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Reflections on Visualization Research Projects in the Manufacturing Industry

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***Abstract*—The rise of Industry 4.0 and cyber-physical systems has led to an abundance of large amounts of data, particularly in the manufacturing industry. Visualization and visual analytics play essential roles in harnessing this data. They have already been acknowledged as being among the key enabling technologies in the fourth industrial revolution. However, there are many challenges attached to applying visualization successfully, both from the manufacturing industry and visualization research perspectives. As members of research institutions involved in several applied research projects dealing with visualization in manufacturing, we characterized and analyzed our experiences for a detailed qualitative view, to distill important lessons learned, and to identify research gaps. With this article, we aim to provide added value and guidance for both manufacturing engineers and visualization researchers to avoid pitfalls and make such interdisciplinary endeavors more successful.**

INTRODUCTION AND BACKGROUND

With the digitization of the manufacturing industry, enormous amounts of industrial data are collected. Expectations regarding quality, costs, delivery time, durability, and environmental aspects are rising. Data-driven manufacturing is a promising way of keeping up with these demands. It opens up unprecedented opportunities to understand the impact of decisions on engineering performance and customer satisfaction. The ability to turn industrial data into actionable decisions plays a key role in remaining competitive.

Data-driven manufacturing strategies range from design and process optimization to predictive maintenance. Data is acquired across all stages of a manufacturing process, from design through production to quality control and maintenance. Heterogeneous sources collect large, multivariate, and often time-dependent data sets.

This data needs to be analyzed to understand the behavior of a measured or simulated system, explore phenomena and trends, discover dependencies, and finally make an informed decision about the situation at hand. Despite companies having recognized its value[1], we recognized that many of them struggle with how and where to start making sense of their data. As a consequence, its potential remains largely unused.

With this paper, we share retrospective reflections on our personal engagement in developing visual-interactive strategies that foster the use of data to solve analytical tasks in manufacturing. We report and reflect on our involvement in application-oriented research collaborations with industry partners to provide hands-on insights. By identifying commonalities among our projects, we aim to contribute to a shared understanding of the role of visualization in manufacturing.

We present a collection of 13 projects where visualization played a major role in product development or manufacturing processes. The overview provides information about the manufacturing context, the usage scenario, visualization idioms, and further details. From this, we derive lessons learned regarding our interdisciplinary collaborations as well as insights into the role of visualization for industrial data analysis. We also share our view on possible future directions for visualization research.

RELATED WORK

Industry 4.0 describes the ongoing transformation of manufacturing processes towards increased interconnectivity and automation. This development comes with the need for elaborated analysis functionality for large, multivariate datasets with high levels of precision in all dimensions [1]. It is therefore not surprising that visual computing has been recognized as one of the key enabling technologies in Industry 4.0 [13]. Only visual interfaces allow users to capture, analyze, and interact with both the real and the virtual production world. Their combination with data mining algorithms, referred to as visual analytics, has proven to be an effective approach to making decisions based on large and complex data [9].

Visualizations in industrial manufacturing have already proven their potential for a variety of purposes, e.g. to improve the efficiency of production processes [17], to improve the quality of products, e.g., by realizing large manufacturing schedules [8], or to monitor the performance of production lines [19]. However, reflections mainly target the individual case study contexts, resulting in isolated lessons learned.

In their literature review, Zhou et al. collect visualizations of industrial data across a spectrum of analysis scenarios and phases of the manufacturing life cycle [20]. Their findings underline the wide range of data, users, and analytical tasks that make general recommendations regarding visualization support difficult. Although they

Visualization in Industrial Practice
The interplay between visualization research and industrial practice is also a common subject to scientific workshops. Recent contributions to the VisGap Symposium were dedicated to the conflicting interests of research and industry[a] as well as the role of visualization in decision support systems[b]. VisInPractice panels have targeted the impact on industry[c], industrial case studies[d], or practitioner collaborations[e]. Criteria for developing and maintaining visualization software have been subject to a NII Shonan meeting [14]. While such discussions encourage further evolution of directive experiences and lessons learned, their advice is mainly agnostic to the application domain. In contrast, application spotlights at IEEE Vis showcase practical uses of visualization, e.g. in industrial production[f] or to optimize real-world decision-making[g]. As spotlights, however, they shed light only on individual facets. In contrast, we combine our experience from a range of applications to convey a broader picture.

