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Digitized, networked optics production

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Abstract

The increasing demands on the quality of high-precision optical components mean that established manufacturing processes are reaching their technical limits. While individual processes can therefore hardly be improved any more, networking production machines digitally throughout the entire process chain offers high potential for meeting the tight tolerances in the optics industry and increasing the production output.
To gain these benefits, first, an infrastructure is needed, containing a flexible and module data structure to satisfy different requirements from the processes. Second, the idea of offering services such as initial data analytics, artificial intelligence (AI) and machine learning (ML) must be integrated. In this paper, we present a digital infrastructure, that contains data from the entire process chain of glass and polymer optics production including simulation, process and measurement data. Services to optimize the production process are integrated and provide an outlook on how AI/ML can be added.

Keywords: digitalization; production; optics manufacturing; AI; ML

1. Introduction

Optical systems are demanded to be high performance and to follow the trend towards miniaturization. This leads to increasing demands on the quality and complexity of high-precision optical components, their handling and assembly [1]. Not only with rising costs but also with growing economical awareness, waste must be reduced. As the production of complex optical systems consists of multiple challenging process steps, the tolerances of each individual process step are extremely tight in order to archive high-quality results. Established processes are reaching their technical limitations [2]. A considerable increase in production output can be brought out by widening the tolerances by networking the process steps. This allows the identification of dependencies between the processes' parameters and the properties of the product across different production steps and therefore, is the basis for the optimization of the entire process chain. Consequently, there is enormous potential, especially within the optics industry, for the digitalization of processes and process chains.

In order to network the different processes and be able to use the generated data to optimize production as well as process developments, there are three key elements that have to be taken care of: Data acquisition, data storage and data usage [3]

1. Data acquisition: Digitalization of single processes

In order to map the respective processes completely digitally, it is not only necessary to have knowledge of the process interrelationships, which is equivalent to a detailed process model, but also to capture the most important data, if necessary with adapted syntax and structure. Once the relevant data has been identified on the basis of the process model, it must be possible to place it in relation to one another in order to digitally map the process model and assign individual influences to the process model. When the relevant data is defined, it is furthermore necessary to be able to acquire and store it. Optics manufacturing single processes are highly individual and therefore, there is no standardized approach. [4]

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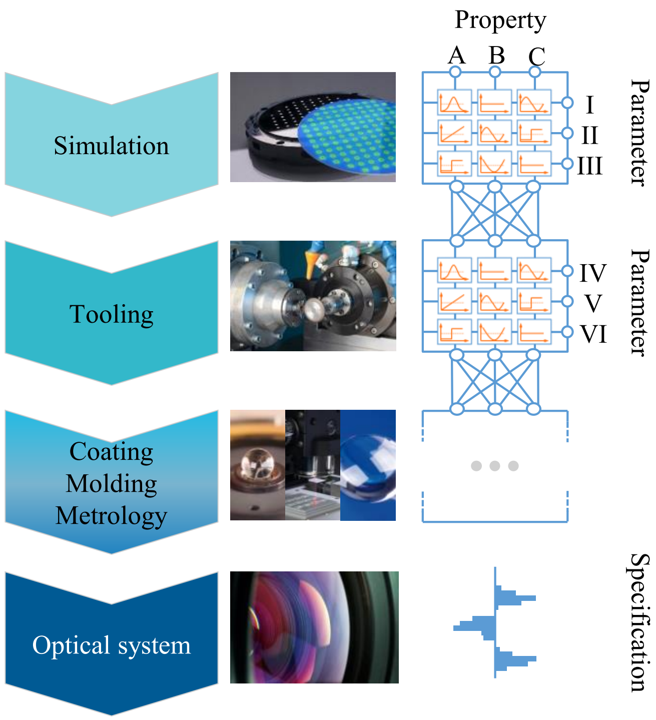

Fig. 1. Adaptive process control using correlations across multiple manufacturing steps

