Future of PV production: Impact of digitalization and self-learning concepts on wafer, solar cell and module production

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Abstract
Many of today's crystalline silicon (c-Si) PV production plants produce high-efficiency cells and modules on multi-GW scales. As the ratio of highly skilled development staff to production volumes decreases, there is greater demand for automation and production control, which will ultimately yield a higher return of investment in the form of better efficiency distributions, higher yield and improved equipment uptime. There are many feasible incremental improvements as a fab with a minimal degree of process control shifts towards sophisticated automation. An important Industry 4.0 concept is the *digital twin*, the detailed mapping of process and systems to physical and statistical models that will enable high-level optimizations for production and minimize maintenance downtime. Another concept developed at ISC Konstanz is *FlexFab*, which allows different cell types to be produced in one production line, with automatic scheduling according to demand. This paper explains how these modern production concepts are implemented in ISC's lab, and details the plans for their utilization in future production sites, with illustrations of the key benefits in practice. With these modern manufacturing concepts, it will even be possible to bring future c-Si PV production back to the EU with the choice of an appropriate cell concept (high efficiency but proven technology, e.g. interdigitated back-contact (IBC) cells, such as ZEBRA) and a sound business plan.

Introduction
Following the excellent article by Fraunhofer ISE on this topic in edition 42 of *Photovoltaics International* [1], this paper discusses in more technical detail a number of topics relating to modern manufacturing concepts.

Industry 4.0 in PV
The transition to a smart factory is present in the roadmap of all manufacturers, SMEs and machine builders in every domain, not least PV. Most of the PV manufacturing facilities, including those of the top manufacturers, have integrated advanced automation and remote operation functionalities. In the next two years, most fabs will introduce automated fab logistic systems with machine learning, according to the 2019 International Technology Roadmap for Photovoltaic (ITRPV) (Fig. 1).

Although there have been relatively significant technical advances in machine technology and integration of automation technologies, manufacturers are still not leveraging the value of the data generated in order to provide tangible improvements in production. Revamping and upgrading all the production equipment to support Industry 4.0 features are critical. A brief overview of the adoption of these concepts in several production facilities is presented next.

The Tongwei Solar Unmanned Production Line [2], opened in the last quarter of 2017, is the world's first Industry 4.0 smart-manufacturing high-efficiency cell production line; it comprises a 200MW monocrystalline solar cell production line, expanded in 2018 with 400MW HJT technology [3]. All the process technologies are automated and remotely controlled.

Jinko Solar [4] demonstrated an increase in cell efficiency as a result of the introduction of advanced automation and the inclusion of data analytics in the production life cycle, which facilitates a consolidated data-collection mechanism, enabling yield traceability, improving workflow efficiency and optimizing material transportation.

Silicon Module Super League (SMSL) member GCL System Integrated Technology (GCL-SI) presented the fully automated unmanned module assembly workshop in China to test manufacturing tools and software, with a test phase lasting about two years. Their ambitious targets included a 50% increase in efficiency, a 21% improvement in product quality, a 60% reduction in online manpower and a 30% decrease in processing costs.

SunPower has initiated the move towards lower-cost manufacturing with the introduction of its fab consisting of manufacturing tools with a high degree of automation for both high-efficiency cells and high-efficiency modules.

While a few examples can be observed, the adoption will ultimately depend on the price–performance ratio, as the return on investment (ROI) will be a critical factor for manufacturers.

A survey of manufacturing companies from different domains conducted by Ernst & Young and Bitkom Research shows that around 80% of the companies responded that Industry 4.0 plays

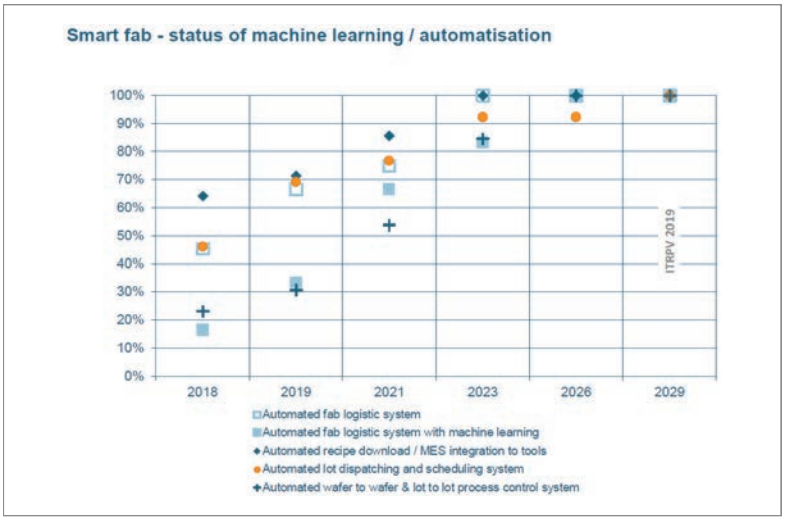

Figure 1. The high growth rate of automation predicted by the ITRPV 2019 [6].

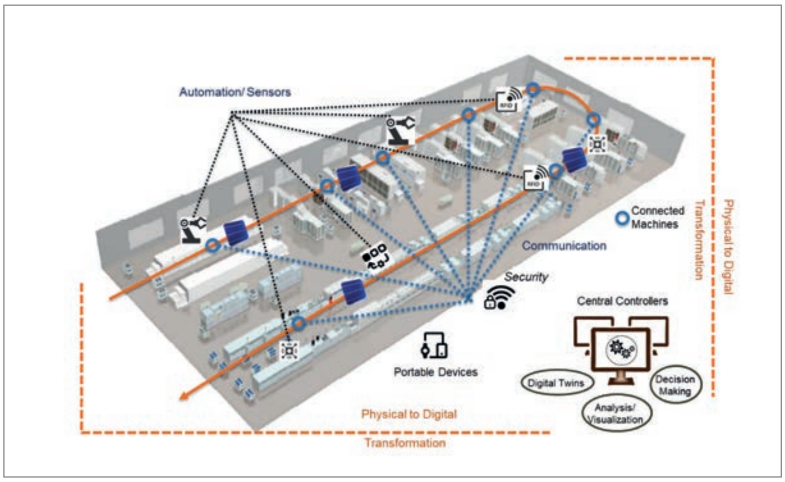

Figure 2. A smart factory visualization.