[a] P. Gospodnetic et al. "From Research Topic to Industrial Practice: An Experience Report". *VisGap 2020*.
[b] B. Kämpgen "The role of visualization in decision support systems - Differences between academia and industry". Capstone at *VisGap 2021*.
[c] VisInPractice at IEEE VIS 2017, Phoenix, Arizona.
[d] VisInPractice at IEEE VIS 2018, Berlin, Germany.
[e] VisInPractice at IEEE VIS 2021, Virtual.
[f] P. Gospodnetic et al. "The Role of Visualization in Industrial Production". Application Spotlights, IEEE VIS 2020.
[g] J. Ahrens et al. "Feature-based Visual Interactive Systems to Optimize Decision Making". Application Spotlights, IEEE VIS 2019.

[1] The analogy *"data is the new oil"* is often used to describe its relevance as a resource that drives digitization.

have already been successfully applied, interactive visualization techniques have not yet reached the expected dissemination [3]. The availability of industrial data, the shift towards data-driven decision-making, and the vague understanding of visualization in manufacturing contexts raise the need for further discussion about the use of industrial data visualization in practice.

METHOD

In this work, we take a retrospective look at visualization introduced to different stages of industrial manufacturing processes. Our goal is two-fold: 1) achieve a better understanding of methods that are currently applied and 2) summarize our essential lessons learned so far. Visualization design depends on the experiences, views, intuition, and interests of both researchers and engineers [10]. To address this, we draw on a wealth of personal experience with representative projects, on which we can base our findings. In contrast to a systematic literature review, we opt for a qualitative approach of introspecting our own visualization research experiences. This allows us to dig deeper into contextual information, failures on the way, or particularly challenging aspects that would otherwise be difficult to extract from the outside based on scientific papers only. None of the analyzed projects was carried out collaboratively between subsets of the authors. Thus, we were able to collect a diverse range of projects. We are confident that we can provide representative results that can be generalized to a certain extent.

In the further course of this paper, we use the terms *researchers* to refer to visualization researchers, *engineers* for domain experts from the industry, and *partners* to mean both of them.

Project Selection and Description

We reviewed 13 projects that represent different applications of visualization in manufacturing. All projects were conducted within the last four years. They involved collaboration with industry partners from Austria and Germany. An initial discussion yielded a number of characteristics to gather for each of these projects. Starting with basic information like project name, topic, and goal, we iteratively refined the collection and ended up with a total of 29 aspects. In the context of this article, we focus on 14 of these aspects that best reflect the core characteristics. Interested readers are referred to the supplementary material for further details. We used a large matrix to gather this descriptive information based on documentation, software prototypes, project reports, and discussions with co-workers.

Analysis and Reflections

From the tabular overview of the projects, we first derived a characterization scheme including categories for data sources, analytic tasks, and visualizations. Using open coding and aggregation, we collected commonalities and differences among the projects. At multiple points in the tagging period, we discussed the definitions of tags among all authors and adjusted their use according to the consensus reached. Commonalities hint at potential trends, whereas differences point at situational characteristics. In multiple discussion sessions among all authors, we finally collected lessons learned about both success factors as well as challenges.

SELECTED RESEARCH PROJECTS

In the following, we discuss our experiences with research collaborations in different industrial data analysis settings. We categorize them according to the four phases design, operation, quality control, and service of the manufacturing life cycle. Table 1 provides a structured overview and characterization of the investigated projects.

Design Phase

Engineering design is about creating a functional system or process that fulfills desired needs and specifications within given constraints. At the core of this phase are multi-criteria decisions. An objectively optimal design generally does not exist. Instead, engineers need to apply their experience to choose the most-preferred compromise.

PAVED: In close collaboration with a mechatronics research company, a parallel coordinates visualization has been designed to support motor designers in exploring which level of motor performance is achievable under different conditions [4]. The visualization provides a compact and lossless overview of the design options generated by an optimization algorithm (Figure 1). Observing the effects of both formal constraints

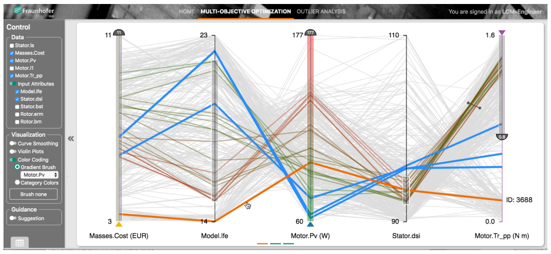


Figure 1: PAVED: Interactive parallel coordinates help motor designers choose a compromise from a number of Pareto-optimal design options [4].

