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5G++ FlexiCell: 5G location-based context-aware agile manufacturing

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Abstract

Manufacturing machines need to be retooled approximately 15 times per week and in the future even more often because of decreasing batch sizes and increasing short-cyclic demands. Collaborative robots promise to offer a versatile automation approach for priorly manual tasks in small and medium-sized enterprises. However, their configuration needs to change at least as often as the retooling rate because different parts are produced by the machines or might require different handling in general. Therefore, it would be great if robots and autonomous factory systems, in general, would automatically adjust to these changes in an intelligent way. In our approach, we propose a context-aware and location-based approach for agile manufacturing, in which the manufacturing plant parts, especially the collaborative robots, store i) their constellation, ii) their configuration, and iii) their adaptation strategy, and can react to retooling changes and even re-location changes adaptively. For example, moving one collaborative robot to a different location next to the plant will automatically load its new configuration and consult the operator on the adaptation strategy (i. e. the safety requirements). To realize the localization and the network capabilities, we propose to use a multichannel 5G-enabled communication base station and an intelligent asset management strategy.

Keywords: adaptive manufacturing, 5G, collaborative robotics, self-x, cpps, industry 4.0

1. Introduction

Flexibility and changeability became the main enablers of staying competitive in global markets. Especially SMEs have played an essential role in supplying large enterprises with (customized) parts for products/intermediate goods which are produced in small batch-sizes in a high-mix low-volume (HMLV) production. In order to meet these challenges, efficient retooling and the optimization of the setting-up time is mandatory [1]. Retooling is performed on average 15 times per week per machine, which roughly represents around 1.8 hours of lost manufacturing time [1]. As indicated by [2], manufacturing processes continue to increase the amount of required retooling effort for a variety of reasons, like smaller batch sizes and more spontaneous requests by customers. Retooling is one aspect of the general discussion of agile manufacturing, which aims to facilitate technology-driven enhancements for manufacturing purposes. As outlined in [3], manufacturing companies intend to adopt new digital technologies, like Industrial Internet of Things (IIoT), robots/cobots, automation platforms, and AI-enabled tools to increase operational efficiency - all of them part of the so-called fourth industrial revolution manufacturing.

During this ”Industry 4.0” process [4], but even more during the pandemic [5], the benefits of digital transformation have become apparent in the manufacturing industry. There is evidence that companies using technology for digital interconnection of their production lines are more motivated to onshore their production to Germany and Europe [6]. Nevertheless, there are still huge differences between SMEs (small and medium-sized enterprises) and large enterprises [7, 8], specifically regarding new technological approaches. The new communication standard 5G promises new communication opportunities to enable more flexible wireless interconnection. Although there are already promising approaches to use 5G to enable more flexible (and more dynamic) manufacturing processes [9], mainly large companies carry out these examples and target large production lines. According to a German study [10], most SMEs think that 5G ”is not relevant for my company”. This is because the showcased 5G scenarios are rather expensive regarding purchase and operation, but because of their complexity and scalability are not suited for the requirements of SMEs.

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This is why we propose a 5G architecture specifically targeting HMLV needs. In comparison to existing applications of 5G in manufacturing, our approach aims at using flexible 5G small cells with a federation possibility. The 5G campus net in a nomadic island operation mode is further developed into a heterogeneous industrial communication and localization network, which uses open interfaces. This enables a dynamically configurable constellation on the shopfloor, representing the reality of small and medium-sized manufacturing companies with HMLV manufacturing requirements.

In this paper, we will discuss the usage of 5G location-based context-aware production cells. First of all, we will summarize the current state of research in section 2. In section 3 we will describe architecture and components of our approach. In the last section 4 we will discuss the results of this article and outline further necessary research steps.