a part in their roadmaps. While the adoption rate was low, around 22%, most of the companies were in discussions to incorporate the concepts into their infrastructures. The biggest hurdles, according to the respondents, were the demand for investment, the lack of standards and the need for the transformation of the workforce in order to acquire the requisite skills to transition from having expertise in the field to having both software and subject expertise. The Sino-German Industry 4.0 Demonstration and Training programme on intelligent manufacturing and Industry 4.0 highlights the need for the training programmes to secure the transformation of both the manufacturing facility and the workforce. Platforms such as RAMI [5] define the framework of Industry 4.0 as a step towards its standardization.

State of digitalization

PV production is witnessing a shift in perception, moving from conventional manufacturing to smart manufacturing with the integration of functionalities from multiple domains, such as the Internet of Things (IoT), data analytics with artificial intelligence, and robotics. This integration is now accepted as *Industry 4.0* [7], a term coined by the German strategic programme in 2011, and is achieved by the seamless incorporation of information technology (IT) and operational technology (OT) [8]. *Operational technology* includes the production-floor machines, automation units, sensors and actuators, and resources, which are now slowly transformed into a digital space. *Information technology* encompasses all software-related aspects, including (but not limited to) manufacturing execution systems (MES), enterprise resource planning (ERP), and supervisory control and data acquisition systems (SCADA).

The digital twin, a core component in a self-learning fab, is seen as one of the most promising technologies around the smart factory and the concept of Industry 4.0, because both in research and in industry it plays the role of bridging the physical and digital worlds. *Digital twins* are virtual representations of the physical assets/ machines; they can store and display in real time the exact data, values and actions of their analogue twins, as well as simulating products, machines, etc. that are not yet available. These twins should be available for the entire production line, i.e. from each individual machine, as well as from the product itself. The concept is already being used in various industries – such as the automotive sector (Daimler, Audi, BMW) and the semiconductor sector (Applied Materials, Infineon, Texas Instrument, STMicroelectronics) – to make production more cost-effective and to accelerate the product development. Gartner predicts that by 2021, more than half of the big industries will have functional digital twins, resulting in a 10% improvement in overall effectiveness.

The large set of data coming from the heterogeneous data sources and digital twins, within the connected factory, will be the biggest game changer for the manufacturing sector. It opens up the field for analytical models, simulation and optimizations, with a move towards deriving value from the data, leading to significant improvements in cost and process efficiencies. Although data is generated from the current manufacturing facilities, most of it is not converted to intelligence that could transform the operations to minimize downtime, decrease ramp-up and optimization times, maximize production and reduce costs. A gradual evolution is required in order to incorporate the self-learning features by establishing intercommunication between the connected components to enable

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diagnosis and prediction of equipment failures, self-configuration of parameters and adaptation to changing production environmental factors. This will facilitate improved flexibility in production, traceability, optimization and thereby manufacturing productivity.

The factory of the future

The set-up of fully digitalized PV factories requires a high degree of robotic workforce, and the entire production ecosystem is interconnected. The transformation from the physical space to the digital one is represented in Fig. 2; it shows a production floor with PV equipment and the movement of the wafers through the production steps. All parameters and measurements are easily accessible by those who need them, and alerts are sent to operators or to management on multiple devices. There should be a common standard for underlying communication, so that machines from different vendors can be installed hand in hand with automation. Single-wafer tracking is also necessary in such a factory.

Fig. 3 shows the flow of information, from an architectural perspective, with the various building blocks of a connected fab. The first layer represents a production floor with the processing equipment (such as diffusion furnaces and CVDs) and measurement devices (such as IV flashers and inline sheet resistance measurement for diffused emitters). In addition to the machines, the production floor is equipped with various platforms, such as embedded PCs with connected sensors (temperature, humidity, vibration) and actuators, which provide contextual information. Other sources of data include details about maintenance, resources and personnel, all of which contribute to the semantic enrichment of the digital twin.

The second layer represents the digital twin layer. A *digital twin* can be defined as an evolving digital representation of the physical object, which captures both current and historical states and measurements. It is built with the help of real-time cumulative data sources and can provide an overview of the process/product, insights into the performance, etc. Digital twins have standard interfaces to communicate with the production floor to continually update and reflect the real-world states.

The architecture also includes the *self-learning loop*; this refers to the cycle of monitoring events and data from the production floor through the digital twins, analysing the data using models, algorithms and simulations, and providing feedback to the production floor operators and machines. With the digital twin layer, statistical patterns can also be detected and then further interpreted. For example, Fig. 4 shows an often-seen correlation between a midstream measurement tool which reads the IR reflectance of a wafer after phosphorus diffusion, and end-of-line cell efficiency. Because the IR reflectance is sensitive to the peak dopant concentration, the digitalized PV factory, which maps this relationship and is capable of cell device simulation and diffusion process simulation, will have the ability to build a parameterized model that recommends steps towards optimizing the diffusion process or equipment. The initial phase includes a human expert in the loop who provides recommendations to the operators. Finally, the fab system will offer suggestions for improvements. Visualization and integration of tools such as CAD are also foreseen to be valuable in presenting a real-time view of the machines and the movement of the cell through the various process steps.

