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Development of a Smart Manufacturing Execution System Architecture for SMEs: A Czech Case Study

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Abstract: This study investigates the application of a smart manufacturing execution system (SMES) based on the current controlling structure in a medium-sized company in the Czech Republic. Based on existing approaches on the architecture of SMESs, this paper develops a sample architecture grounded in the current controlling structure of small and medium-sized enterprises (SMEs). While only a few papers on approaches to the given topic exist, this approach makes use of operative production controlling data and uses a standardisation module to provide standardised data. The sample architecture was validated with a case study on a Czech SME. This case study was conducted on two different entities of one production company suggesting differences in the entities due to the nature of production. The research showed that simple tasks with intelligent welding equipment allow for a working SMES architecture, while complex assembly works with a high extent of human labour, and a high number of components still remain an obstacle. This research contributes to gathering more understanding of SMES architectures in SMEs by making use of a standardisation module.

Keywords: production controlling; Industry 4.0; OPC 4.0; machine learning; computer-aided standardisation; smart manufacturing; smart manufacturing execution system; sustainability

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1. Introduction

Industry 4.0 and the Internet of things (IoT) have been popular and widely discussed topics in recent years. Expecting substantial changes to happen to companies of all kinds in the upcoming years [1,2], these trends will have a persistent effect on companies, the way of work, and society as a whole [3]. Since the introduction of the term in 2011 [4], various research has been conducted on Industry 4.0 [5,6], as its introduction will have an impact on management and operations in companies. Industry 4.0 is described as a new paradigm [7] of changes in organization and technical aspects throughout the value chain leading to new business models [8], whereas IoT describes technologies for network-connected machines and devices that are expected to enable companies to introduce Industry 4.0 principles [9]. IoT enables the horizontal and vertical integration of tasks, information systems and their data, and decision making, leading to higher requirements for the supporting systems [10]. The application of new, smart technologies based on the IoT [11] allows companies to make use of data in a far wider range than before [12]. To introduce Industry 4.0, further approaches, technologies, and methodologies are discussed, such as artificial intelligence (AI) [13], multi-agent systems (MAS) [14,15], cloud-based manufacturing [16,17], and blockchain technologies [18].

Using data through interconnected IoT services and devices provides companies with the opportunity to further automate and to facilitate communication within the IT networks [19]. These IT networks belong to the internal company network, as well as to supply chains where data have to be exchanged with suppliers and customers [20]. Assuming the potential of computers and devices in the future, in 2004, White already expected information systems to be able to provide and exchange data in almost real time (referred to as "right time") [21]. Interconnected IT networks exchanging data form a cyber-physical network (CPN) [22,23]. Based on the integration of heterogeneous multi-source data and the integration of knowledge into production processes, CPNs allow for integrated and interoperable manufacturing processes [20].

Allowing for an interoperable manufacturing process, Industry 4.0 may also be understood as an intelligent production flow from machine to machine based on data [24]. Equipping manufacturing with IoT devices leads to data-driven smart manufacturing capable of adapting fast to changes and triggers [25]. According to Kusiak, the core of smart manufacturing is material handling, including logistics and supply chain management (SCM), being integrated into the operations of the company [26]. A further embedding of smart manufacturing into a whole company network working on smart principles results in the concept of a smart factory [27]. Smart factories are based on the use of the most recent information technologies in order to provide further integration of company processes [11,28].

Expecting a purely data-driven factory requires the collection, storing, and distribution of data [29] from sensors and devices paired with a boost in data analysis and the development of predictive engineering [26]. According to [30], this calls for smart production control, being able to monitor and assess flows and requirements. Furthermore, smart production control has to be able to make decisions [31]. The issue of requiring the most exact scheduling and controlling of smart production for decision-making processes persists up to today [32]. Smart production control and management is one of the central topics of smart factories, as realization is progressing slowly [33]. Treating the data as a digital twin of smart manufacturing devices, products, and components, the physical circumstances are digitally resembled to facilitate distribution, processing, and assessment of data [34].

While ideas have been produced in the last decades, the fundamental issues of smart production control have not yet been solved [33,35]. Moreover, small and medium-sized enterprises (SMEs) struggle with lacking technology, knowledge, and finances to support their transition towards Industry 4.0. Existing theoretical frameworks lack practical applications due to the missing technical means [32]. While smart devices are evolving and approaches are created [36], this paper looks at how SMEs might set up their production control and management for the transition that has begun towards Industry 4.0 [37] while making use of existing systems. While LEs are assumed to use technology, knowledge, and resources to invest in new technologies, such as IoT, SMEs are believed to require other downsized frameworks with regard to their resource situation and with regard to their capabilities [38]. It is the aim of this paper to propose a framework based on today's existing components, taking into account the principles of Industry 4.0. This is done through qualitative research as a multiple case study on two production sites of one single Czech production company.

2. Materials and Methods

2.1. Literature Review

2.1.1. Smart Manufacturing

Smart manufacturing assumes the principles of manufacturing under Industry 4.0. Developed as the manufacturing framework within a smart factory (also a digital factory, digital manufacturing, a smart factory, an interconnected factory, integrated industry, or Industry 4.0 [39]), it represents an alternative framework to multi-agent systems (MAS) [14,15] and cloud-based manufacturing [16,17].

Smart factories and smart manufacturing rely on the combination of smart objects and big data analytics [15]. Big data includes technologies and analytical approaches for extracting value from information through a transformation being characterised by high volume, velocity, and variety [40]. The concept of big data provides the potential to collect, process, and distribute a vast amount of data. Industrial big data analysis makes use of these data for diagnostics, optimization, and reconfiguration of the whole system [41]. Data for big data technology may be collected from the CPN within the company or from external online resources [42]. Big data is therefore seen as an important component for data-driven manufacturing approaches, such as smart factories, to achieve higher effectivity and productivity [43].

Smart manufacturing should provide cost-effective, sustainable, and safe manufacturing. In these measures, it is estimated to be far more capable than usual manufacturing processes [44]. Industry 4.0 gives a boost to computer-integrated manufacturing (CIM), allowing for a more decentralized architecture based on CPN [45]. IoT allows for integrating devices and equipment into the company's information system infrastructure [46]. While Industry 4.0 is based on M2M communication [47], CIM was initially developed with a focus on human employees [48]. This includes self-organized diagnostics and repair requests communicated to machine and equipment suppliers and allowing for smart and intelligent predictive maintenance (SIPM) [49]. Components within the Industry 4.0-framework act as autonomous agents [44]. The transition from usual manufacturing towards smart manufacturing usually passes through the stages of connected (computerization and connectivity), transparent (visibility and transparency), and intelligent (predictive capacity and adaptability) [50].

