The digital twin of a smart learning-factory

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Abstract

During a project involving more than 50 SMEs it became evident that the communication gap between researchers, automation experts and SMEs is real.
This paper presents how a Smart Learning Factory with an accompanying Digital Twin can enable university researchers, SMEs and automation integrators, to co-develop highly innovative and powerful manufacturing setups, that fits the diverse needs of the SMEs. The unique aspect of this research is the digital twinning between Digital Twin and a scale model of the real world, providing a sandbox between the real-world manufacturing setup and the Digital Twin. Hence, an opportunity of fast risk-free testing.

Keywords: Smart Factory, Digital twins, Learning factory

Introduction
Smart manufacturing technologies and digitalization are on most global companies' agenda and many companies not least SMEs are struggling how to make effective use of the upcoming technologies to form systems that are reactive to market needs (Hansen, 2016; Faller & Feldmüller, 2015). Digital Twin (DT) is emerging as a functional system for continuous process optimization by integrating physical production systems with digital copies(Vachálek et al., 2017). The idea of digital twins with regards to manufacturing engineering finds its roots with the "SIMCON" project presented at the Technical University of Denmark in year 1991 (Bilberg & Alting, 1991). The concept is largely compliant with the later definitions of Digital Twin (Negri et al., 2017) (Rosen et al., 2015) (Tuegel et al., 2011) that emerged at the outset of Smart Manufacturing era. For manufacturing sciences, the concept of digital twin is agreed as an evolvable virtual copy of a physical system that mirrors the dynamic behavior of the real system thus enabling various assessments and analysis (Uhlemann et al., 2017; Um et al., 2017).

Practitioners and scholars describe how physical systems and Learning Factories, that showcases I4.0, can help companies understand new manufacturing technologies (Prinz et al., 2016; Faller & Feldmüller, 2015; Abele et al., 2015; Kagermann et al., 2013). Several companies and universities have built different setups, as an attempt to accommodate the need for showcases (Abele et al., 2015). These systems are indeed functional and displays the technologies, but currently most showcases are built to be actual manufacturing systems, this makes them rather product specific and, unless a company operate in the same industry, the technologies in use can be hard to relate to in a specific company context. So even though the systems answer what I4.0 manufacturing can look like, the question "what can I4.0 look like in my manufacturing company" is still to be answered.

Our approach to answering the question was to build a modular physical scale model of a factory floor (Smart Learning Factory), where companies can map their production and build in technologies from I4.0, to see what the benefits of the technologies can look like in their company. Further a digital twin of the physical setup in the Smart Learning Factory was developed to simulate and thereby evaluate the performance of the layout. The Digital Twin is connected to the sensors and actuators in the model, and displays the performance, possible errors and remedy suggestions, on a dashboard.

This paper presents:

- A physical smart learning factory for IoT and modularization
- A digital copy of the smart learning factory (Digital Twin)

Digital Twins for manufacturing control

A prototype of a physical system mirroring the real-time operating conditions of a physical system is a twin (Rosen et al., 2015). The digital part can be utilized to assess the performance of the physical system, make predictions and apply logics to make the system responsive and intelligent. This concept of digital twinning evolved from a physical twin developed in NASA's Apollo program consisting of two identical space vehicles. During the mission, one vehicle went up to the space while the other vehicle remained on ground mirroring the flight conditions enabling the ground experts to better assist astronauts in space. Later, (Kahlen et al., 2016) presented a different approach to the concept of DT at University of Michigan for product lifecycle management with the idea that a system can be viewed as a subset of two systems. One system is a physical system while the other is a virtual system but contains all the information of the physical system. In manufacturing context the DT concept for manufacturing control was presented by (Bilberg & Alting, 1991) as "SIMCON" project to describe a two-way communication of a physical production system with virtual simulations that can enable control logics for production control. This approach realizes digital simulations as an integral part of the lifecycle of the production system. A comprehensive definition of DT was presented by Grieves (Kahlen et al., 2016) to design, test, build and use a digital informational construct of a physical system.