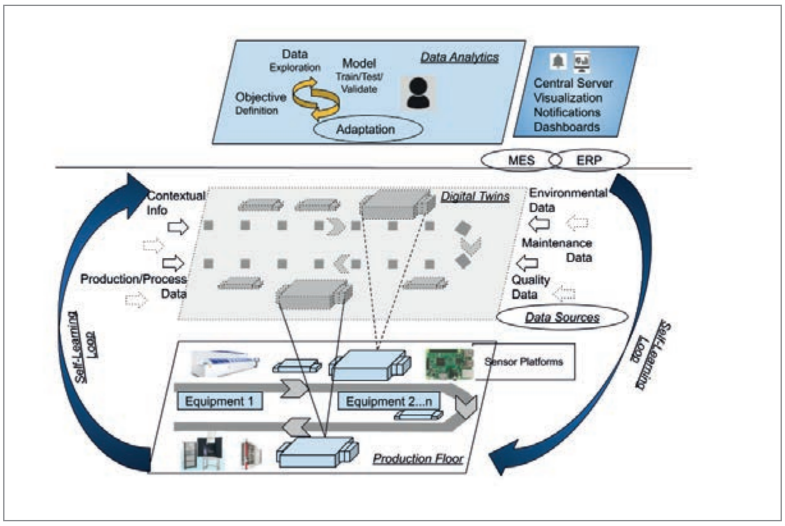

Figure 3. Architectural overview of Industry 4.0.

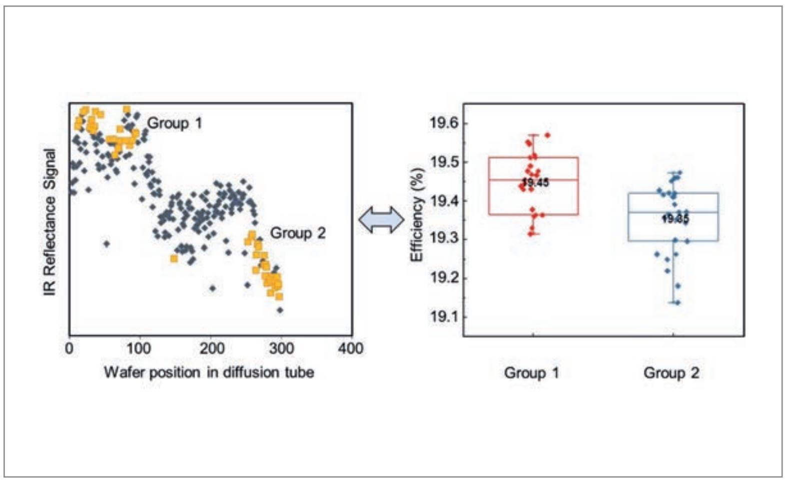

Figure 4. Correlations between the IR reflectance signals on phosphorus-diffused emitters, and the end-of-line cell efficiency.

"The introduction of standard communication technologies and the horizontal integration of information flow from several data sources enables the possibility to analyse and provide improved contextual real-time responses."

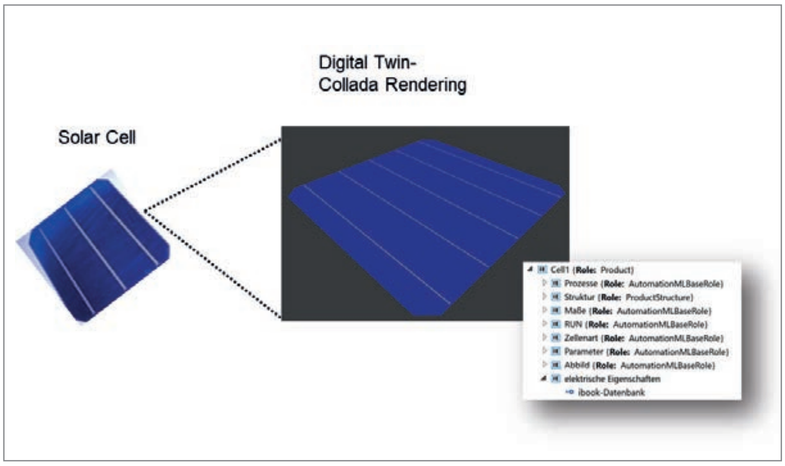

Figure 5. Visual representation of the digital twin of a solar cell.

What is Industry 4.0?

While Industry 4.0 is a culmination of several technologies, here an overview is presented of the contributing technologies from which functionalities will be integrated. In the current scenario, there are vertical information silos where the data flow is restricted to command and control. The introduction of standard communication technologies and the horizontal integration of information flow from several data sources enables the possibility to analyse and provide improved contextual real-time responses. The maturity of such cohesive interconnections along the entire value chain will then lead to the realization of the true value of Industry 4.0. The main drivers are:

- Advanced manufacturing technologies: this refers to the application of advanced technologies in product and process handling and also in management, e.g. scheduling, logistics and resource management. The use of robots and increased automation that will eventually be capable of intercommunicating help in achieving better production targets and in lowering manufacturing costs.

- IoT and sensor technologies: this refers to the networking and the management of interconnected sensors, tools and devices within the manufacturing facilities; it includes enablers such as cloud computing, edge computing and data analytics. From the smart factory perspective, parallels to the IoT architectural frameworks can be drawn in order to create distributed and horizontal information sharing possibilities.

- Data analytics: the analysis of the production requires a framework to monitor and collect relevant data from several sources. There should be interfaces to both statistical and machine-learning-based algorithms. It is foreseen to use open-source frameworks, such as Google's Tensorflow or Microsoft's Cognitive Toolkit. In PV, a lot of processing is done using statistical tools, such as JMP, which are used for the design of experiments and statistical analysis. In order to remain compatible with the current tools, the digital twins need to interface with them. In addition, simulation tools, such as Quokka, which can simulate solar cells should also be interfaced to run a digital twin of a solar cell in order to provide improved simulations.

- Security: currently, the various components of security are managed individually. With the use of standard communication technologies, it is imperative to have security measures in place, as the system is more vulnerable to threats. It is also essential to have secure access management in place. Several companies collaborate with cybersecurity experts in the development and deployment of such interconnected systems.