2. Research Review

2.1. Convergence of Communication and Localization Technology for Manufacturing

The flexibility of the information and communication technology (ICT) used by production solutions—as an enabler—must keep pace with the requirements of flexible productions. Therefore, it is expected that the 5th generation of mobile communications (5G), together with its impact on the network infrastructure, will become a key factor in achieving the objectives of Industry 4.0. The changes introduced by 5G not only relate to the new radio interface but especially to the core network, where innovation is driven through software and virtualization. While an architecture for 5G, which includes aspects regarding network slicing and the radio access network, has been developed by the 3rd Generation Partnership Project (3GPP), factory of the future use cases have been proposed in the 5G Alliance for Connected Industries and Automation (5G ACIA) in [11], whose requirements led to 3GPP study items in preparation for 3GPP Rel-16 and subsequent. By mid 2022, 3GPP will finalize the standardization of 5G Rel-17, which will include as new features ultra-reliable and low latency communications (uRLLC) for wireless control and network slicing, i. e. different levels of quality of service in one 5G network for different applications. First communication modules supporting these features are expected in Q1/2023. A subset of these features is already available in Rel-16, where the first modules have been available since the end of 2021. Localization with precision below 1 m are planned for Rel-18 (finished by mid of 2024). Further improvement in localization precision is a topic in the context of the beginning 6G research on joint communication and RADAR sensing.

Despite the developments of 5G for verticals, including private networks using dedicated spectrum locally on their premises, its introduction faces a significant number of hurdles and challenges. Many of them relate to the problem of *How to (securely) integrate a 5G network into a (existing) manufacturing environment with all its peculiarities?* In order to address the challenges of integrating ICT with the operation technology (OT) of a factory, reference architectures have been published in the literature: The Industrial Internet Reference Architecture (IIRA) [12] vertically integrates production technologies in the IIoT. It contains different views with respect to different dimensions: Functional domains, system characteristics, and crosscutting functions. The latter explicitly names connectivity as such a crosscutting function, generally enabling an IIoT. Complementary to the IIRA, the Reference Architectural Model of Industry 4.0 (RAMI 4.0) [13] addresses three different dimensions related to higher-level layers, including communications, the life cycle value stream and hierarchy levels, the latter essentially resembling the automation pyramid, which classifies technologies into six levels from sensor/actuators to enterprise resource planning. How to integrate a 5G system into these reference architectures was proposed in [14]. In [15] this approach was extended towards including other communication technologies, such that they build a heterogeneous communication system. The two reference architectures see localization of objects—by any technology—as sensing, and the omlox initiative [16] seizes support of heterogeneous localization technologies on an abstract system level. Hence, similar to (wireless) communications, future ICT will have to support a heterogeneous set of localization technologies on the physical layer such that they converge with communications.

2.2. Asset Management in Manufacturing

From a theoretical perspective, asset management originated as a method to optimize the usage of assets along their lifecycles. As discussed and outlined in the systematic literature of [17], asset management was firstly adopted by the Oil & Gas industry due to regulatory requirements regarding safety standards. Furthermore, the paper shows that asset management is being used and part of an ongoing scientific discussion in many industries/sectors, including manufacturing. The paper identifies three areas of managerial and technical challenges that are crucial for decision-making regarding asset management: i) Data collection, guaranteeing a high data quality with in-advance planning of required data/repositories, ii) data to information transformation, to exploit potentials of big data analysis and prediction and to build KPIs to benchmark with internal/external targets, and iii) information management and integration, to guarantee and drive interoperability of findings between internals and external information systems.

Since asset management covers a broad spectrum from operational to strategic applications within an organization, [18] propose a multi-layered approach of information technology (IT) ecosystems for asset management which includes i) operational level: governing of shop-floor activities, reporting of key performance indicators, ii) tactical level: the transformation of long-term objectives to medium/short-term decisions, and iii) strategic level: governing an organization's entire asset portfolio to support capital investment decisions.

While asset management as a discipline on its own predates the age of digitization, it is inherent that asset management benefits from the availability of systems that are capable of handling large quantities of data to leverage the ability to generate and manage knowledge [19], as well as to achieve the balance between performance, costs, and risks in a company's business objectives [20, 21].

Asset management can also be seen as part of the RAMI 4.0, which itself describes a three-dimensional layer model for industrial technologies [22, 13, 23]. Hereby, asset management is located on all aspects of the "Life Cycle & Value Stream" dimension, which covers all maintenance or usage-related tasks. On the dimension "Hierarchy Levels" and following the discussion of [18], asset management covers all hierarchies from the product level to the enterprise level. On the dimension "Layers", depending on the viewpoint of the definition of asset management (i. e. from a more technical or business-oriented approach), asset management has intersections with all layers. Thus, from a theoretical perspective, asset management can be seen as largely connected with RAMI 4.0.