Learning factories for transfer of knowledge

For the present study, we use the term of Learning Factory to denote to a physical learning environment with realistic production processes. The developed learning factory can effectively be used for experimentation, teaching and knowledge dissemination. Learning environments are an excellent tool for transferring of knowledge and results produced in academic environments can effectively be transferred to industry (Wagner et al., 2012). The usefulness of learning factories has been discussed by various researchers (Uhlemann et al., 2017) to help familiarize the participants with implementation effort and the potential advantages of complex systems. The learning factory can help companies also SMEs to gain an overview of the shop floor enablers with dynamic visualization and digital production planning. In the context of Digital Twins the learning factory helps a company to adapt to flexibility, scalability and service oriented digitalization (Uhlemann et al., 2017). It can provide a sandbox for fast prototyping and flexible production where experiments can be performed virtually as well as physically in the Smart Learning Factory, where these will operate as digital twins. The Smart Learning Factory will contribute with a framework from design, build and testing before final implementation in the production.

This paper focuses mainly on a learning factory for the Digital Twin concept which comprises other focus areas of Industry 4.0 research domain such as IoT and simulations. In our research, we consider the fact that in the past decade the knowledge is being developed at a considerable fast pace in design, development and control of manufacturing systems. For this reason, a developed learning environment may get obsolete or not covering the most modern concepts within years. Therefore, the smart learning factory is developed out of LEGO bricks and LittleBits. Both kinds off objects have been demonstrated in various studies for developing changeable and reconfigurable structures. The use of LittleBits can make the LEGO bricks as mechatronic systems. LittleBits is an open source library of discreet electronic components pre-assembled in tiny circuit boards (Bdeir, 2009) Based on the modularization concept, similar to LEGO, LittleBits are electronic bricks with simple, intuitive, space sensitive blocks. By snapping small magnets of each block LittleBits can be joined to form complex structures. Similarly, they can be combined with other materials e.g. LEGO to form complex mechatronic systems. The maximum size of each module is 2cm x 3cm x 6cm and each module consists of two magnet connectors on two opposing edges. The platform takes care of the basic issues such as polarity and validation making it impossible for the user to connect two modules in the wrong way (Chan et al., 2013).

The term of Learning Factory is composed of two words Learning and Factory and hence it must denote to a system that highlights the features of both i.e. it must have a learning or teaching aspect and a production aspect (Abele et al., 2015). As opposed to teaching, the term learning emphasizes the notion of experimentation or learning by doing which results in greater knowledge retention than traditional methods of lecture.

Concept description

The proposed setup consists of a digital copy of a physical system, where the physical system is a real-world model of a factory with electronics and sensors. The factory layout and processes are developed in collaboration with a company to mimic their actual manufacturing setup (see figure 1). The virtual twin is developed as a discrete event based simulation model. The process of (re)developing a production scenario will start with a simulator to make a first impression of the proposed production scheme thus forming a rough layout and logic. This is further refined by optimization of the logic to develop a detailed and optimized model specification. At this stage, the model is converted to a control program and is tested against the physical system. The sensor output and observations from the test run in the physical system are transferred to the simulation and after the necessary optimizations they form a complete control program. This refined control program is then implemented in the Smart Learning Factory. However, during operation the physical system is continuously monitored and real-time behavior syncing is realized to compare the estimated and actual behavior. If a variation is observed the system can present its possible effect and can suggest solutions to regain the desired operational behavior.

