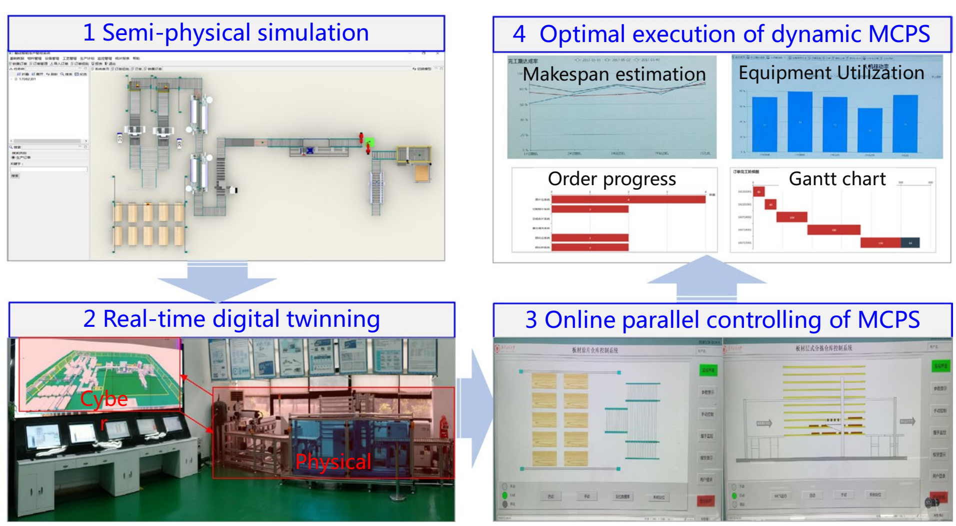


Fig. 11 An illustrative operation procedures of board-type product MCPS

performance, the operating can be adjusted and iterated until obtain the optimal status.

From the organization perspective, contextual-awareness solution in equipment level is an appropriate choice for the complex MCPS, and all the decisions of workpieces and machines are evaluated and made locally using the contextual method. It helps the decision makers by eliminating the subjective judgements. On the other hand, the self-organizing among tasks can reduce the complexities of the dynamic online parallel controlling of production flows in the cyberspace and improve the flexibility of WIP for individualized manufacturing demands. Moreover, the proposed MCPS model is relatively flexible by enabling each smart machine of online setting with different individualized machining parameters and quality requirements, which provides a large variant of options to meet the individualized demands.

There remain many challenges waiting to be solved. The first challenge is to build a set of interoperable digital twin model combining lifecycle management of collaborative manufacturing system across enterprise (Leng and Jiang 2018). The second challenge is how to incorporate more comprehensive big data analytics that could provide more engineering analysis ability and robust decision support (Yang et al. 2018). When compared the cyber system with actual manufacturing result, the deep-fusion of digital twin model with deep learning algorithm can be introduced to identify whether there is a difference and find out the cause (Leng and Jiang 2017b). Integrating cloud technologies in the CPS cyber layer is also promising to ensure the scalability of storage, computation, and cross domain communication capabilities (Tao et al. 2014). The third challenge is to build a deep-aggregated digital twin-driven cyber-physical–social-connected manufacturing system, accumulating industrial-specialized reusable decision-support and optimizing knowledge toward smart manufacturing.

6 Conclusions

This paper takes the smart manufacturing workshop as implementation scenario and presents a digital twin-driven manufacturing cyber-physical system architecture. How the digital twin applies in optimizing system behavior is discussed. Based on a conceptual framework development, four key enabling technologies in the cyber-physical-connected way for mass individualization are analyzed. Through the analysis of the dynamic execution mechanism needed to meet process constraints and complex coupling relationship, this paper proposes an idea of a bi-level intelligence between local decentralized self-organizing and holistic online parallel controlling. Digital twin defines the use of performance metrics to support a manufacturing operation and provides a systems engineering-based approach that enables continuous improvement and strategic adaptability to change. The complexities of mass individualization in the dynamic production flows management are reduced, and the flexibility of WIP for individualized manufacturing demands is improved. Evidenced by a successful case study in board-type product manufacturing system, the proposed prototype can provide manufacturing system with an intelligent optimization engine.

The limitations arise from the fact that mass individualization is not yet practiced on a large scale. Consequently, it will be later to conduct the more quantitative studies to test the propositions of this study. It will also be important to analyze the industrial product manufacturing for a better understanding of the full effect of CPS (Erenay et al. 2015). The technological intersection of CPS, social networks and cloud technology is a critical area to be tackled for a smart manufacturing workshop. Moreover, mining and automation of decision-support knowledge from the interaction contexts are supposed to be major challenges for achieving the self-organized mass individualization in manufacturing system (Tao et al. 2018a, b). Future work will be conducted in incorporating the big data analytics into digital twin model for the operating of manufacturing system.