Rising manufacturing complexity requires information-based technologies working in real time [51]. Concern not only focuses on one department but has to be raised with regard to the whole supply chain and all further processes in the company. Combined with smart logistics that focus on managing and controlling supply chains [52], this leads to smart manufacturing supply chains (SMSCs). SMSCs determine and coordinate production and transportation features, such as quantities and timing, based on real-time data [53]. To resemble the actual state of products and devices, the system applies digital twins [54].

Relying on M2M communication makes data quality and data quantity critical factors for the implementation of smart manufacturing [55]. Big data technologies act as a feeding technology for data-driven analytics in smart manufacturing [56].

The features of big data technologies can be characterized by the features volume, velocity, variety, veracity (data quality), and value [57]. While some sources name only volume, variety, and velocity [58], other sources use value, veracity, and visualization [59]. Anticipating a higher data quantity (volume) and a higher resolution of data (veracity) requires further development in big data technologies [60]. In order to be able to apply big data for manufacturing purposes, data have to be transmitted with a subject-related context for correct interpretation [55]. A study from Günther et al. showed that a continuous restructuring and realignment of processes, data handling, and big data is also required in smart environments [61]. However, today's manufacturing still relies on independent systems connected through various physical and data interfaces [60].

Smart manufacturing reference architectures have been proposed by various authors. Papazoglou et al. developed a reference architecture for automotive industries with a specific automotive sector extension [62]. As manufacturing knowledge is process-bound and product-related, today's settings lack the interrelation of special manufacturing knowledge [63]. A pre-determined interface and query language should respect these interrelations during the retrieval, processing, and distribution of data, information, and knowledge [62]. Another approach is the smart manufacturing systems (SMS) architecture developed for service environments, where components, such as enterprise resource planning (ERP) and supply chain management, are understood as services. Interactions between smart manufacturing and other parts of the company or the supply chain are handled through a business intelligence (BI) tool [64]. For separated company-internal activities, another approach is the integrated CAS system based on standardised data [65].

Other approaches are represented by the smart manufacturing execution system (SMES), focusing on the elimination of machine-to-human and human-to-machine interfaces to retain the existing manufacturing execution system (MES) resources [66]. The MES acts as a centre point for data collection in order to keep the existing structures of the company intact (see Figure 1). A message broker element ensures both-sided communication between the components [67]. A further difference between MESs and SMESs is that MESs focus mostly on management support, while SMESs work in a broader range in supply chains [68]. A service-based SMES approach has been proposed for SMEs using an Android-based interface in order to reduce the widely existing paperwork in these companies [69].

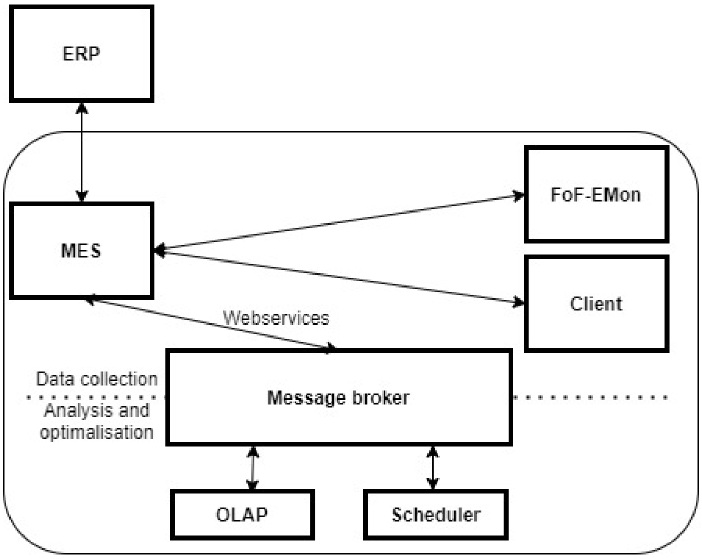

Figure 1. Sample SMES architecture (adapted from [67]).

2.1.2. Smart Production Control

Handling a vast amount of data in smart factories and SMESs requires a control system. It is assumed that previously perceived issues, such as the dilemma of the job shop scheduling problem (JSP), may be solved with the help of new technologies and MAS [70]. Due to the various influences of factors, the JSP is impervious [71]. MAS approaches are able to trigger production and control in a decentralized way, where each agent acts autonomously [72]. Research has been conducted with MAS systems using MES and ERP systems as data hubs [73]. This implies that agents may be found on various levels, such as order fulfilment agents, product agents, machine agents, supervisor agents, coordinator agents, and AI agents [74].

The reference service-oriented architecture (SOA) proposed by Papazoglou et al. places the production scheduling into its centrepoint, as the production schedule contains information on all crucial variables for the company network [62]. All approaches have in common that they work based on real-time data gathered through sensors from the CPN [75]. Auto-identification (Auto-ID) and radio frequency identification (RFID) are expected to allow for complete in-process tracking [76]. The application of these sensors can be applied within the company, as well as in supply chains [50].

While data and prediction models are missing for many situations, AI is applied through machine learning. Research conducted with machine learning approaches for planning and control enabled companies to predict disruptions in supply chains [77]. Deep learning approaches have been found to learn 57 Atari games without prior knowledge of the games [78]. Even though the best results were achieved in model-free environments, real-time scheduling was tested with a reinforcement learning approach [79]. Research studies have been conducted in logistics [80] and in the chemical industry [81].

However, these approaches relied on full information with model-free learning with uncertainty [82]. Management decision support was explored in model-free case studies in investment applications [83]. Due to the complexity of its learning, the application is limited to laboratory case studies [84]. Case studies applying machine learning conducted on the smart production planning and control (smart PPC) model of Oluyisola et al. showed ERP systems to be the centre of smart manufacturing [50], matching with findings from previous research [85].

Chinese research proposed a self-adaptive collaborative control (SCC) mechanism as part of a smart production logistics system [86]. This integrated approach of production and logistics assesses the acquired data with data from the knowledge base in order to retrieve deviations and learning triggers [87]. The control model is applied vertically through the three layers of the smart production, while monitoring is set horizontally. Manufacturing process information is processed by the collaborative control [86].

While large companies tend towards a smart process design, smaller companies may focus more on smart products [50]. An issue for the transition towards smart manufacturing is the existing implication of human resources, which will slowly progress through further-advanced companies [88,89]. Hence, it is questionable whether smart production control approaches are feasible for SMEs.

2.2. Small and Medium-Sized Enterprises (SMEs)

According to the European Commission, small and medium-sized enterprises are defined as companies with a maximum of 250 employees and with a maximum revenue of EUR 50 million. Above these numbers, companies are considered to be large enterprises [90]. While small in number of employees, SMEs account for the vast majority of companies globally in various economies. In Germany, SMEs represent more than 90% of registered companies [91], which is in line with the percentage for the whole European Union. Furthermore, this matches with the structure of Asian economies [92]. Due to the number of enterprises, SMEs employ 60% of all employees in Germany [91].