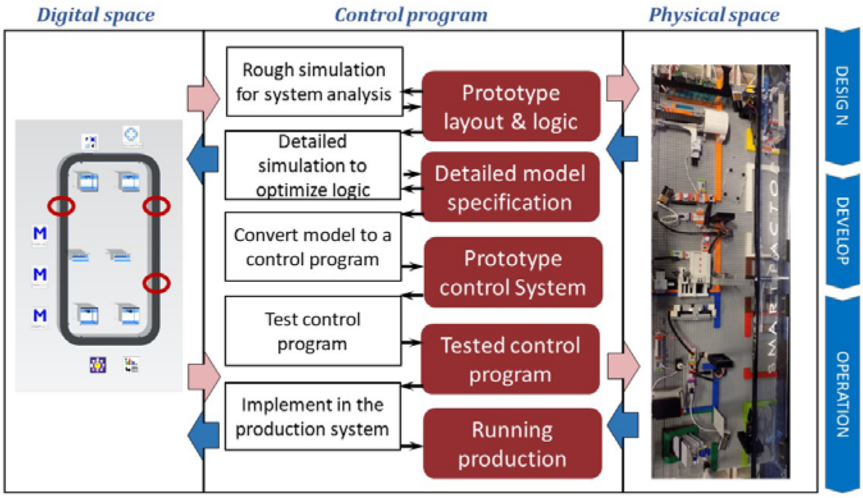

Figure 1 The Data and Information flow in the Smart Learning Factory

Sensor data from the machinery, materials and tracking devices are processed by microcontrollers and PLCs which forward the partly refined data to a data hub called Smart Interconnect Access platform (SIA). The data acquisition from the physical space involves collecting the volatile data (Uhlemann et al., 2017) that consists of motion of employees, flow of material, time of production and utilized capacity. The system represents the operational activities of a production facility e.g. utilization of resources, fault diagnostics, layout optimization and provide traceability. To get insights into the processed data the user should log into a cloud service where a web based interface provides an itemized overview in a dashboard. The above description of the modular smart learning factory represents the physical space for the digital twinning. To form the digital space the event based simulation tool Tecnomatix Plant Simulation is used.

The Smart Learning Factory in use

In general SMEs are different compared to Global Enterprises (GE), they do not share the same challenges (Grube et al., 2017) and their manufacturing system is different to the core (Brunoe et al., 2017). When evaluating the role of DT, Negri et al. (2017) implies that the DT concept will have different usage for different manufacturing setups, in GEs the DT can help in the entire production system lifetime, from design over engineering to manufacturing and disposal. Whereas in SMEs the DT will be better suited for elevating performance in production and operations. The Smart Learning Factory accompanying the DT helps SMEs to better understand the technologies of the fourth industrial revolution, and especially it helps understanding less tangible technologies such as simulation. The value for the SMEs is to gain an overview of the shop floor enabling better operations and production planning. But to reap the positive impact of DT the SMEs will have to be able to understand some of the underlying technologies, and the usage, this has been the main obstacle for the research group when approaching SMEs. Hence the Smart Learning Factory (see figure 2) was developed, to make the digital world more tangible. The current layout in the scale model is a Danish sheet metal processing factory, with models of the actual machines and processes. In figure 2 the setup that laid the foundation for this research is depicted