2.3. Supervisory Control

Supervisory control has been discussed in the literature over the last 50 years. While the term originated in production automation, it has been adopted in a computer science-oriented context since the mid 1970ies [24]. An early definition can be found in [25] which defines supervisory control as a "paradigm [that] applies to situations where a person allocates his attention [...] to a computer which itself is in continuous direct control of a physical process".

While these definitions focus around humans and their role regarding automated systems, the role of the automated system and the human supervising it has changed a lot: As outlined by [26, 27], automated systems are being replaced by smart cyber-physical systems that incorporate humans with their cognitive strengths with machines and their procedural strengths. In such a system, supervisory control of the system is even more critical. One might – for example – think of a production cell in which a robot collaborates with a human to operate on a certain task. If an unexpected change occurs, the human might intuitively adapt to the new circumstances, while the robot could also self-adapt to the new situation instead of halting due to an error. During this adaptation, the human still needs to be enabled to i) keep oversight over the entire system, ii) keep control over the system, and iii) change dynamically, efficiently and effectively the system's configuration.

In the upcoming "AI age" [28] or "Hybrid intelligence" [29], the question of human supervisory control over self-reorganising systems will need a considerate societal debate which has only just begun [30] [31]. A self-adapting dynamic production system will also raise concerns regarding worker health safety, which have to be addressed before such a system can be used in real-world scenarios.

Controllability is also a matter of "understanding what is going on" before making decisions. This overview has been named "Situation Awareness" [32] and describes the overview of the current situation and also the possibility to predict future developments. The amount of data produced by a production plant – by its digital twin – is too large to be ever intuitively processed by a human. Research has shown that Augmented and Virtual Reality can successfully be used to visualize data in the direct context of their source to give the human a better overview [33] [34].

Furthermore, advanced Information Engineering [35] in the user interface can improve learning speed for new processes, enhance a worker's overview and improve process safety.

Keeping this in mind, the main research question regarding a context-aware agile manufacturing system is: How can the capability of human operators to supervise a self-adapting production system be eased by a good selection of user interface elements, especially in terms of the system's situational awareness, e. g. an overview of the current state, and the possibility to predict the future development of the system's state.

The ability to link data, information and knowledge with a specific situation or context is also related to the ability to group data, information and knowledge into categories, that allow interoperability—or "knowledge reuse"—between situations and contexts. These discussions are often linked to the term "Ontology". As discussed in [36], knowledge can be split up into different ontology levels to allow a situational composition/decomposition of an otherwise complex data model.

2.4. Self-X

Modern production systems tend to become less and less controllable due to the increased complexity of applications and the increased size of the systems themselves. Especially in the context of cyber-physical systems [37], the question has been raised, whether a system can become self-controllable. These systems should adopt new situations and facilitate error diagnostics and error corrections.

This leads to the so-called "self-X" capabilities [38]. Systems having these capabilities shall be self-configurable, self-optimizing, self-healing, self-explanatory and self-protecting. Besides these, an extensive catalog of additional self-X capabilities can be used differently based on the specific context. Since production systems are also often described as "cyber-physical" production systems [39], self-X capabilities are increasingly discussed in a production context (i. e. [40, 41]).

Depending on the definition, Industry 4.0 is described as a process of digitizing complex production plants and the transition of the technology and principles typically used in the IT industry towards the manufacturing industry.

In the context of a connected production system, the large quantity of data available (see SECTION) can be used to enable automation components to self-adopt their task profile based on the specific context, i. e. regarding a location-based service. Using the term "Self-organizing Manufacturing Network", this is discussed in [42] as a "a network of autonomous manufacturing things (e. g. manufacturing software tools, manufacturing equipment, and operators) connected in situation-dependent ways that can change their internal structure, organization, and functions with minimum external intervention" and regarded as the next step after the mass personalization/individualization trend of the 2010s [43, 44].