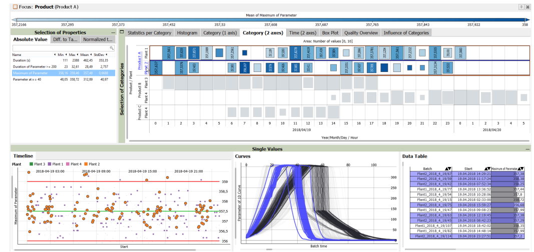


Figure 2: INGRESS: Visual views enabled process engineers to compare different runs (batches) of a manufacturing process.

and informal preferences allows the engineers to understand which trade-offs are involved and to justify their decision accordingly.

*COMPO*SED*: In a follow-up of the PAVED project, the visualization design is adapted to further support the design of systems that consist of multiple interacting components.

En2VA: Visual analytics techniques also help using and validating simulation models. Understanding the influence of parameters on the simulation results and comparing different results are important tasks in engine design. To this end, a visual framework for analyzing simulation ensembles was designed, where it is possible to rank simulation results based on different criteria.

Operation Phase

The operation phase transforms the previously chosen design option into a physical result. The main goal is to achieve high quality, while keeping production time and costs low[2]. Tasks like planning the production, monitoring the operating status, troubleshooting downtime or high scrap rates, determining when to best replace machine parts, and identifying systematic process flaws highly benefit from an analysis of process data.

Planning The optimal planning of production processes includes a multitude of constraints such as production steps, necessary machinery, personnel, and order dates that need to be taken into consideration. In largely custom-made and built-to-order production, this step is decisive for the success of a company.

InnoFIT: In this project, a consortium of scientific and industry partners works on the improvement of forecasting processes and forecast quality with the use of statistical methods, visualization, and data analytics tools. These methods are used for the analysis of forecasted and current orders, visualization of the forecast evolution, visualization of forecast error measures with respect to its evolution, as well as the clustering of similar products with same forecast behaviour [11].

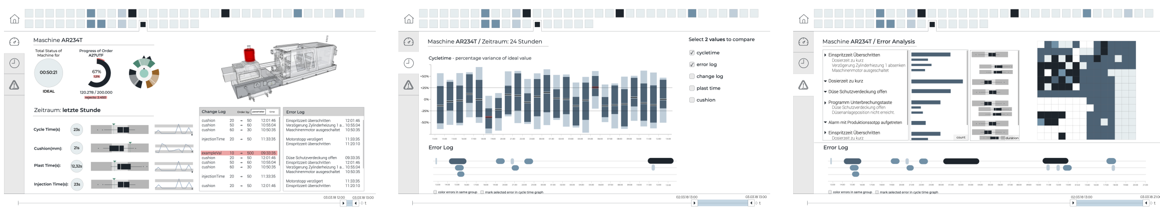
Monitoring Production monitoring is probably one of the first areas that come to mind when thinking about the application of visualization in manufacturing. The application of graphical methods to display machine and production states for monitoring and quality assurance has a long tradition and includes analog shop-floor boards as well as digital and interactive dashboards.

Greiner BigDataVis: Together with a plastic packaging manufacturer that uses injection moulding machines, a set of novel visual interfaces was designed to monitor sensor data of machines and the environment as well as machine error logs (Figure 3). The main goal in this project was to ensure consistently high production quality and low numbers of rejects.

INGRESS: In the project, several views were combined to enable the comparison of different runs in a production process. In this example, refractory bricks are produced in different batches, and one aim of the process engineers was to compare different batches. Together with the engineers, a visual framework for the analysis of production batches was designed (Figure 2). In this framework, significant differences between consecutive production runs could be identified.

AARiP: Hearing protections are mandatory for workers in many production facilities. The main idea in this project was to turn them into

[2]The constraints quality, time, and cost mark the corners of the so-called iron triangle (also referred to as triple constraint).



(a) Machine overview (b) Parameter deviation and error logs (c) Error analysis

Figure 3: Greiner BigDataVis: Injection moulding machine monitoring and analysis of error logs.