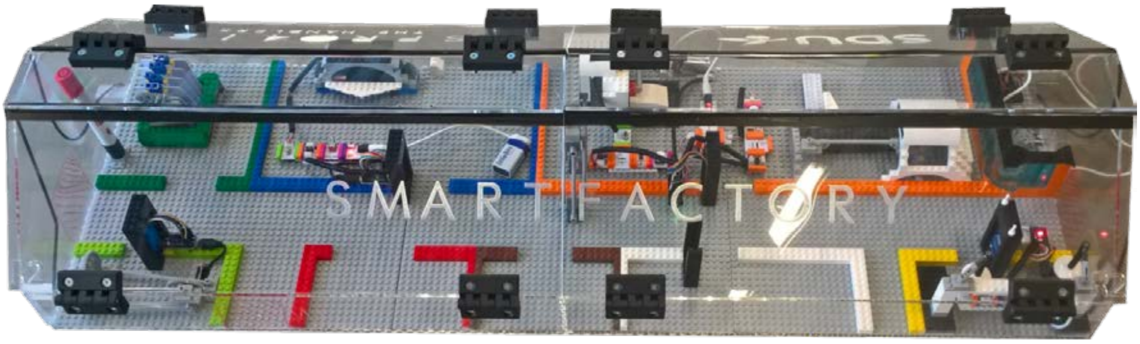

Figure 2 The physical part of the Smart Learning Factory

When we are working with companies we “play” with both the digitally augmented components and the pure physical bricks, to be able to mimic both the layout of the factory floor, and to map material flows, human behavior, and the processing times. The developed framework for the Smart Learning Factory is followed throughout the workshop.

A specific manufacturing SME enters the Smart Factory Lab, where we start out with trying some of the enabling technologies from I4.0, such as Virtual Reality, Augmented Reality, simulation and cobots among others, we strive to make the presentation of the enablers as company specific as possible. The introductory tour through the technological enablers ends at the Smart Learning Factory, at this point the shop floor is empty. Together with the company we map their existing factory layout and discuss and understand their major challenges for how to improve productivity and flexibility. The layout mapping lay ground for a discussion of the control system, how a regular order path can look, and the material flow through the factory.

The layout of the factory floor and location of the machinery is roughly simulated in the digital twin and a set of test runs provide feedback to the physical model where the layout is changed to fit the proposed setup (see figure 1). Now the logic is built into the physical model with LittleBits, RFID readers and preprogrammed Arduinos, the logics connects automatically, through the SIA platform, to the digital twin and enable physical simulation where materials and machines are monitored in real time. Employees from the company now starts to “play” with monitored LEGO men carrying tagged materials, to produce valuable data to the digital twin. Before the final layout is closing in, a in depth discussion on automation possibilities is taking place, here we discuss IoT, Collaborative robots, autonomous robots etc. in the context of the specific SME. Often, we have automation integrators in the loop in such discussions, to elevate the likelihood of providing actual automation solutions. The outcome of the discussion is mapped in the Smart Learning Factory and in the digital twin. A virtual tour in the proposed factory enables the SME of seeing possible places for improvement, and if any, the specific process can undergo process simulation. Now we can run digital simulation on the overall manufacturing system, and see whether the proposed automation, control system and layout will pay off.

The physical part

The physical part of the Smart Learning Factory is highly modular and can be easily reconfigured to fit the layout of many factory floors, as can be seen in figure 2 the flooring is made of LEGO bricks, and all the electronics that have been built into the model adheres to the LEGO building standard. RFID readers are mounted in 3d printed LEGO compatible mounts and can easily be moved around in the factory. The Arduinos are fitted on LEGO bricks and can seamlessly be positioned with the correct proximity to the RFID readers. LittleBits are in their nature made compatible with LEGO and the more than 50 different electronic bits yield virtually endless combinations, further some of the bits are programable, yielding even more opportunities to mimic the actual factory floor. All the hardwiring goes through small holes in the flooring and towards the SIA platform in the upper right corner where all the external connections exits. Most of the data transmission happens wirelessly.

The digital part

The digital part of the physical smart learning factory is developed using Tecnomatix Plant Simulation tool developed by Siemens. It is a discrete event based simulation program. The digital copy of the physical system is reflecting the processing times and sequence of operations of the physical system. In this case a company with 30 employees, operating as a sub-supplier of High Mix-Low Volume (HMLV) sheet metal products for various purposes. The processes include laser cutting, bending, where most of the processes are semi-automated. By having a digital model see figure 3, even without a real-time connectivity with the physical system many experimentations are possible. The digital system can make assessments during the design phase of the production system particularly in layout planning and once the system is developed it can, by simulation, make analysis for the utilization of resources, uptime and downtimes, excessive resources, and can define control logics. With the advancement of information and communication technologies (ICT) and internet of things (IoT) a real-time connection greatly enhances the assessment and control of the physical system.