2. Data storage: Networking of digitized processes

The acquired process and measurement data are typically available in various data formats which are not compatible. The production data is generated by different software solutions in each process step: While for process simulation programs like *Zemax* or *Abaqus* are used, process data itself might simply be saved in an Excel-Sheet and different metrology devices use different data formats depending on the measures data values. In order to network the data and processes, it is necessary to apply interfaces. Existing systems are not modular and variable to be used for different optics production chains. [5]

3. Data usage: Web interface

The third key element is data usage. Therefore, the gathered data should be made available for optimization approaches. The visualization as well as approaches regarding the users' interface like a web application or the usage by smart devices needs to be taken care of.

At the moment no commercial solution meets these characteristics. Therefore, it is necessary to develop a consistent data infrastructure.

In this paper, we present a digital infrastructure for optics manufacturing containing a flexible and module data structure to satisfy different requirements from the processes as well as the possibility to offer services such as initial data analytics, artificial intelligence (AI) and machine learning (ML).

2. Development of the networked, adaptive digital infrastructure

2.1. Requirements

To make the infrastructure interesting beyond the small and medium enterprises of the optics production, it has to fulfill different requirements. The requirements and advantages of such infrastructure were elaborated in the research project »EverPro« and can be presented as follows. They are also used as success factors to benchmark the development with the goals:

- The process steps and chains are independent of the superordinate infrastructure structure; changes have no influence on the structure.
- The concept can be extended by further process steps if required.
- Interfaces and connections of the dependent and also independent process chains are transparent.
- It is possible to obtain an overview of the complexity of the production and the development of the product or the process chain flexibly and in a short time in case of new inquiries.
- The infrastructure and the process chains can be accessed intuitively via graphical user interfaces (GUIs).
- The infrastructure enables the evaluation of product- and process-relevant data and information via the user interfaces.
- Optimization and efficiency potentials are identified with little effort.
- The infrastructure concept can be transferred to any industry sector and production process/chain.

These requirements are resulting in some technical requirements, which have to be taken care of while developing the concept of the infrastructure.

The data backbone consisting of one or more databases has the be designed for enabling the infrastructure to store data in single entities like tables or separate databases. There has to be an overall management (e.g. an database management system (DBMS)) that is able to interlink the different entities and integrate further entities. A transferability into other production domains than optics as to be taken into account.

Therefore, interfaces have to be developed which are able to connect with common standards and protocols like OPC-UA, MQTT or existing databases in production. In an ideal case, these interfaces work fully automated and transfer data when it is generated in the production. Nonetheless, due to organizational and security-related issues, it does not make sense to waive a manual interface, where data could be transferred from databases or from files like log, csv or json files.

To bring the infrastructure to broad use, an easy-to-use graphical user interface (GUI) has to be developed. It gives users the possibility to use the infrastructure without any experience in programming. Besides the user management system, import and export functions for data, generated visualizations and in the long run for models and their performance evaluation have to be integrated into the GUI.

Collecting the data and making it accessible is just the first step. To generate a benefit out of the infrastructure, tools and services have to be implemented. Starting from simple visualizations, the infrastructure has to provide intelligent services using innovative technologies for data analytics such as machine learning (ML) and artificial intelligence (AI).

In conclusion, the development has to take a suitable data backbone, a user-supporting GUI, and the integration of innovative services into account.

2.2. State of the art

2.2.1. Database

Different databases got common in the last years. They can be divided into two general groups: relational (SQL like mySQL, PostgreSQL, Oracle) and NoSQL (not only SQL, like Apache Cassandra, MongoDB) databases. The main difference is that relational databases handle data in form of tables using rows and columns whereas NoSQL databases use other formats to collect, store and manage the data.