Acknowledgements This work was supported by the National Natural Science Foundation of China under Grant Nos. 51705091 and 51675108; the Science and Technology Plan Project of Guangzhou under Grant No. 201804020092; the Science and Technology Planning Project of Guangdong Province of China under Grant Nos. 2015B010128007 and 2016A010106006; and the Fundamental Research Funds for the Central Universities under Grant No. 2015ZZ079.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Alam KM, El Saddik A (2017) C2PS: a digital twin architecture reference model for the cloud-based cyber-physical systems. IEEE Access 5:2050–2062

Battle R, Benson E (2008) Bridging the semantic Web and Web 2.0 with representational state transfer (REST). Web Semant Sci Serv Agents World Wide Web 6:61–69

Boschert S, Rosen R (2016) Digital twin the simulation aspect. Springer International Publishing, Basel

Brenner B, Hummel V (2017) Digital twin as enabler for an innovative digital shopfloor. Proc Manuf 9:198–205

Cavalieri S, Pezzotta G (2012) Product-service systems engineering: state of the art and research challenges. Comput Ind 63:278–288

Cerrone A, Hochhalter J, Heber G, Ingraffea A (2014) On the effects of modeling as-manufactured geometry: toward digital twin. Int J Aerosp Eng 439278:1–10

Cochran DS, Hendricks S, Barnes J, Bi Z (2016) Extension of manufacturing system design decomposition to implement manufacturing