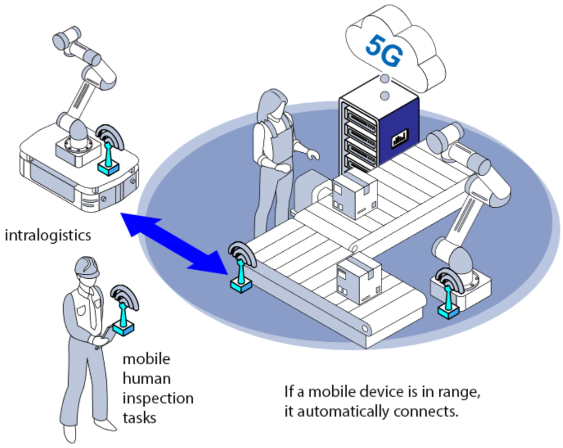

Fig. 1. Scenario 1: Single Cell

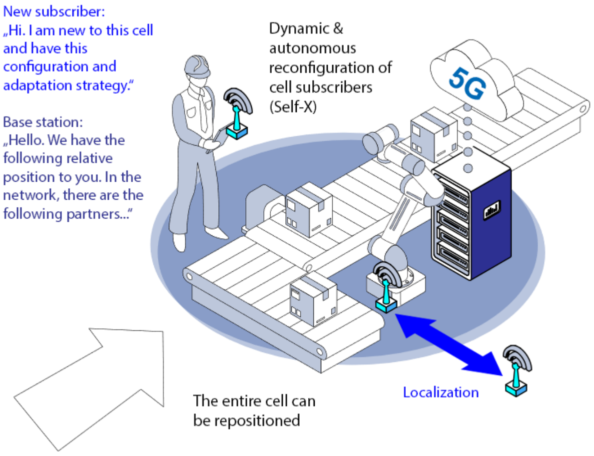

Fig. 2. Scenario 2: Move Cell

In [45] the capabilities required to form a self-organizing manufacturing network are described as: i) self-configuration: ”plug-and-produce” approach, that allows a dynamic linking of manufacturing things, ii) self-optimization: automatic adjustment of every node of the network to increase the network's overall performance, and iii) self-healing: capability of the network to detect abnormalities and make adjustments to restore itself to normal behavior.

3. System Architecture

Based on the state of the art, we aim at using 5G technology in order to enable a context-aware CPPS. We came up with the following four key scenarios, which would help particular SMEs with HMLV production to enable a faster retooling and reconfiguration of their production line.

3.1. Scenarios

Scenario 1: Single Cell: For each production station, a ”small cell” will be built up as displayed in fig. 1, which has a 5G core station in its center. Different manufacturing components can use the 5G network for i) synchronization, ii) M2M communication, iii) the detection of safety zones (detection of people in range), and iv) the relative localization of the component and other objects. In addition, mobile devices carried by users or mounted on automated guided vehicles (AGVs) automatically connect to the cell as soon as they are in range. So this design covers intralogistics tasks and mobile manual inspection tasks as well as more classical 5G application fields.

Scenario 2: Move Cell: We consider specifically small and medium-sized companies with high variety / low volume demands. They need to reconfigure their production line (cf. fig. 2). To adhere to these requirements, the repositioning of the 5G++ Flexicell needs to be possible. In addition, new subscribers need to connect and configure themselves autonomously (Self-X) via container solutions provided by the Edge Computing of the small cell. The core automatically estimates the position of new mobile participants like workers or AGVs and notifies them to start negotiating a necessary interaction routine.

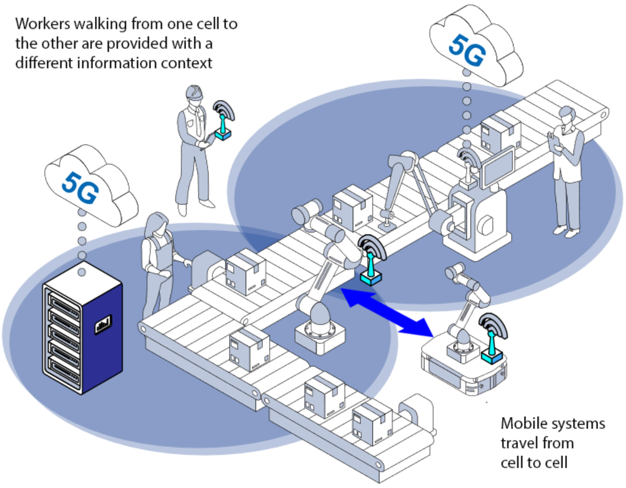

Fig. 3. Scenario 3: Cell Handover

Scenario 3: Cell Handover: Multiple small cells (cf. fig. 3) are deployed in a manufacturing site and act as a federated system that provides communication and localization functions. The handover between cells needs to be possible in heterogeneous technologies. As a result of a non-disruptive handover, mobile subscribers can maintain their communication in the entire production site. Furthermore, they can profit from the additional localization information by getting contextual information based on their position. It provides the possibilities of context-aware applications, like changing workers' data display on mobile devices (for example, for maintenance information) or for an automatic docking of AGVs.