SQL is the more common approach. It has benefits in handling structured data and is expandable as a vertical approach (adding new rows instead of columns). NoSQL has its benefits in handling very different data types and is more expandable in the vertical, meaning adding new features or objectives to the existing structure. Hence, indexing is a performance issue for SQL, NoSQL approaches perform better while adding and reading data from the database. [6, 7]

2.2.2. Infrastructure

To organize and manage the general infrastructure a platform is needed. Docker is a very common platform to develop, test, deploy and manage applications. Furthermore, docker is open source and therefore opens up a lot of opportunities to virtual production environments. Applications in docker are managed as containers, which can be shared with other developers using a Docker platform. Another very popular open-source container system is Google's Kubernetes. Kubernetes is able to manage large clusters of containers and users interacting. The management is more efficient and load-balanced than in Docker. It is also possible to combine Kubernetes with Docker, what opens up the possibility to integrate the existing Docker structure in a Kubernetes cluster. Other, more uncommon, approaches are Podman, OpenVZ, Virtual Box, Linux Containers (LXC), Microsoft Azure Container Registry, Containerd, Rancher, Vagrant and ZeroVM. They all have different benefits and reasons for existence. [8, 9]

2.2.3. GUI

To complete the overall infrastructure a GUI is needed to provide access to the data and the available services. Therefore, the GUI has to be available independent from the operational system (OS), the used device or the used software environment. One opportunity is to provide the GUI via the local web browser using a web application (Web-App). There are several ways to develop a Web-App. Possible libraries are *Flask*, *React* or *Django*.

2.2.4. AutoML

The developed infrastructure and the GUI provide the enabler for a service infrastructure. To fulfill the requirement of having data analytics available for users, who are not experienced in data science, AutoML provides a general framework. AutoML in general is capable of modelling without further knowledge of the user. Basically, AutoML follows an approach to automatically perform the ML pipeline or at least parts of it. AutoML is still a fairly new topic. In recent years, however, several frameworks have already emerged with different functional scopes and different backgrounds. In their study, Truong et al. [10] elaborate on the history of AutoML. One of the first approaches was Auto-Weka [11], which was implemented in 2013. It uses algorithms provided by Weka [12], which was also one of the first ML libraries in the 1990s. In the following years, other frameworks were developed. Starting with Auto-Sklearn [13] in 2014 by the University of Freiburg and TPOT [14, 15] in 2015 by the University of Pennsylvania. Both build on the ML package scikit-learn [16]. All of these and most of the early frameworks were academically driven. Apart from these, some start-ups have also developed AutoML frameworks. Starting with DataRobot [17] in 2015, followed by H2O, which released an AutoML framework in 2016 with H2O-Automl [18] and a commercial product in 2017 with H2O-DriverlessAI [19]. This also introduces the third group of frameworks. After the academically driven and the start-up solutions, the third group is the commercially driven frameworks. Many cloud providers and technology companies have also started to develop AutoML frameworks that are usable within their offered infrastructure. These include Google Cloud Automl, Microsoft AzureML and Amazon SageMaker.

Important for the developed infrastructure is, that the AutoML framework is open access, has python as a core language, covers the whole ML pipeline and that the framework will be developed to a stable state. Furthermore, there are some soft criteria (popularity, documentation, final results, model export possibility and OS restriction), which are also taken into account. The three frameworks Auto-sklearn, TPOT and H2O AutoML are promising to provide a good basis for the services, as they are all widely used and meet all the specified criteria well.

3. Infrastructure development

The chapter gives a short introduction of the development activities including the used software. Furthermore, the view of the user on this infrastructure is introduced.

3.1. Development

Based on the requirements presented in Chap. 2.1, the infrastructure has to be developed. Therefore, a functional environment has to be set up, which handles the queries of the user via the Web-App and into the data infrastructure.

The whole infrastructure is set up on a server using different gateways and Application Program Interfaces (APIs).