Digital twins

As mentioned earlier, digital twins represent the digital counterparts of the physical assets. All physical things – machines, automation, materials and solar cells – can, and should in the future, have a digital twin. Digital twins are classified into several types [9]: product twin, process twin, entire production line twin or performance twin. The functionality is designed as per the requirements of the production plant. The different types of digital twin have different requirements: a machine requires sensors and actuators, while a product consists of different parameters.

One of the most important points in modelling is *granularity* (the level of detail). It is important to show some pragmatism and avoid academic completeness; incorporating every single detail can consume unnecessary computing power, slowing down the structure and possibly rendering real-time processing unfeasible. A digital twin requires a visualization tool that is clear and concise for both managers and operators. The facility should have the infrastructure to handle the real-time processing of large volumes of data. It should include interfaces to several algorithms that can model the data.

A clear advantage of using a digital twin is that the product can be 'produced' before it is actually physically created. This simulation of the product can then be used to carry out a wide variety of tests and put it through its paces. Fig. 5 shows a digital twin of a solar cell rendered using COLLADA, sourced from an AML file (described in the next section). For the production machines, a real-time view of the working components and the parameters can be easily made.

Digital twin: data model

With the various types of digital twin defined, two examples are considered here in the context of PV manufacturing: a 'product twin' corresponding to a solar cell, and a 'process twin' corresponding to a piece of processing equipment, i.e. an inline wet-chemistry tool or a diffusion furnace. A digital twin of the solar cell enables us to analyse the cell through the various process steps. This further facilitates the possibility to optimize parameters in order to ensure that all the following cells fit the final quality evaluation criteria. The possibility to simulate virtual cells in real time speeds up the technology development cycle, as the number of development iterations can be reduced.

With regard to a product twin example, the design phase consists of identifying the relevant parameters to represent the asset; thus, the digital twin consists primarily of an underlying data model with all the relevant attributes of the solar cell. This structured representation allows information to be exchanged across components and systems. The data model includes metadata, process data, measurements and related contextual information. The life cycle of the product needs to be understood and captured in the digital twin.

A tight coupling of the physical object and the digital twin is established through communication interfaces and update mechanisms. Fig. 6 shows the modelling components in the realization of a digital twin. The physical assets here are the solar cell ('product') and an inline wet-chemistry process tool ('process'). All the parameters to be modelled are selected.

The modelling language adopted here is AutomationML, an emerging standard for the description of digital twins [10]: this is a standardized mark-up language for modelling and unifying all information used by engineering tools. AutomationML covers plant topology, geometry and kinematics, logic information, reference and relations, and referencing of other formats. It is an open standard and uses the XML format for programming. The language can be used to map and describe entire production lines in their hierarchy; it can also capture the inter-relationships between the several components. AutomationML comes with an in-built tool for conversion to the OPC UA data format. In addition, it can be interfaced to modelling tools for geometry and kinematics information, such as COLLADA and PLCopenXML.

The AutomationML editor provides a user-friendly interface in which it can be clearly programmed. A sample of the view of the digital twin data model for a solar cell designed using AutomationML using the editor is shown in Fig. 7, along with the corresponding XML schema. The figure indicates an instance hierarchy of a solar cell; metadata of the cell, the measurements made, the process steps performed and details relating to the process steps are included. The AML file can be used for sharing all the information relating to the solar cell twin; this file can then be converted to objects which can be accessed to update the parameters in real time or near real time.

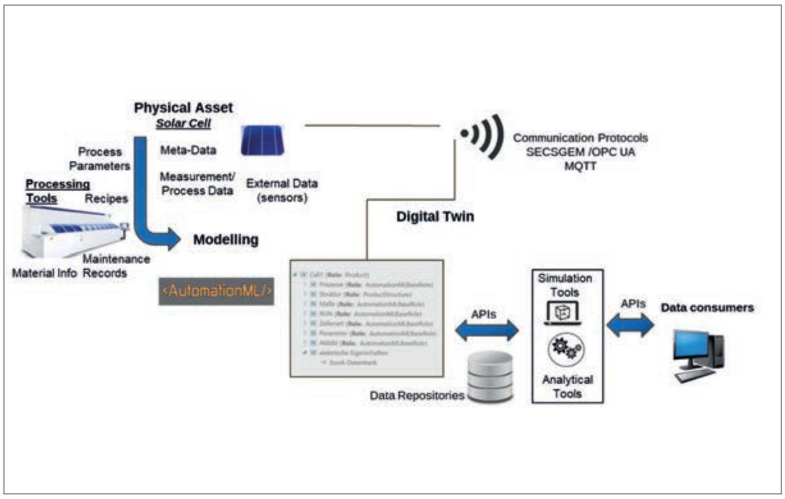

Figure 6. Communicating with the digital twin.

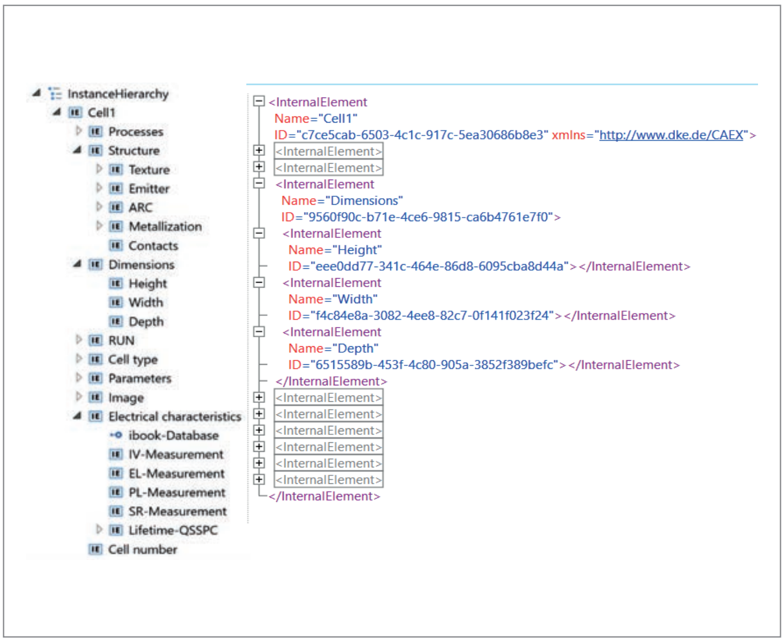

Figure 7. AutomationML and XML schema.