SMEs are known to face several constraints in human, financial, and technical resources [93]. Due to financial limitations, a South Korean study comes to the conclusion that financial government incentives will help to defeat the lack of finances, as this hinders SMEs in their innovation and development of forces [94], and SMEs seem unable to generate the required financial funds themselves and struggle in acquiring funds from banks [95]. Besides the mentioned constraints, the Organisation for Economic Co-operation and Development (OECD) identified missing managerial capabilities and low productivity as reasons for lacking competitive ability [96]. SMEs therefore seem unable to leverage their smaller size and lower transaction cost to gain competitive advantages [94].

With regard to digital factories and smart manufacturing, research also identified constraints for SMEs in IT [97]. With the integration of various IT systems, IT security is also coming into focus [98], being added into supply chain risk management (SCRM) [99]. Even though LEs are usually well equipped in IT security, SMEs in supply chains represent a threat [100] by opening a backdoor for intruders and malware searching for the knowledge of LEs [101]. Although IT security is considered to have a deciding role for enterprises in the future [102], SMEs seem to hesitate to invest in IT security. This might also explain why SMEs in the logistics industry were found to lack skills in IT competence [52]. A German study found that while LEs are looking for long-term strategies to secure benefits when implementing production planning and control, SMEs are focusing on short-term benefits [103].

While SMEs are struggling with their constraints, research approaches have tried to develop downsized small-scale strategical frameworks, adapted to the reality of these companies [38]. While Mittal et al. found 15 articles on smart manufacturing paradigms in SMEs [93], these approaches lacked taking the reality of SMEs into account. As a result, SMEs do not feel fit for adopting smart manufacturing [104], and managers and owners do not see the benefit for their companies [105]. Hence, Mittal et al.'s own approach is the smart manufacturing adoption framework (Figure 2), based on five stages: (i) identifying already available manufacturing data in the SME, (ii) assessing readiness of the SME, (iii) winning over SME management and staff for smart manufacturing, (iv) developing an individual smart manufacturing vision, and (v) identifying tools and practices needed for realization [106]. SMEs need to develop their own individual tool kit in order to be able to conquer their individual challenges [93]. However, it seems that SMEs lack an understanding of the importance of data [107].

Figure 2. Smart manufacturing adoption framework for SMEs (adapted from [106]).

Publications listed different stages of maturity for smart manufacturing in SMEs. A five-stage model was proposed by Qin et al. (1. single-station automated cells, 2. automated assembly system, 3. flexible manufacturing system, 4. computer-integrated manufacturing (CIM) system, and 5. reconfigurable manufacturing system) [108] and Mittal et al. [109] to assess the development of SMEs towards smart manufacturing. Schumacher et al. instead proposed a maturity index [105]. Another approach suitable for SMEs proposed a three-stage model (1. initial, 2. managed, and 3. defined) [110]. Further approaches have applied up to nine stages of maturity but lack applicability with regard to SMEs [109]. In order to pay attention to SMEs' realities, Weyer et al. suggest adopting a standardized and modular approach to implement only the required components tailor-made for the given company [22].

As SMEs will have to deal with Industry 4.0 and smart manufacturing in the future to stay competitive in the market [111], this paper attempts to develop a downsized and small-scale SMES framework for SME manufacturing companies. This SMES framework will be verified by a case study on a Czech production company.

2.3. Development of the Standardized SMES Framework

According to previous research, the requirements of a particular SME in smart manufacturing may be identified by the smart manufacturing adoption framework for SMEs proposed by Mittal et al. This framework assesses the readiness and requirements of SMEs in five steps: (i) identifying already available manufacturing data in the SME, (ii) assessing readiness of the SME, (iii) winning over SME management and staff for smart manufacturing, (iv) developing an individual smart manufacturing vision, and (v) identifying tools and practices needed for realization [106,109].

Step 1: Identifying already available manufacturing data in the SME.
Smart manufacturing attempts to gather data of a product from all phases of production in order to improve manufacturing processes and products [56]. While smart manufacturing works on an in-depth analysis of the acquired data [112], the results are used for company decision-making processes. Furthermore, data from manufacturing may be used not only within the company but also at the interface of the company with other entities in supply chains [25]. In order to build a system for the data provided by the particular SME, the individual reality, ability, and needs of the SME have to be taken into account. Small-sized companies were found to primarily store their data on local PCs rather than in systems, while in medium-sized companies, a trend towards centralization was observed [113]. These data may be related to the organizational dimensions of (a) finance, (b) people, (c) strategy, (d) process, and (e) product [106].

Step 2: Assessment of readiness of the SME.
According to an Irish study, the format of the gathered data tends to be stable over time and does not depend on the age of the company [113]. With SMEs being known for having individual financial, human, and technical resource constraints [93,96], the level of readiness of the company should be assessed before action [109]. The level of readiness in Industry 4.0 may be assessed by various maturity models and indices (Lin, Wang, and Sheng, 2019a). For SMEs, the assessment of maturity level may be done by the Singapore smart industry readiness index, initially assessing 16 dimensions in the 3 dimensions of process, technology,

and organisation [114]. Mittal et al. extended the application to the mentioned five dimensions [106].

Step 3: Winning over SME management and staff for smart manufacturing.
Human resource constraints have been identified as a characteristics of SMEs [93]. This also includes the management skills of these enterprises [96] that have a crucial impact on their sustainability and long-term performance [115]. Future job profiles are believed to differ widely in their requirements from what workers have to provide today. It is on the managers to already be involved during the design-stage of processes, which has shown to have a positive outcome on the long-term development of the SME, creating a clear job profile for human resources [116]. The transition towards smart manufacturing therefore requires the involvement of SME management and the adoption of a new corporate culture [117] striving for overcoming human resource constraints.

Step 4: Developing an individual smart manufacturing vision.
Due to the realities of SMEs, researchers have come to the conclusion that SMEs are working in a small-scale and downsized environment [38]. Due to the broad bandwidth of these companies and their specialization, the approaches in smart manufacturing should also be tailor-made around a standardized core [22]. Being closely related to the companies' strategic setup, the aim of this step is to boost the level of data from a mere data acquisition to a data distribution, allowing for data-based decision making [106]. Industry 4.0 and smart factories as an approach are striving for making use of a broad base of data gathered, processed, and distributed in order to allow for fast decision making [118].