To meet the requirement of being flexible and modular the infrastructure is set up using docker container. Every service provided by the infrastructure is developed as one docker container. To manage the different containers, Portainer is used, providing a web interface to administrate the containers. For the developer, the access to the docker infrastructure via Portainer and to the database via PGadmin is a very efficient way to manage these parts.

To have a very flexible DMBS, PostgreSQL is chosen as the leading DBMS because it is able to handle structured data as well as unstructured data. The benefit is here, that it is not necessary to set up different databases to take care of the different available formats. If this should be needed in the future, it is possible to develop e.g. a MongoDB in its own container and connect it with the rest of the infrastructure.

Traefik is used as a router handling all types of queries coming from the GUI, the interfaces of Portainer or PGadmin.

To realize the GUI, Flask and React were used. React is very common in designing and providing Web-App frontends. Flask is providing a web framework, having the benefit that it allows to integrate already existing libraries and supports the direct integration of PostgreSQL.

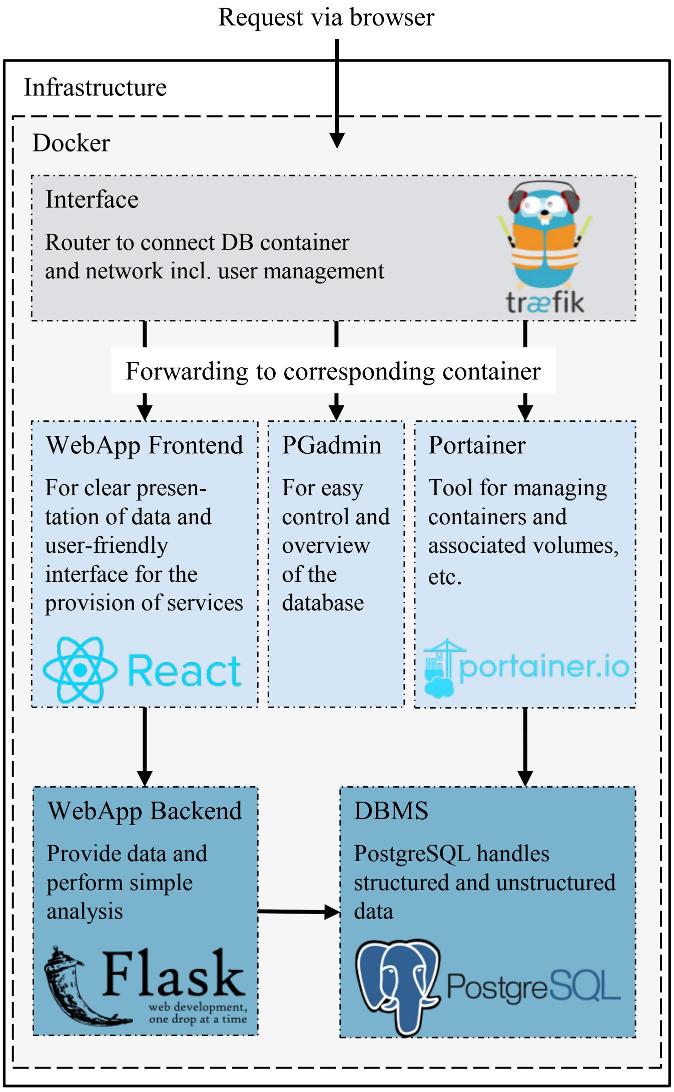

Fig. 2. Concept of the adaptive, networked infrastructure

Regarding the connection of the machines and the infrastructure, UPC-UA was used for most interfaces.

3.2. Usage

From the user's perspective, the infrastructure provides one interface, the Web-App, to provide different services. In general, two user groups are addressed. The first one includes the users, which are working with the machines on the software level. They need to have a simple modus to upload and provide data to the infrastructure. Therefore, standards like OPC-UA were used to connect the machine controls with the infrastructure. In most cases, automatic interfaces were developed. In other cases, already existing databases had to be included and in others again manual interfaces had to be provided. The manual interface has been deployed in the Web-App as well, whereas the other interfaces were developed as extended software on the edge. In addition, first visualizations of the data in the database are available using the Web-App, enabling the machine users to get a first overview of the process data.