Digital twin: communication and interfaces – how to talk to machines

A critical component is the connectivity in order to ensure reliable and seamless connection of the digital twin to the heterogeneous data sources. While some factories have central information control software, such as MES, many facilities do not. Digital twins aim to use standard communication interfaces and to also facilitate a horizontal sharing of information in cases where MES is unavailable. Creating a single digital twin from a manufacturer might not be difficult, but having a standardized way to model and access several assets from different manufacturers is a challenge. For PV/semiconductor

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production equipment, ISC has identified three communication categories adopted by the machine builders. The categories include:

- SEMI PV2 (SECS/GEM) [11]
  The integration of the standards SEMI SECS-II (E5), GEM (E30) and HSMS (E37), which are already in use in semiconductor manufacturing, was recommended as the foundation for host communication throughout the PV industry. The SECS/GEM standard establishes the protocol for the communication link between a host computer and the machines. The host can issue remote commands to retrieve parameters, perform process program functionalities (such as run recipes), monitor material movement, etc. The information retrieved from the machines is classified into: 1) status variables – current parameters and measurements of the processing machine; 2) alarms – all the errors and warnings raised which indicate a non-optimum functioning of the machine; and 3) events – the possibility to monitor events and relevant machine parameters so that the host can continually get reports in a publish–subscribe mode. Additional functionalities include the possibility of using data spooling features to ensure no loss of information in the case of connectivity issues, defining and monitoring limits of parameters, and tracing functionalities.

- OPC UA [12]
  This is the open-source communication protocol developed by the OPC foundation for machine to machine communication. It is a service-oriented architecture, supports multiple platforms and has an integrated information model and security features. The protocol includes the following specifications: data access (DA), historical data access (HDA), alarms and events (A&E), XML data access (XML-DA), data exchange (DX), complex data (CD), security, batch, express interface (Xi) and unified architecture (UA). The main advantage of the OPC is its acceptance and use in several associated manufacturing sectors, such as automation, robotics, process control and manufacturing.

- Proprietary protocols
  Several machines still follow proprietary communication protocols in the retrieval of data by a central server. This requires the development of drivers, wrappers and other translation tools to communicate with the machines and retrieve data in the required format. A standardized approach will reduce the amount of reworking that such proprietary protocols impose, but until the definition of the standards and widespread adoption occurs, workarounds will need to be in place.

- IoT and related protocols
  For sensors and actuators, standard communication over TCP/IP is adopted. The highly adapted MQTT [13] transport protocol, which uses a publish/subscribe architecture, is suited to devices with smaller footprints. *REST interfaces* refer to the scalable architecture which facilitates communication over the hypertext transfer protocol (HTTP) to establish communication from an asset to a central web server.

An accepted standard for machine communication and a digital twin representation in the PV industry are needed in order to enable successful implementation of smart factories. Machine builders will have to offer this along with their machines and digital twin representation. SECSGEM or OPC UA are candidates for this standard, while AutomationML is a possibility for the digital twin representation.

Flexible factories

The digital transformation of the factory and the merging of all the data sources open up other interesting use cases of designing a flexible PV production line; for example, special cell types for certain niche products, or products with known variable demand, can be produced in this 'FlexFab'. (Work on the concept of such a flexible factory is funded by the German Federal Ministry for Economic Affairs and Energy within the framework of the FlexFab project.) The changeover processes must be minimized and well known (e.g. necessary cleaning processes). The preparation of machines and the instruction of operators must be automated. The production schedule must be optimized automatically by a scheduler, as shown in the example in Fig. 8.

The requirements and design phase for this are twofold. The first is to identify commonalities and

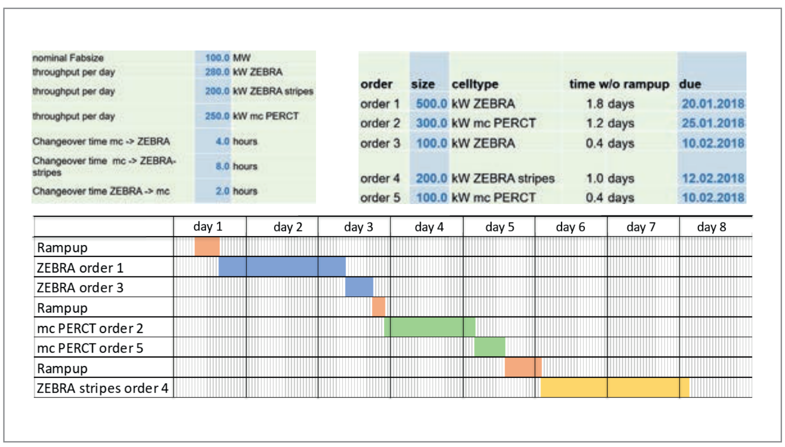

Figure 8. Example of a scheduler for a flexible production line: input fields for different cell types that can be produced at the site (top left) and orders for the fab with due dates (top right). The optimum schedule is then generated (bottom), and necessary information is sent to machines and operators.

differences in the technologies; this is established through several experimental batches to identify sources of contamination, possibilities of reuse of process steps, etc. A detailed design of experiments will allow the detection of conflicting and constructive factors.

The second is the possibility to remotely control and configure the parameters of the processing equipment. With the framework described above, ISC is working on the networking aspect for communicating with machines. A central control software is used to control and monitor equipment. In addition to control, the booking of machines is also handled by the software (presented later in this paper; see Fig. 14). On the arrival of a request to change the cell technology in a production line, all the required dependencies are checked and the machines are reconfigured to adapt to the new technology requirements. The basic requirement for doing this is to have all the machines connected and store all the necessary information in one place.