Step 5: Identifying tools and practices needed for realization.
As with the previous steps, the identification of appropriate tools for the realization of a smart manufacturing and SMES approach is also tailor-made for SMEs according to the given company. A toolkit for smart manufacturing was developed by Kaartinen et al. in [119] and has been adapted for the reality of SMEs by applying a toolkit for transition (Table 1) [93]. The developed toolboxes in the toolkit provide an overview of maturity levels, usually using five maturity levels to characterize the transition status of the SME towards smart manufacturing. Some researchers propose level 0 as the starting point for companies towards smart manufacturing, representing a fully analogue company. The jump from level 0 to level 1 is considered the hardest to overcome for these SMEs [103]. Concerning the step of data processing in the process, the toolbox may be characterized according to Mittal et al., 2019 (Table 1).

Table 1. Smart manufacturing toolboxes corresponding to the data hierarchy steps (adapted from [106]).

	Data Hierarchy Steps			
Smart Manufacturing Toolboxes	**Data Generation**	**Data Transmission**	**Data Storage**	**Data Analysis**
Fabrication/Manufacturing toolbox (FMT)	YES			
Design and simulation toolbox (DST)	YES	YES	YES	YES
Robotics and automation toolbox (RAT)	YES	YES	YES	YES
Sensors and connectivity toolbox (SCT)		YES		
Cloud/Storage toolbox (CST)			YES	YES
Data analytics toolbox (DAT)				YES
Business management tools (BMT)	YES	YES	YES	YES

3. Methodology

The research methodology can be found in Figure 3. The research will be carried out in three steps according to Figure 3 by (a) developing an SMES model architecture for SMEs, (b) carrying out a case study with the proposed model architecture, and (c) applying the results from the case study to adapt the proposed model.

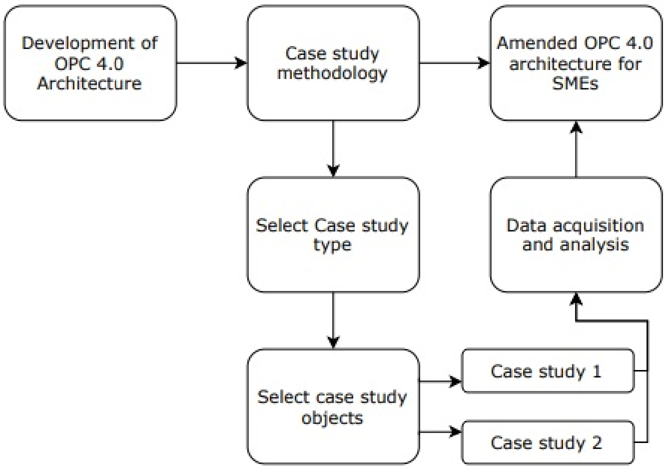

Figure 3. Research methodology.

3.1. *Development of SMES Model Framework*

SMES models try to make use of ERP systems and the existing components of the information system architecture. The information system architecture components are linked through M2M communication. Industry 4.0 and smart concepts are assumed to depend on the quality and quantity of data in the company [55]. While Industry 4.0 approaches suggest big data to deal with a higher amount of data in a higher resolution, data today are still retrieved from various interdependent systems [60]. As companies make use of various systems today, high-level data for management decisions may be found in the ERP and MES system [73], while operative data may be handled in lower-level information systems for operative controlling. In production companies, this refers to the production organization and planning and requires production indicators for input (resource usage) and output (productivity, quality) [120].

Operative controlling is a discipline of controlling that may go into the daily ongoing operations. It has the task of supporting the operative management decisions. These decisions are done quickly with a limited range [121]. The production controlling does not go beyond the production. It is part of the logistic controlling and has interfaces with the procurement controlling and the sales controlling [122]. According to Oluyisola et al., SMEs may be able to focus on smart products to monitor production [50]. Smart products may be equipped with auto-ID or RFID sensors [76].

The required technologies for an operative production controlling architecture were defined by Heimel and Müller [123]. The system requires big data technology, as there are data warehouses or BIs. These systems should be able to provide planned and required data on request within almost real time [124]. Another way to provide these data is the usage of standardisation technologies, such as computer-aided standardisation (CAS). In order to unify and in order to simplify processes on the operative level, the CAS may take over the role of a data warehouse for a specific line. In this case, all required information on standardized technological steps, times, consumptions, etc., is available for the controlling system [125].

Operative production controlling relies on actual values from production. To a certain extent, today, such processes also already exist in production companies. The difference in Industry 4.0 is the quantity of data that has to be retrieved and processed, while SMEs should be able to work with a downsized architecture and downsized data management. While LEs might think about decentralized approaches with immediate correction through agents, SMEs may struggle to make use of the generated data. The whole system works on an actual basis, providing all functions of operative production controlling. As these data are directly consumed for the operative production management, the circle is closed, providing data and feedback.

Making use of the controlling structure of a company, the operative production controlling will be able to process and assess the status of production. The information of planned parameter values may be fed from a standardisation module or system, such as the integrated CAS system [65]. It may contain standardized and thus planned data on any process, such as on time parameters and consumptions and further requirements, including drawings and tool information. By integrating the CAS system into the controlling structure (see Figure 4), the author derived a controlling architecture and named it Operative Production Controlling 4.0 (OPC 4.0). This controlling structure was assumed to work in a particular production line, being fed by big data or CAS and by the APS. The big data or CAS contains the database of existing standards and planned values with which production data are assessed in right time.

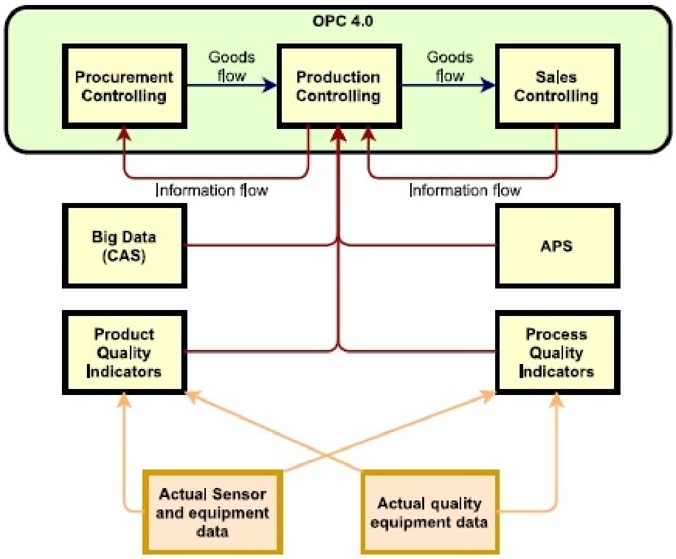

Figure 4. General OPC 4.0 architecture (own processing).