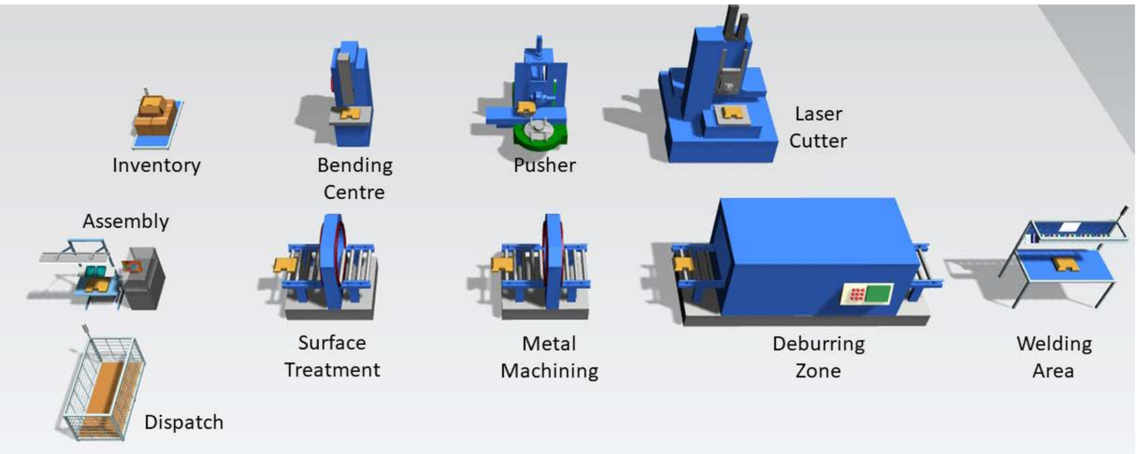

Figure 3 The digital twin in simulation

Data flow:

The physical model generates data from a variety of different sources, the different data sources and refined information flows are depicted in figure 4. Blue arrows indicate raw data while orange arrows represent information.