Self-learning factory

Imagine a factory that gets better all by itself… efficiencies steadily rise, small variations of production parameters are done automatically, and the fab achieves optimum production conditions unassisted. Take, for example, the introduction of a new silver paste for contact formation: the diffusion, printing and firing conditions are changed for some thousand wafers in a running production, and the optimum conditions and potential of the new paste are determined within hours. Fig. 9 shows a self-learning loop moving between the production floor and the digital data it generates to build models that will lead to the development of several applications.

The digital twins provide the interfaces to access the real-time and historical data from the machines; these data need to be converted to knowledge that can be leveraged. Traditional systems, such as ERPs, have rule-based routines in place. The production environment, however, is non-stationary and evolving; it is therefore necessary to build models that can learn and adapt in real time. The data analysis cycle starts with the identification of relevant data; the data are cleaned and filtered, and the appropriate statistical and learning models are then applied to the data. The inference obtained from the data is subsequently used in the decision making, for example in parameter optimization. Some of the applications include:

- **Predictive maintenance.** This is a disruptive approach [14] to performing maintenance, with the normal operations and parameters being continually monitored. Simulations and the 'memory' of the digital twin can be used to predict when a component or components within the production line will be faulty or even fail. It is also possible to avoid expensive on-site maintenance by experts from the manufacturer. If the company allows an online connection to the manufacturer, they can now use the digital twin to remotely service the machines. The likelihood of machine downtimes is estimated on the basis of load and usage patterns and environmental factors in order to reduce the mean time between failures (MTBF); estimates based on statistical and machine-learning models are provided. Errors in the equipment are anticipated by modelling (artificial neural networks), leading to early detection of failures, which means that warnings of abnormal patterns can be issued at an early stage. According to Deloitte [15], predictive maintenance will: 1) reduce the maintenance planning time by 20–50%; 2) diminish total maintenance costs by 5–10%; and 3) increase equipment uptime and availability by 10–20%.

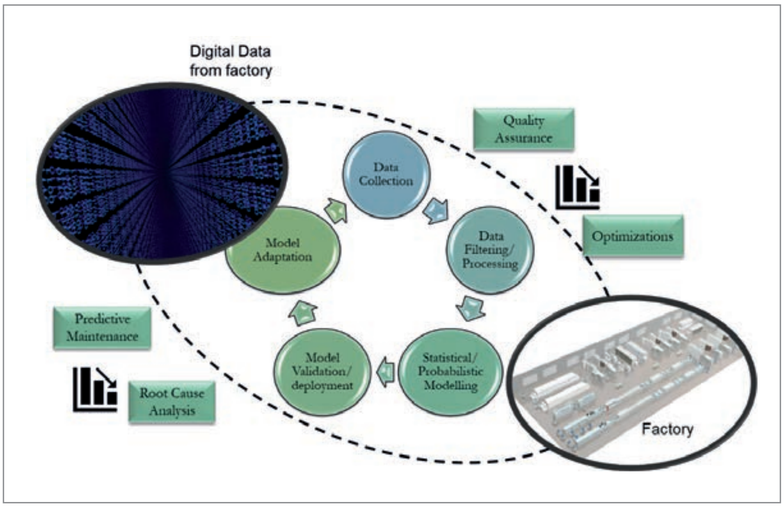

Figure 9. Applications based on learning from data.

- **Simulations and optimization.** A digital twin can be connected to simulation tools used by scientists in analysing production data and measurements. Simulation tools include Quokka3, PV Lighthouse and PC1D, which can be programmed to take in the data generated from the digital twin. While the implementation in the current state requires the development of wrappers and translation tools, a better integration is foreseen. By leveraging the digital twin data, improved simulations can be performed, thus mirroring the real-world status more accurately. Cost savings in the integration of simulation tools with the digital twin will be tremendous, and entire process chains can be simulated before production actually begins.

"It is necessary to build models that can learn and adapt in real time."

- **Root cause analysis.** During the ramp-up phase, or during the introduction of newer technologies into the production line, several optimization cycles that are cost and time intensive are required. Identification of the source of errors or performance deviations can be performed with, for example, multivariate regression models.

- **Quality assurance.** The quality of the cell/module at the end of production can be ensured throughout the process line on the basis of the models.

ISC is also working on self-learning factories in the framework of the SelFab project, funded by the 'Ministerium für Wirtschaft, Arbeit und Wohnungsbau Baden-Württemberg' (Ministry of Economic Affairs of Baden Württemberg state).

Lab 4.0 at ISC Konstanz

In the development and integration of Industry 4.0 concepts for the factories, ISC's first step was the development and integration of a prototype using the same technologies, but on a smaller scale, i.e. in a solar cell research lab. The lab has all the production and process equipment for the complete fabrication of a solar cell; it also has the machines required for module development. Automation tools, such as loaders and unloaders, are not available, given the low throughput needed in a lab environment.

A pilot implementation provides an opportunity to explore specific aspects such as equipping the lab with sensors, exploring the standards for communication to the existing machines, identifying the gaps, collecting data and exploring analytical tools. The first phase was a survey of the equipment, resources and requirements for identifying the key areas of development and the possible challenges. The labs were fitted with environmental sensors, such as temperature, humidity and pressure sensors; Fig. 10 shows the historical trend of some of the values recorded in the labs.

Process equipment tools selected for communication include a diffusion furnace, a CVD, a firing furnace, an IV flasher and an inline wet-chemistry processing tool. Because some of the equipment was not PV2 compatible, upgrades were necessary in order to standardize the communication with all the equipment. This is an integral part, as it requires the development of one solution that can be extended to all the equipment. In the case of equipment that cannot be upgraded to support PV2, alternative communication strategies have to be in place.