Integrating the OPC 4.0 architecture into SMES allows for the usage of standardized data within the whole framework. According to other SMES frameworks, this framework also makes use of the MES system in its centre. The major difference with regard to proposed SMES frameworks is the additional standardisation module with standardised data feeding the MES and indirectly feeding the advanced planning module. Instead of big data technologies, it makes use of standardised company internal data. The required components already exist. A major difference in this is the elimination of human–machine interfaces for data acquisition, processing, and distribution. The whole architecture consists of M2M interfaces only, allowing for faster retrieval, processing, and full control.

OPC 4.0 works in a closed system within the production line. This system requires several interfaces with other systems and subsystems. These systems include BI, CAS, advanced planning systems (APS), and ERP systems, which are able to provide required data for processing. Depending on the concrete application, these systems may differ. However, the basic logic of the system remains the same.

Such an architecture relying on CAS, APS, and ERP systems is shown in (Figure 5).

As OPC 4.0 is only the operative part of the controlling structure, higher-level controlling functions have to be covered additionally for LEs. Heimel and Müller assume the big data technologies to be a vital part of the strategic controlling [123]. Big data has the ability to consider not only internal standardized information but also information from external sources. Technologies such as text mining retrieve their data from any text found providing information, e.g., for marketing purposes that are required to be timely [126]. However, for an SME, the downsized framework for SMEs will work with a CAS instead of a BI and further big data technologies due to its limited complexity. The CAS contains standard process information for production, maintenance, and further processes. Such downsized architectures are represented by SMES frameworks. For the case study in this paper on a medium-sized company, the OPC 4.0-based SMES architecture, as developed in Figure 5, is used.

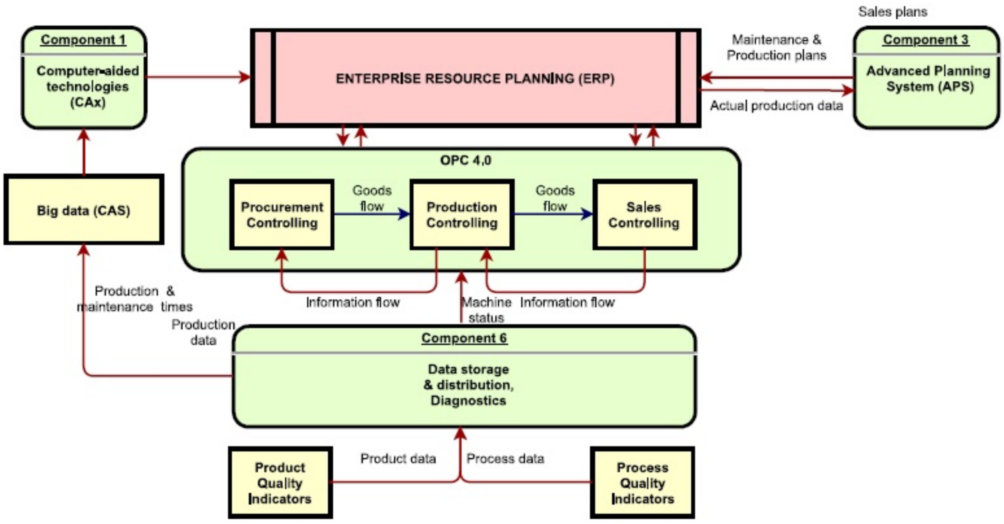

Figure 5. Example of SMES framework based on OPC 4.0 architecture (own processing).

3.2. Validation of the Proposed Framework

This paper makes use of a multiple case study design. There is no agreement on the number of required cases for a case study. Some researchers argue with reference to quantitative methods that there should be a large quantity of data available in order to eliminate interdependencies and the overevaluation of one random parameter. Other researchers argue that even one case study should be valid and enough [127], as long as it is able to go into crucial details [128]. Case studies therefore have the advantage of comparing not only number-based data but also qualitative data with a textual relation [129]. As SMES frameworks are believed to be specific and should even be tailor-made [22], the validation in two different entities, welding and assembly, of one company may provide vital insight into whether complexity and production technology have to be taken into consideration for the proposed SMES framework.

While this case study has been conducted on one company, methods and architectures have been applied to two different organizational entities. These two different entities both underwent a case study based on the developed framework. Hence, while one company is targeted, due to the two entities used, a multiple case study design is applied. The case study is constructed to confirm the validity of a theory, as the theory was built prior to the analysis [130]. Furthermore, the paper makes use of the comparative advantage of case studies within the paper itself [131].

The multiple case study framework should secure the same results from multiple sources [132]. It allows for assessing data from different viewpoints [133] and has been used in research papers of a similar kind recently [106,134,135]. As research of SMEs with respect to smart manufacturing execution systems has been scarce, case studies allow for acquiring knowledge on SMEs in particular fields. As SMEs represent more than 90% of European companies in total, these companies represent a vital component of the Czech economy and the economies of other European countries. With the challenge of the transition towards Industry 4.0 ongoing, these companies are required, due to their limited opportunities resource-wise, to find other ways to survive by staying competitive. This multiple case study should provide an insight into the potential of SMEs to conquer smart manufacturing with a downsized environment.

In order to evaluate and assess the case study, the research has features from the embedded case study framework, such as analysing sub-units [136]. In this case, the paper makes use of two sub-units, one assembly shop and one welding area. However, making use of an application for only a short time period, a multiple case study approach was applied. These approaches were found to have a higher transferability of results to reality than embedded case study approaches [137]. Due to their flexible and tailored nature, case studies may combine qualitative and quantitative methods in design, realisation, and validation [138]. Additionally, in the case presented in this paper, the validation of the case study was done by a set of key performance indicators (KPIs). These KPIs were chosen by the company management based on the current controlling and reporting structure. Thus, while part of the case study is based on qualitative information, such as project phases and amended components, the evaluation of success was done through an approach of a quantitative evaluation of the production KPIs for one week of monitoring. For the further proposal process, qualitative data from expert interviews were gathered.

3.2.1. Acquired Data

The case study acquired data from two entities of a manufacturing and assembly company with regard to the subject of the case study. With the proposed case study SMES architecture on hand, this architecture was realized in the company's welding shop and in the company's assembly line. The selection of tools and practices was left to the company, while the tools were pre-defined due to the existing company information system architecture. The proposed case study SMES architecture was applied in a one-month trial. A step-wise plan was established to understand the stage in which the company understands itself to be in. After the trial, the participants were asked for their impression of the results, where a group of experts decided on the status of the project and its further ongoing development. Hence, the prior plan and the subsequent results were compared, providing the result of the case study and being a trigger for further amendments.