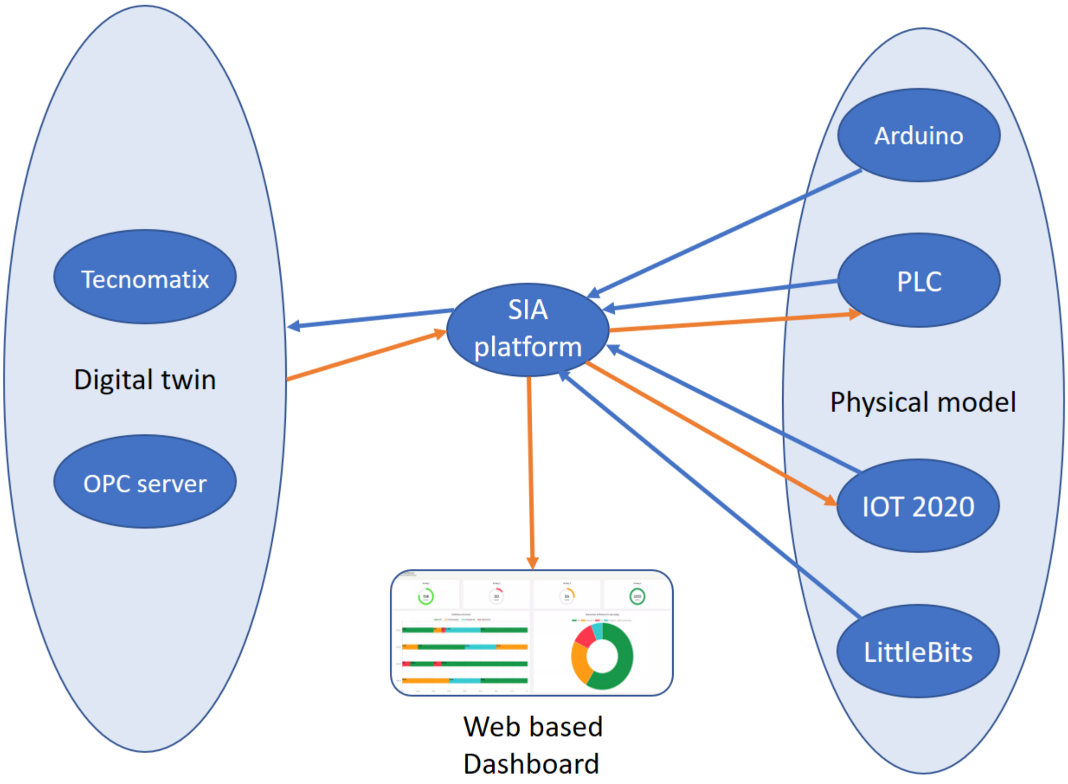

Figure 4 Data Flow in the Smart Learning Factory

The Arduino works as an interim between the RFID readers and the SIA platform, and generates data on the movement of materials and employees in the production. The Siemens S1200 PLC gathers machine data, and acts as the communication channel between machine performance and the SIA platform. LittleBits are configured during the physical simulation process to measure and actuate different parameters and processes respectively, in the current physical setup, they generate data on how the employees work with the machines, whether the machine is running fully automated or under supervision by the employee. The SIA platform is gathering data from the above-mentioned data sources it is APP based and can communicate with more or less anything as long as a specific APP for the communication channel is specified. The SIA platform further has a build in function that can be setup to function as a data filter, monitoring overall data but only process and log data that is within specified limits such as a specified voltage deadban or values surpassing a given bit/byte threshold etc. Most of the filtered data is forwarded to the digital twin in Tecnomatix, though some of the data is processed, directly in the SIA platform, and turned into information which is then displayed in the web based dashboard. The unprocessed data that is forwarded to Tecnomatix simulation, through an OPC server, is tested in the digital twin to verify whether the physical system performs equally to the simulation. If major deviations are identified the SIA platform will present possible affects and suggest solutions to regain the desired operational behavior. Some prior specified input/output in the Siemens S1200 PLC can be controlled from Tecnomatix directly through the SIA platform and thereby the system can perform self-remedy if the safety precautions have been met.

Conclusion

SMEs very seldom have a dedicated department or employees dealing with technology and other I4.0 related matters. It is found that the learning factory and the digital twin will benefit SMEs getting insight and use of upcoming digitalization technologies that may result in innovative and even disruptive solutions in their companies. In the learning factory the companies can perform experiments and by the DT test out technologies. This has proven to not only enlighten SMEs technologically, but also enable the SMEs of understanding the possibilities and potentials in their specific company. One of the main reasons for the success of the Smart Learning Factory, with the accompanying DT, is that the physical part enables SMEs to convey their challenges and current setup, in an understandable way for university researchers. Yielding that researchers understand what happens at the factory level, also called Gemba in lean language, enabling bringing the newest knowledge from the universities in play in an understandable way for the experts close to the process. Thus, enabling highly innovative solutions that are developed in collaboration between SMEs and the university. This link between universities and SMEs provide a mutual augmented understanding which lead to tailor made solutions for the SME. This is of great importance because of the diversity in the landscape of SMEs both in terms of products, production, business model etc.

The solutions for the SMES are the so called lean automation solutions, meaning it is automation in collaboration with humans. Here it is very important that solutions are working and are super flexible in collaboration with the humans. Productivity comes by higher level of automation, flexibility often comes from the humans or perhaps collaboration between machines and humans.

Future Research

In the near future, we will test the Smart Learning Lab further, through working with more SMEs in a project called AutomationBoost, to test how the framework, procedure and tools work in practice in various manufacturing SMEs. We are also working on automating the layout mapping from the physical part to the DT, speeding up the process of mapping and seeing the results of different layouts.

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