The initial prototype uses the open-source Thingsboard platform [16] to visualize the data, device management and access management. A PostGreSQL database is the back-end database for storing all the data retrieved from the equipment and sensors. Fig. 11 presents a sample snapshot of connected devices in the lab.

The graph in Fig. 12 shows a sample overview of the trend in the machine parameters over a period of time. The data originate from the firing furnace and display the trend of temperature values of the furnace and the drive velocity. Fig. 13 shows some sample trends in the pressure values recorded from the inline wet-bench processing tool. This demonstrates the amount of information available for the analysis and study of cross-correlations, variance, etc. between parameters and final cell performance.

To integrate the concepts of a flexible factory, a web-based software management tool was developed. Referred to as the *ibook* (ISC booking tool), the front end offers a user interface for the managers and the operators to access all the information about the machines and booking information, as well as providing the ability to plan experiments (RUNs). In the case of the latter, the easy-to-use web interfaces have templates to choose cell technology, machine parameters, recipes, cell parameters, etc. here; for every RUN, all the associated data will be assimilated (see Fig. 14). The back end is again a PostGreSQL database. In addition, iBook will include information about personnel, maintenance statistics, details of the wafer (e.g. manufacturer, dimensions), etc. Communication between the iBook and the digital twin is planned through REST interfaces. The digital twin uses the ibook interface to retrieve metadata parameters and review information relating to booking times.

Impact of Industry 4.0

Industry 4.0 brings together a cohesion on all levels, linking investors, suppliers, consumers and other persons with a vested interest, creating a connected ecosystem. With the continuous stream of data, a degree of transparency is brought to the system, and everyone involved is able to take a proactive role in the functioning of the ecosystem. A shift from the vertical information silos to an interconnected open system will result in a transformation of not only the business models but also the way in which collaborative environments can be developed (Fig. 15).

Summary and outlook

A change in perspective is brought about by digitalization and Industry 4.0 in the manufacturing space. An adaptive system capable of learning from the environment and providing real-time recommendations and optimizations is the logical next step in the industrial evolution. Moving from rigid information silos to combining data sources to generate useful knowledge would result in improvements in several areas of manufacturing, focusing on the self-x functionalities of self-optimization, self-maintenance and self-configuration.

Incorporating Industry 4.0 into PV cell and module production will lead to significantly less downtime and improved efficiency through the higher level of process and inter-process control.

Figure 10. Environmental parameters – digital records.

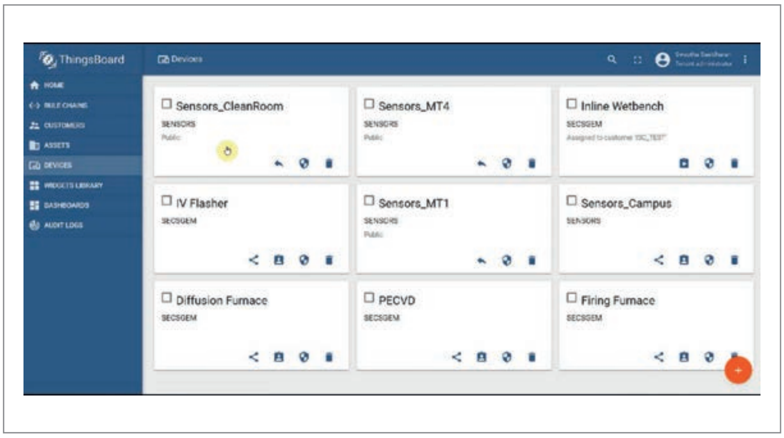

Figure 11. A view of several connected machines and sensors. MT1 and MT4 are characterization rooms in the ISC lab.

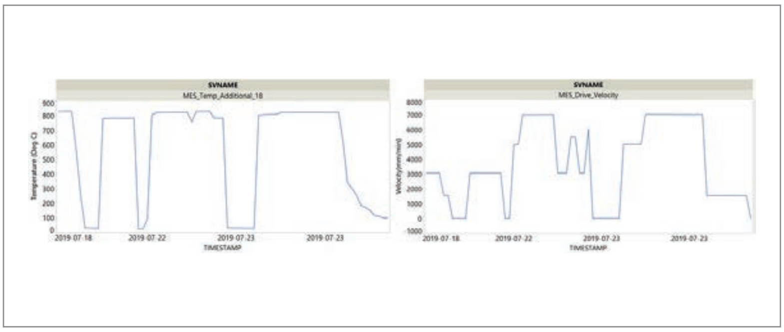

Figure 12. Machine parameter trends for the firing furnace.

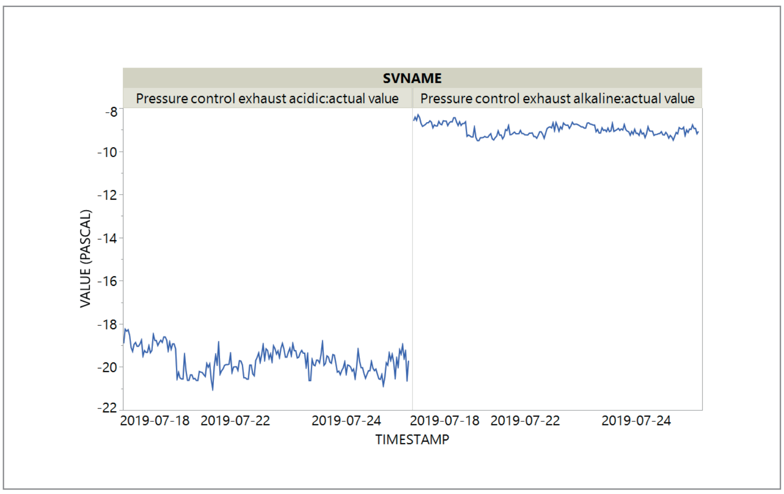

Figure 13. Machine parameters for the inline wet-bench processing tool.