3.2.2. Case Study Description

The company of concern belongs to the Czech manufacturing industry as a machine builder. In this function, it belongs to class 28 of the NACE rev. 2 classification. During the time of monitoring, the company comprised a headcount of 219 to 236 in the organisation scheme. This includes employees of all areas and of all hierarchical levels in six departments. The organisation had a maximum of four hierarchical levels. The shop floor included a machining shop with CNC machines (milling, drilling, lathes), a cutting shop for raw material, a welding area for manual welding, and a paint shop for wet and powder paints. All materials produced in this shop floor go to the assembly shop that works with external and internal material.

With just under 250 employees, the company may be still counted as an SME according to the definition of the European Commission [90]. The company has decided to go into a restructuralisation concerning its information system infrastructure. Furthermore, it assumed that additional changes would happen in the organisation, such as production, logistics, and controlling. With this understanding, it decided to make use of the before-mentioned OPC 4.0-based SMES architecture.

Concerning the technology level of the company, mostly in production, the shop floor uses mainly craftsmanship from human beings (electricians, assembly workers, welders). Machines are only used in the machining shop. In addition, the paint shop relies solely on the skills of the workers. For the restructuralisation, this was not planned to be changed, as the company management had the perception of still not belonging to the big players in the field, focusing on investment and low labour cost much more than on transaction cost.

The initial IT system consisted of an ERP from Sweden, called IFS, that also includes the MES. This system was implemented in the company in the early 2000s. While being modular, it was not able to keep up with the growth of the company in the following years. Despite the global economic crisis in 2009, the company faced steady growth of organisation size and related requirements. This led to the company deciding on a newer version of the existing ERP system, with the target of implementing even further modules.

An important part was the automatic booking of shop floor orders, linking them to a workflow in the system.

According to the booked and finished shop floor orders, other activities should be coordinated, establishing a pull system for leaner production. The module that should help to coordinate and overcome the previous shortcomings was an advanced planning and scheduling (APS) module. This module was meant to substitute excel planning habits with a data-based approach. The result should be a fine planning that directly assesses available capacities, materials, and workplaces. A short overview of the two case study objects is given in Table 2, where 100% of the employees directly dedicated to the given production area were taken into account.

Table 2. Cases in the case study.

Dimension	Case A	Case B
General company information		
Industry	Machine builder	
Ownership	Private	
Number of employees	239	
Manufacturing location	Czech Republic	
Customer location	Europe, mainly Czech Republic	
Yearly turnover	EUR 18 million	
Production step	**Welding**	**Final Assembly**
Number of workplaces	5	20
Number of employees	11	23
Average hourly output	28 parts	0.4 machines
Average no. of components for one unit of output	3.2	267
Number of workplaces a unit of product goes through	1.2	4.7

3.2.3. Conducted Case Study

While the aforementioned approach of an OPC 4.0-based SMES architecture seemed to be designable, this SME required a downsizing of the approach. This downsizing mostly focused on areas where it assumed transaction cost to be lower than the cost for the system. Having 16 computerized numerical control (CNC) machines on the shop floor, it was decided to not equip these with any additional sensors for tracking the process. Furthermore, these CNC machines were not connected to the company network in the first step. The booking of orders was done on a separate terminal as a workaround. A cyber-physical system was not considered.

As the ERP system ought to be the heart of the architecture, the system requires exact data on a frequent basis. While real-time data in the required volume could not yet be realized, all data have to be stored in a tailor-made CAS system. This system should be filled with all standardized data available: manufacturing data for each machine, required tools, maintenance data and tools, and the required process times had to be entered and used carefully. An issue found in this area was the case of insufficient knowledge, standardisation, and standardized data, mostly for auxiliary processes.

In order to meet the financial and organisational possibilities of the SME, the project had to be downsized, meeting the reality of the company. The five steps identified for a downsized and amended environment may be found in Table 3.

The ERP system incorporated data from several years and from different processes, as well as from outdated and already eliminated processes. While the new system had already been implemented, in trying to copy the structure of the previous version, data was only copied. Thus, before adding shop floor terminals for the production booking and the further tracking of production, all data that were corrupt and not needed had to be removed.

Table 3. Overview of project phases in the case study.

#	Item	Actual Status
1	ERP system upgrade	Upgrade to current actual version from same supplier Clean-up of database entries Migration of database
2	Shop floor terminals	Purchase of shop floor terminals for confirmation of production order finishing Training of personnel
3	Standardisation of activities	Standardisation of main process activities Standardisation of auxiliary and service activities Establishing of database for migration
4	Implementation of CAS module	Definition of tailor-made CAS module Implementation of CAS module into ERP system Interface with ERP system
5	Implementation of autonomous controlling structure	Assessment of plan versus actual Alert to shop floor leader, in case of deviation
6	Filling of CAS database with further shop floor data	New data from production New data from maintenance New data from internal logistics
7	Connecting of machines and devices into network	New data from production New data from maintenance New data from internal logistics

The standardisation of activities was done with the help of work sampling. With the work sampling, the general characteristics of a given process or activity may be monitored [139]. During this, the activities were monitored in two independent areas: (a) for the welding line and (b) for the assembly line. The major output characteristic during standardisation for the company was understood to be the time standard. However, the standardisation of activities may also provide data on further required inputs for the given processes, such as tools and materials [125]. The gathered data were used as input for the CAS. With the implementation of the CAS module, the module was then filled with the gathered data from the work sampling. The data of the work sampling were taken as input.

The fifth step was to implement the autonomous controlling structure for the two analysed cases. The new controlling module had to have logic relations with the APS module for advanced planning and with the execution module. Based on the individual requirements of the company, managers of different levels then determined performance indicators to be tracked in the case study. These performance indicators were the same as the KPIs already reported to management prior to the case study. For the case study, the company management decided to have a maximum of 10 indicators to be tracked and compared for evaluation, such as the inventory level, station idle time, and efficiency.

While the provided case study steps are the same for welding workplaces and for the assembly line, these two areas also have similarities in their characteristics. Data-wise, both lines transfer a set of inputs (usually at least two parts) into one product. However, the difference is in mostly in the number of inputs that have to be processed to meet one product. Furthermore, the number of workplaces that one product goes through in a production line is higher than for a component in the production line.

3.2.4. Case Study Analysis

Trying to implement the proposed framework, the company had to downsize several components of the original OPC 4.0-based SMES architecture (Figure 5) in order to make it compatible. In a gradual approach, the company conquered the first six steps. A difference was found between the assembly line and the welding line as far as step 7 is concerned. Due to the assembly of several parts into one machine by more than one worker, the smallest details of the process cannot yet be tracked cost-efficiently. As this production line differs significantly from the production line in LEs with a short production tact, the steps are huge. A digital twin would have to copy this complexity. The amount of data that is assessed by the system is still date limited. The welding line had automatic welding equipment that was, by default, able to provide data on the welding process that can be stored in databases.