The second user group includes non-data science specialists, who want to analyze existing data without having the corresponding machine connected to the infrastructure. Therefore, the manual import functions of the infrastructure are ready to use. For data analysis, an AutoML service has been developed. This service allows the analysis of data without deeper knowledge in data science and is easy-to-use by using the GUI.

Three AutoML frameworks were implemented as a service into the developed infrastructure as introduced in Chap. 2.2.4. To be able to use the already implemented data, the AutoML service is directly connected to the database of the infrastructure. To satisfy the second user group, the manual import of CSV-files, SQL dumps and other available databases is possible using the front-end. The user is able to choose the input and the target data (both based on the columns, which were imported). Afterwards, the AutoML framework can be chosen from three different ones. The only decisions which have to be made are choosing the learning task (classification or regression) and the computing time. In addition, there are some advanced parameters, which open up the opportunity for advanced users to adjust some hyperparameters, using the front-end. After modelling, the users have the opportunity to get an overview of the used parameters, the evaluation results, depending on the learning tasks and the feature importance. In addition, the model, predictions, scores and feature importance can be downloaded using the front-end.

3.3. Benefits

It is necessary to distinguish two user groups that benefit from the developed infrastructure. On the one hand the scientists and on the other hand the industrial users. From the scientific side, the developed infrastructure offers the possibility to quickly connect different machines to the infrastructure and display data about them. Thus, the transparency of scientific results is further increased and the effort for the presentation of results is significantly reduced. In addition, results can be integrated in the form of further services, so that an economic exploitation of the results is significantly simplified and the accessibility is increased. The economic side links up directly with this. The infrastructure provides them with accelerated access to the latest developments, giving them the opportunity to test research results that would otherwise require a costly transfer. For the business processes, in this case the production processes, this means, especially in the optics industry, a utilization of

This is a resupply of March 2023 as the template used in the publication of the original article contained errors. The content of the article has remained unaffected.

potentials that were previously inaccessible. SMEs are thus able to benefit directly from research results in the field of digitization without tying up their resources in development outside their core competencies.

4. Conclusion and Outlook

The presented infrastructure is built to the requirements of optics production and production in general. It is providing several interfaces for two different user groups, who are able to upload their data into the infrastructure. For this, data can come from machines using automated interfaces or be uploaded manually. To get a first overview, data can be visualized in plots, which can be downloaded together with its data. This opens the opportunity for the user at the machine or measuring device to get a first impression of the data without manual effort. Furthermore, the infrastructure is the foundation for the development of a service infrastructure, which is able to provide different services. The first one is an AutoML service, using automated machine learning. This tool helps to overcome the gap between experts in production and data science by providing an easy-to-use front end implemented in the infrastructure GUI. In combination with the Aachen Center for Optics Production (ACOP) as the group of main users, the impact on the optic producing industry is very high. The ACOP is therefore used to accelerate the transfer from a research level to the industry level with minimal effort and in constant exchange with the developers.

Future activities are targeting two different expansions. On the one hand, more services have to be developed which will be directly implemented in the infrastructure. Therefore, research activities like informed machine learning and physics-informed machine learning have to be taken into, leading into production-related developments like hybrid modelling, where simulation models and ML are combined to improve the model performance furthermore. These approaches generate opportunities for conditions, in which simulation and data-driven modelling cannot be performed at the moment, for example when made assumptions are too far away from the real process, or real data is not available because the feature is not measurable. However, these new streams have to be developed as further services such as predictive quality, or predictive maintenance.

On the other hand, the infrastructure has to be developed in a way that other production technologies are able to connect with. Therefore, the module structure can be used and other process chains than the one of optics productions could be implemented.

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