systems that are sustainable. J Manuf Sci Eng Trans ASME 138:1–10
Derberg RS, Rmefjord KW, Carlson JS, Lindkvist L (2017) Toward a digital twin for real-time geometry assurance in individualized production. CIRP Ann-Manuf Technol 66:137–140
Erenay B, Suer GA, Huang J, Maddisetty S (2015) Comparison of layered cellular manufacturing system design approaches. Comput Ind Eng 85:346–358
Ferguson S, Bennett E, Ivashchenko A (2017) Digital twin tackles design challenges. World Pumps 2017:26–28
Gang X, Fenghua Z, Xiwei L, Xisong D, Wuling H, Songhang C, Kai Z (2015) Cyber-physical–social system in intelligent transportation. IEEE/CAA J Autom Sin 2:320–333
Gao J, Yao Y, Zhu VCY, Sun L, Lin L (2011) Service-oriented manufacturing: a new product pattern and manufacturing paradigm. J Intell Manuf 22:435–446
Grieves M (2014) Digital twin: manufacturing excellence through virtual factory replication. Web Pages, https://www.researchgate.net/publication/275211047_Digital_Twin_Manufacturing_Excellence_through_Virtual_Factory_Replication. Accessed 30 Jan 2018
Grieves M, Vickers J (2017) Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems. In: Transdisciplinary perspectives on complex systems. Springer, Cham, pp 85–113
Heinrichs H (2013) Sharing economy: a potential new pathway to sustainability. GAIA 22:228
Hussein D, Park S, Han SN, Crespi N (2015) Dynamic social structure of things: a contextual approach in CPSS. IEEE Intell Syst 19:12–20
Jiang P, Ding K, Leng J (2016) Towards a cyber-physical–social-connected and service-oriented manufacturing paradigm: social manufacturing. Manuf Lett 7:15–21
Leng J, Jiang P (2016) A deep learning approach for relationship extraction from interaction context in social manufacturing paradigm. Knowl Based Syst 100:188–199
Leng J, Jiang P (2017a) Dynamic scheduling in RFID-driven discrete manufacturing system by using multi-layer network metrics as heuristic information. J Intell Manuf. https://doi.org/10.1007/s10845-017-1301-y
Leng J, Jiang P (2017b) Mining and matching relationships from interaction contexts in a social manufacturing paradigm. IEEE Trans Syst Man Cybern Syst 47:276–288
Leng J, Jiang P (2018) Evaluation across and within collaborative manufacturing networks: a comparison of manufacturers' interactions and attributes. Int J Prod Res. https://doi.org/10.1080/00207543.2018.1430903
Leng J, Jiang P, Ding K (2014) Implementing of a three-phase integrated decision support model for parts machining outsourcing. Int J Prod Res 52:3614–3636
Leng J, Jiang P, Zheng M (2017) Outsourcer-supplier coordination for parts machining outsourcing under social manufacturing. Proc Inst Mech Eng Part B J Eng Manuf 231:1078–1090
Leng J, Chen Q, Mao N, Jiang P (2018) Combining granular computing technique with deep learning for service planning under social manufacturing contexts. Knowl Based Syst 143:295–306
Liu MR, Zhang QL, Ni LM, Tseng MM (2004) An RFID-based distributed control system for mass customization manufacturing. In: Cao J, Yang LT, Guo M, Lau F (eds) Lecture notes in computer science. Springer, Berlin, Heidelberg, pp 1039–1049
Park JH, Yen NY (2018) Advanced algorithms and applications based on IoT for the smart devices. J Amb Intel Hum Comp. https://doi.org/10.1007/s12652-018-0715-5
Schleich B, Anwer N, Mathieu L, Wartzack S (2017) Shaping the digital twin for design and production engineering. CIRP Ann Manuf Technol 66:141–144
Shardaa B, Banerjee A (2013) Robust manufacturing system design using multi objective genetic algorithms, Petri nets and Bayesian uncertainty representation. J Manuf Syst 32:315–324
Sheth A, Anantharam P, Henson C (2013) Physical-cyber-social computing: an early 21st century approach. IEEE Intell Syst 28:78–82
Tao F, Zuo Y, Xu LD, Zhang L (2014) IoT-based intelligent perception and access of manufacturing resource toward cloud manufacturing. IEEE Trans Ind Inform 10:1547–1557
Tao F, Cheng J, Qi Q (2017) IIHub: an industrial internet-of-things hub towards smart manufacturing based on cyber-physical system. IEEE Trans Ind Inform. https://doi.org/10.1109/TII.2017.2759178
Tao F, Cheng J, Qi Q, Zhang M, Zhang H, Sui F (2018a) Digital twin-driven product design, manufacturing and service with big data. Int J Adv Manuf Technol 94:3563–3576
Tao F, Qi Q, Liu A, Kusiak A (2018b) Data-driven smart manufacturing. J Manuf Syst. https://doi.org/10.1016/j.jmsy.2018.01.006
Tu M, Lin J, Chen R, Chen K, Jwo J (2009) Agent-based control framework for mass customization manufacturing with UHF RFID technology. IEEE Syst J 3:343–359
Tuegel EJ, Ingraffea AR, Eason TG, Spottswood SM (2011) Reengineering aircraft structural life prediction using a digital twin. Int J Aerosp Eng 154798:1–14
Uhlemann THJ, Schock C, Lehmann C, Freiberger S, Steinhilper R (2017) The digital twin: demonstrating the potential of real time data acquisition in production systems. Proc Manuf 2017:113–120
Vargoa SL, Luschb RF (2008) From goods to service(s): divergences and convergences of logics. Ind Mark Manag 37:254–259
Wang F (2010) The emergence of intelligent enterprises: from CPS to CPSS. IEEE Intell Syst 25:85–88
Wang XV, Wang L (2017) A cloud based production system for information and service integration an internet of things case study on waste electronics. Enterp Inf Syst UK 11:952–968
Wang C, Jiang P, Ding K (2017) A hybrid-data-on-tag-enabled decentralized control system for flexible smart workpiece manufacturing shop floors. Proc Inst Mech Eng Part C J Eng Mech Eng Sci 231:764–782
Xu B, Xu LD, Fei X, Jiang L, Cai H, Wang S (2017) A method of demand-driven and data-centric web service configuration for flexible business process implementation. Enterp Inf Syst UK 11:988–1004
Yang Y, Hu T, Ye Y, Gao W, Zhang C (2018) A knowledge generation mechanism of machining process planning using cloud technology. J Amb Intel Hum Comp. https://doi.org/10.1007/s12652-018-0779-2
Zhang F, Jiang P, Li J, Hui J, Zhu B (2017a) A distributed configuration scheme for warehouse product service system. Adv Mech Eng 9:1–13
Zhang H, Liu Q, Chen X, Zhang D, Leng J (2017b) A digital twin-based approach for designing and multi-objective optimization of hollow glass production line. IEEE Access 5:26901–26911
Zhang C, Wang J, Zhang C (2018) Two-agent scheduling on a single parallel-batching machine to minimize the weighted sum of the agents' makespans. J Amb Intel Hum Comp. https://doi.org/10.1007/s12652-018-0741-3
Zou J, Chang Q, Arinez J, Xiao G, Lei Y (2017) Dynamic production system diagnosis and prognosis using model-based data-driven method. Expert Syst Appl 80:200–209

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.