The system retrieves information on the production times and the production lots reacting flexibly to the current logistic and production settings. The cyber-physical network including sensors was only done in (a) a test on two machines and (b) a simulation. The test (a) was conducted with one CNC machine that had an additional testing set of vibration sensors. Furthermore, the welding equipment was directly connected to the company network, being able to give direct information on the parameters. As, for the moment, the welding process is still manual, the feedback data were used for assessing the quality of the process. Deviations in the feedback parameters led to a direct exclusion of the product from the further production flow. The products were re-checked manually in order to obtain knowledge on what these parameters may indicate. This evaluation is an ongoing process of production fine-tuning.

The mentioned simulation of the production equipment was limited to artificially created signals that the system interpreted as coming from the production equipment in the moment of checking. The control mechanisms were checked for a potential future development. While the simulation of the sensors and the operation of the system were successful, the automatic circle of the OPC 4.0-based SMES architecture worked as required. The amendments and tests conducted may be found in Table 4.

Table 4. Amended components due to the case study SME framework.

#	Item	Actual Status
1	ERP system upgrade	Upgrade Remaining system supplier
2	Shop floor terminals	A few shop floor terminals instead of machine terminals No connection to machines
3	Standardisation of activities	Standardisation of main process activities Standardisation of auxiliary and service activities to be added during operation Database prepared for CAS module
4	Implementation of CAS module	CAS module starting only with standard work times Standard procedures, process, and drawings to be implemented at later stage
5	Implementation of autonomous controlling structure	Actual: Not all data assessed, prioritisation by shop floor or area leader Test-run and dry test with automatic sensor feedback realized
6	Filling of CAS database with further shop floor data	Ongoing Only time-data filled Further process data neglected
7	Connecting of machines and devices into cyber-physical network	Test-run conducted Dry-test run conducted, basic routines implemented, amendable Used in welding device Too expensive for CNC devices at the moment Assembly process too complex to be tracked with smart devices or with smart products

Due to the possibilities of the IoT and the current situation of the company, the company allowed itself to take a first test for future development. With the assumed future development of IoT, the company seemed to be able to include the cyber-physical network into their system. Whether the preparations and tests done in this study would still be valid in the future depends on the development of these technologies.

The element implemented from the last stage of the project is the welding area. The welding devices were able to monitor parameters and to compare them to the optimal parameters by default. Hence, the welding equipment was able to send a feedback signal on whether the aggregated sensor states were as planned or not. For CNC machines, the process should be implementable, as a short simulation showed. The simulation was needed, as the CNC machines are usually not equipped with sensors and able to track all required parameters.

As Table 5 shows, the assembly line still remains an issue for the company, while the welding line made up for a lot as far as rework, scrap rate, and efficiency are concerned. With the help of parameter-based standardisation of the welding equipment, the company was able to reduce rework and to increase the output of the welding line, while maintenance indicators did not show any relevant changes during the case study. Further indicators, such as worker idle times and efficiency, show positive tendencies. In an interview, the shop floor leader proposed that the increased efficiency should come mainly from the reduction in rework.

Table 5. Overview of key performance indicators—values in percent.

#	KPI	Before Value	After Value	Percentage of Fulfilment
	Welding Line			
1	Number of produced pieces (per hour)	28	33	118%
2	Equipment availability	88%	103%	118%
3	Efficiency	1.22	1.43	118%
4	Downtime	17%	15%	88%
5	Worker idle time	3%	3%	100%
6	Rework rate	15%	8%	53%
7	Scrap rate	9%	7%	78%
8	Equipment maintenance and repair time	4%	3%	75%
9	Number of equipment breakdowns	4	4	100%
	Assembly line			
1	Number of produced pieces (per hour)	0.4	0.6	150%
2	Equipment availability	80%	120%	150%
3	Efficiency	3.2	4.8	150%
4	Downtime	9%	5%	56%
5	Worker idle time	13%	11%	85%
6	Rework rate	87%	32%	36%
7	Scrap rate	0	0	N/A
8	Equipment maintenance time	1%	2%	200%
9	Number of equipment breakdowns	3	4	133%

The assembly line shows more difficulties. Due to its higher quantity of components and its higher complexity, the assembly process lagged behind the improvements monitored in the welding line. The assembly line showed only a moderate increase in the produced pieces, while the number of machines to be reworked decreased by 64%. However, during the case study, the company was not able to rapidly increase the efficiency of the assembly line. Thus, it seemed that the assembly line lagged behind in performance compared to the welding line in the company. However, the numbers also suggested a positive trend for the assembly line.

3.3. Improvement of the Proposed Framework

According to the findings of the case study, SME frameworks will require a substitution of big data software. The company should focus on a standardisation system, either independently or as an ERP module. This system provides the database for comparison with the actual state. The architecture amended for the SME in the current time may be found in Figure 6.

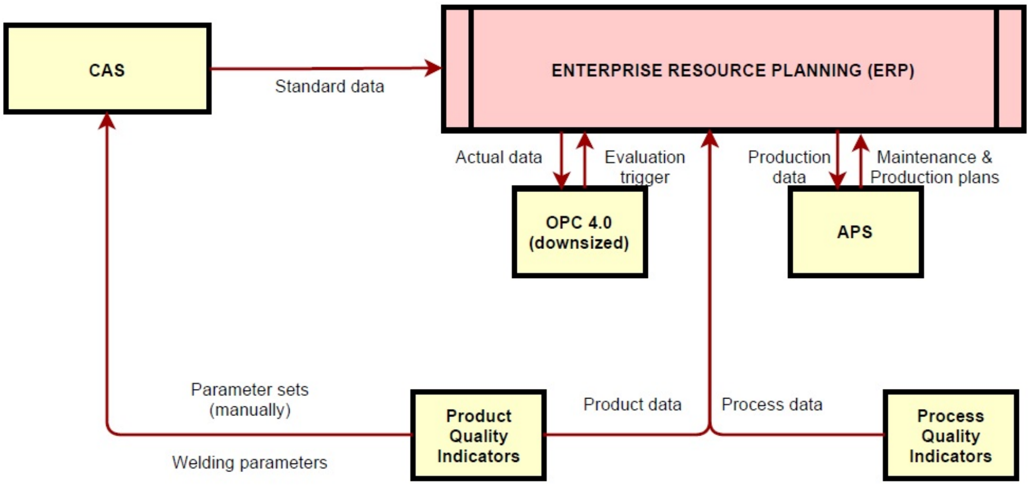

Figure 6. Case study architecture, including OPC 4.0 module.