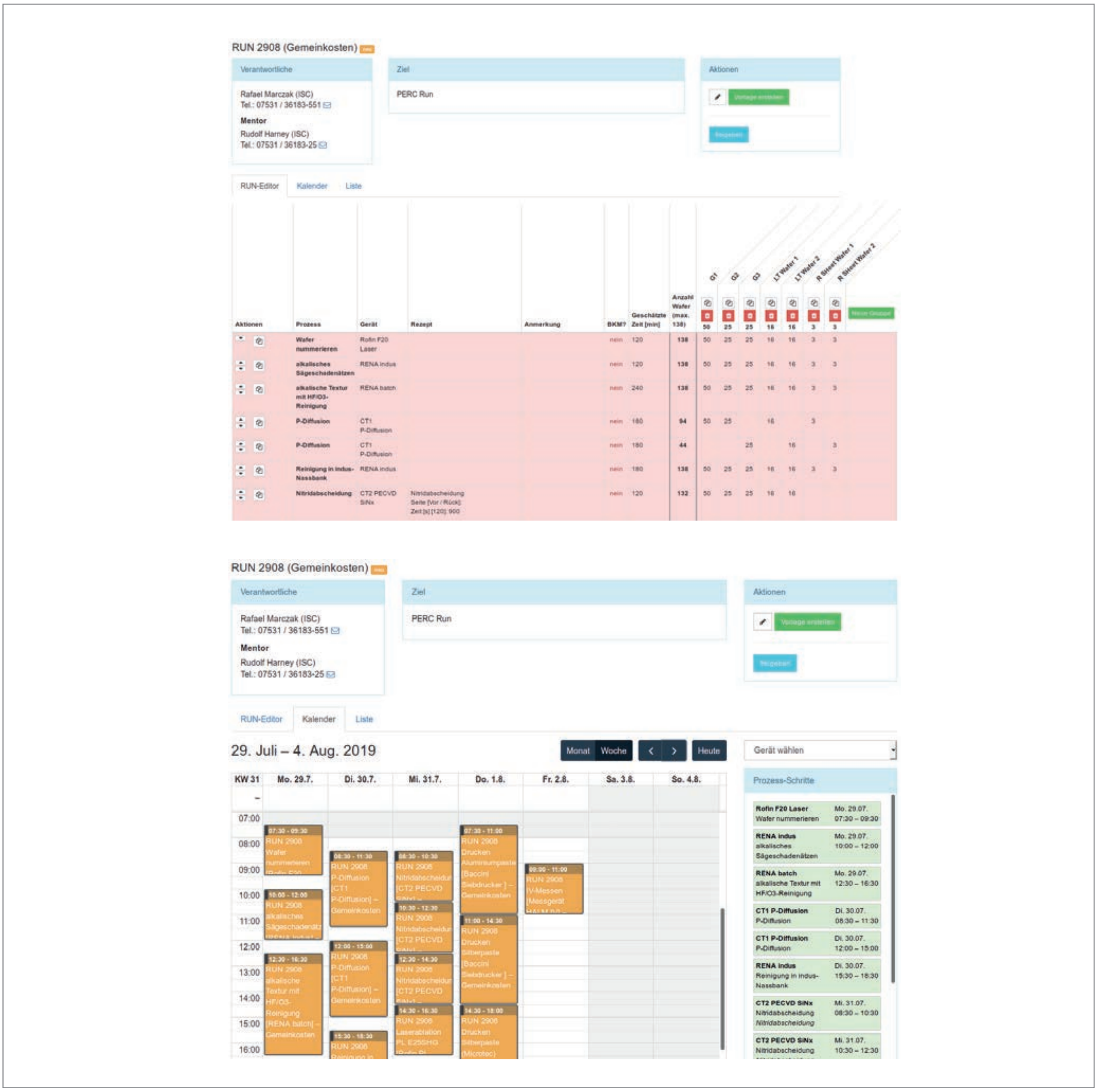

Figure 14. With the use of ibook ('ISC booking tool'), experiment planning, including group planning (a) and scheduling (b), is easily possible, as well as assignments to the operators. The earlier-described machine planning in a FlexFab is based on this system.

However, standards for communication interfaces (PV SECS/GEM or OPC UA) and digital twin representations (AutomationML) are essential (the authors' assumptions in brackets). Cell/module manufacturers will need to request appropriate interfaces and digital twin representations from their machine suppliers.

"Incorporating Industry 4.0 into PV cell and module production will lead to significantly less downtime and improved efficiency through the higher level of process and inter-process control."

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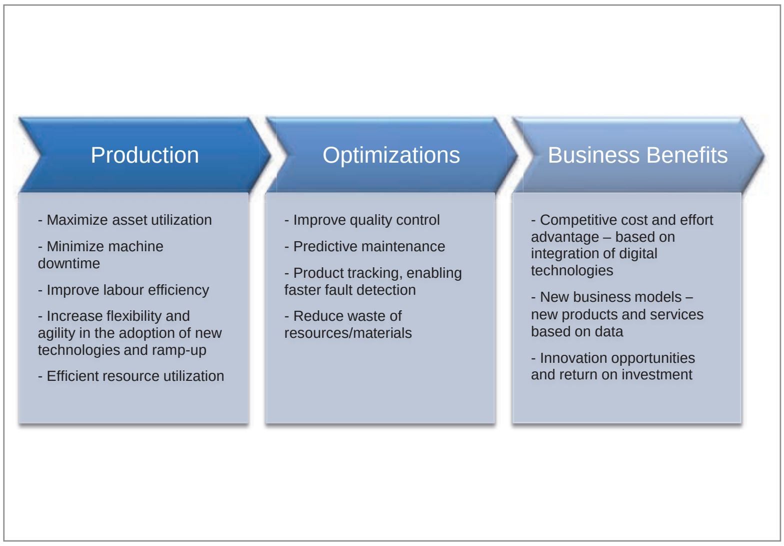

Figure 15. Impact of Industry 4.0.

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