Scenario 4: Human Supervision: Multiple small cells need to be configured and supervised. This is displayed in 4. In this scenario, in order to carry out supervisory control of the entire system, he or she needs to have a sufficient amount of situation

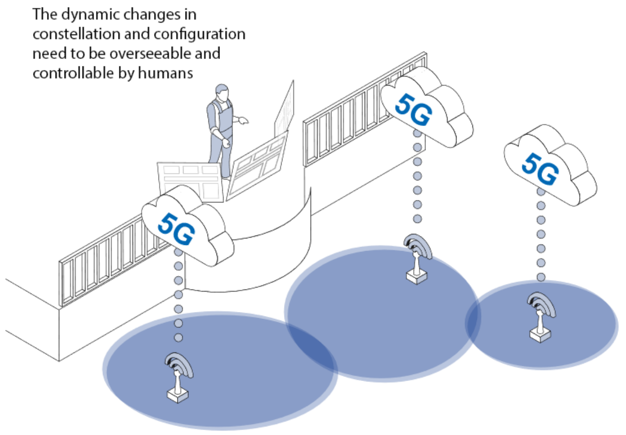

Fig. 4. Scenario 4: Human Supervision

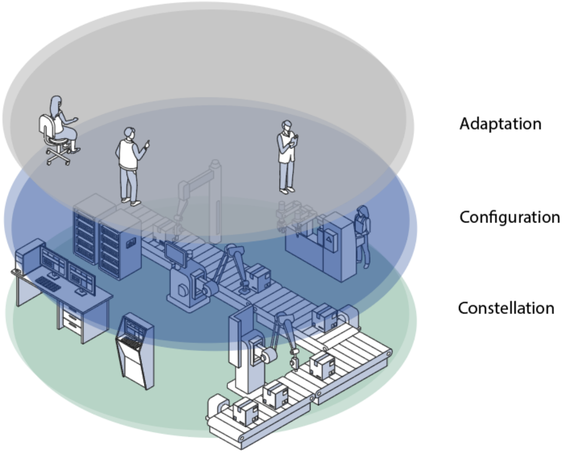

Fig. 5. 3 Layers of information: Constellation, configuration and adaptation

awareness. It is necessary to understand the configuration of the components in order to be able to reconfigure them.

3.2. *Asset and Configuration Management*

In order to realize the four described scenarios, we came up with the principle architecture depicted in fig. 5. First of all, we need traditional asset management, which keeps the hardware configuration and the location of the devices. We call this the constellation level. On a second layer, we regard the software configuration of the different assets. Then, they can be copied to the devices in a container approach. For the collaborative robots, this would be the program code. This somehow corresponds to the CPS architecture proposed by [46], which encompasses the layers i) smart connection, ii) data-to-information conversion, iii) cyber, iv) cognition, and v) configuration, whereas they do not consider specifically the localization aspect. In addition to this, we would like to propose the adaptation layer, in which the devices interact with humans. Although [46] considers autonomous self-organizing systems and only plans to include visualization for humans in the ”cognition” layer, we believe (in consensus with [24]) that there will be still a human-interaction layer. We think, for example, that the safety features need to be (at least partly human-assessed), but mainly reconfiguration activities will - in our opinion - still be human-led in future factories.

4. Conclusion

This paper proposes a theoretical concept for a flexible architecture for context-aware manufacturing reconfiguration, which can be enabled by 5G. Whereas the different layers (constellation, configuration, and adaptation) could enable a ”Self-X” production equipment, the impact on the real manufacturing industry needs to be proven. The described architecture is currently built up in the project ”FlexiCell” funded by the German Federal Ministry for Economic Affairs and Energy. Together with company partners, we are going to investigate the applicability of the proposed architecture in three real-life scenarios: i) a reconfigurable cobot-machine tending scenario in a plastic molding application, ii) a highspeed data sensor on an industrial manipulator as part of a mobile measurement cell, and iii) an intralogistics scenario carried out with the help of a mobile manipulator.

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