At the moment, the analysed SME does not have a viable database and needs to focus on vaster data-acquisition activity for a further implementation of an SMES approach with an OPC 4.0 framework. While the underlying basics of the OPC 4.0 architecture were implemented, the downsizing of the architecture implemented CAS and OPC 4.0 as modules into the ERP system. The ERP system itself remained the core of the architecture. The basic thought of a direct feedback and controlling loop was only implemented for the welding equipment, as it was an internal default function of the equipment that could be activated.

3.4. Results and Discussion

The architecture and components for OPC 4.0 already exist today. The investment into a fully autonomous production line that is self-learning and self-correcting is cost-intensive. SMEs, with their financial constraints, are usually not able to invest into such an environment. This is why ERP-based SMES approaches were invented. The presented approach is based on the existing controlling structure of the SME. According to Abée et al., Controlling 4.0 is a process of trial-and-error where immediate positive results should not be expected [140].

Results show that equipment able to provide viable data on a manufacturing process may boost quality and reduce manufacturing and logistic cost by an early detection of errors. With a working APS, the system can adapt quickly to the errors and to the new circumstances. While research on the applicability of smart manufacturing approaches in SMEs is rare, the authors realized the importance of separating approaches for LEs and SMEs, also requiring an individual toolkit [93]. SMES approaches have shown the potential to work in SME environments [106]. Other approaches in the literature have only come to a simulation stage or to a case study of a prototype manufacturing environment [67].

According to the findings of previous research, SMEs are focusing on fast benefits and returns on investment [103]. In addition, the managers of the herein-mentioned case study company seemed to have a different understanding of the needs than their experts in production. While the initial framework was developed based on managerial input, the second, improved framework allowed for expert input in order to eliminate the shortcoming of the first version. The ex-post evaluation found a certain management myopia by focusing mostly on finances and reporting. Long-term strategies, such as the transition of a company towards smart principles, can therefore only be met with downsized frameworks [38]. In order to stay on the market, SMEs will also have to deal with smart approaches and principles [111]. While the proposed approach does not meet all principles yet, it fit the actual reality of the company in the case study. Approaches on MAS are far-fetched for SMEs, and the JSP is an apparent conflict in SMEs. As in previous research studies [50,85], the ERP with the included MES may be assumed to play a crucial role as the centre of the SMES architecture.

The proposed approach was built on the company's current controlling structure. While research was done on smart production control in the past, the human interaction was seen as a conflicting element that should be eliminated [88,89]. SMEs show a currently high extent of human participation in processes, such as in the assembly area in the case study. In the case study company, this could not be overcome easily by smart products, as Oluyisola et al. suggested [50], due to the high number of components contributing to one assembly step. The complexity of these steps combined with manual work provides obstacles for an introduction of smart principles. Less complex assembly steps, such as the welding process, show that the fundamentals may be implemented and work in SME assembly as well.

4. Conclusions

This research paper attempts to propose a smart manufacturing architecture for SMEs. There are only a few papers dealing with this topic to date. Building on previous SMES approaches that put the MES system at the centre of the architecture, the proposed architecture showed its feasibility for SMEs with the ERP including the MES. However, it also showed shortcomings in cases of increased complexity, standing in conflict with the persistent financial constraints that SMEs have to deal with. As components such as the ERP, MES, and APS are available and also used in SMEs today, the financial burden may not be as high as a completely new investment. Making use of already existing or easily retrievable data within the company should be secured by a system or module that substitutes a BI. These data might be stored in a CAS or in a similar system. The case study suggests that obstacles may be found in activities with a high degree of manual work and human implication.

While the provided OPC 4.0-based SMES architecture is the framework outcome in this case study done in one SME with two production entities, the framework should be further validated and researched in other SMEs. As there are only a few papers available on this topic, also usually in the form of case studies on production companies, e.g., [106,134,135], the proposed SMES frameworks have only been applied and scientifically monitored in a small number of cases. Qualitative research through case studies goes into detail more than striving for generalizability based on quantitative data [128,129]. However, the case study shows that SMEs have issues in the full monitoring and tracking of production in the assembly area, due to its increased complexity and human work. An area for future research is the applicability of the OPC 4.0-based SMES architecture to different production areas and to different industries. While the OPC 4.0-based SMES architecture is assumed to be suitable for the production area, it is a question of whether there will be further application in other areas and industries.

Future research should further investigate whether the proposed approach in particular and SMES frameworks in general are suitable for all subcategories of SMEs. These three subcategories according to the European Commission (micro, small, medium-sized) [90] might show differences in their behaviour, in their organization, in their complexity, and in their way of approaching SMESs. While assuming the further development of cyber-physical network technology and the IoT in the coming years, the exact outlines of the architecture in SMEs and LEs have to be further monitored in practice. It is a question of whether the described OPC 4.0-based SMES architecture would also be able to suite LEs.

It remains to be seen in future research and development whether SMEs will be able to survive with SMES architectures by avoiding cyber-physical networks and more sophisticated IoT technologies. While Kotler assumes SMEs to have a wider range of opportunities in Industry 4.0 by eliminating their disadvantages in comparison with LEs [141], current established SMEs are assumed to take small steps. Research suggests that companies will have to move to new technologies to stay competitive on the market. However, it remains unclear how SMEs will conquer this challenge. The presented approach in this paper may provide an SME architecture for a transition towards smart manufacturing based on production controlling. However, it is questionable whether this approach will secure long-term competitive abilities and how SMEs will climb the next maturity levels towards smart manufacturing.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
APS	Advanced planning and scheduling
Auto-ID	Auto-identification
BI	Business intelligence
BMT	Business management tools
CAS	Computer-aided standardisation
CIM	Computer-integrated manufacturing
CNC	Computerized numerical control
CPN	Cyber-physical network
CST	Cloud/Storage toolbox
DAT	Data analytics toolbox
DST	Design and simulation toolbox
ERP	Enterprise resource planning
FMT	Fabrication/Manufacturing toolbox
IoT	Internet of things
IT	Information technology
JSP	Job shop scheduling problem
KPI	Key performance indicator
LE	Large enterprises
M2M	Machine-to-machine
MAS	Multi-agent system
MES	Manufacturing execution system
OECD	Organisation for Economic Co-operation and Development
OPC	Operational production controlling
RAT	Robotics and automation toolbox
RFID	Radio frequency identification
SCC	Self-adaptive collaborative control
SCM	Supply chain management
SCRM	Supply chain risk management
SCT	Sensors and connectivity toolbox
SIPM	Smart and intelligent predictive maintenance
smart PPC	Smart production planning and control
SME	Small and medium-sized enterprises
SMES	Smart manufacturing execution system
SMS	Smart manufacturing systems
SMSC	Smart manufacturing supply chains
SOA	Service-oriented architecture

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