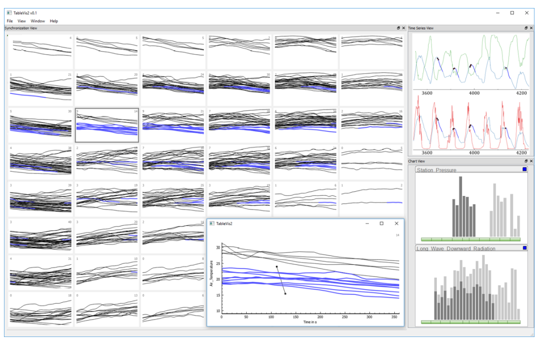


Figure 4: Chassis analysis: Visualization helps determine a set of sensors to replace a malfunctioning sensor. It is evaluated by its ability to consistently capture the target characteristics [5].

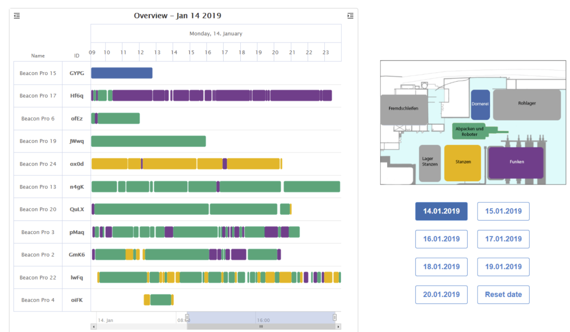


Figure 5: BlueDAT: Keeping track of the location of products in large production sites (Left: time-oriented view with color-coded spatial areas; right: map view) [7].

an acoustic information interface as well as an assistance system. This allows for the communication of real-time information using a different interface modality, which frees workers from the need to look at or haptically interact with other interfaces. The developed methods allow for the acoustic representation of machine and surrounding noises (process-relevant deviations from the norm), machine-related and production-related data (inventory, scope, setup, etc.), and verbal communication [6]. Visualization comes into play for the testing and simulation environment in virtual reality that was used in the project.

Chassis analysis: How to replace a missing or malfunctioning sensor with a virtual sensor was investigated in a project with a German automobile manufacturer. Various car characteristics needed to be measured during a real-world test drive to model the vehicle's driving behavior for a digital twin. Modeling was supported by a visual-interactive feature selection technique [5]. The model-agnostic selection criterion determines how consistently a sensor subset captures the characteristics of a sensor to be replaced (Figure 4). This approach can also be used to model a quantity that is too expensive or difficult to measure using cheaper or more manageable sensors.

proSVIFT: Monitoring machine health is of particular importance for autonomous systems. Without a human operator involved, these systems need capabilities to diagnose and anticipate failures and proactively ask for repair. A visual-interactive model editor is developed to help engineers with the systematic specification of potential component failures, their probabilities, and how severe they affect the surrounding system hierarchy. Based on the probabilistic model, diagnostic and prognostic inference can be performed. The main goal in this project is a condition monitoring approach that balances the safety and availability of the monitored system.

BlueDAT: Another problem area for a specific class of manufacturing companies is keeping track of products and materials within their often very large premises. This can lead to situations where containers are lost or take a long time to find. Asset tracking aims to efficiently monitor the products' whereabouts and analyze the produc-

Figure 6: Bridge vibrations: Linked views depict seasonal patterns (top) and daily trends (right) of bridge transits as well as correlations between dimensions of the resulting vibrations (bottom).

tion flow. In a collaboration with a manufacturer of fittings, localization is realized using Bluetooth LE technology and interactive visualizations are used to show the locations of the assets as well as their position history [7] (Figure 5).

Quality Control and Service Phase

Before products can be shipped, their functionality has to be validated. If a product is defective or does not match manufacturing tolerances, engineers are interested in the root cause to avoid entire batches of rejections. While inspections were predominantly carried out manually in the past, quality control has increasingly become data-driven to shorten production cycles.

EoL: An example is the end-of-line testing project, where visualization researchers and mechatronics scientists work towards an automated failure classification that exploits the domain knowledge of engineers. The unit under test (an electric motor) is exposed to a stimulus and its response (the motor's current signals) is recorded. Interactive visualization is used for the analysis of operating conditions and signal shapes to inform the creation of a data-driven failure model. In particular, it considers the engineers' experience with the unit under test, domain-specific semantics and expectations, previously unknown anomalies, and additional diagnostics to identify and evaluate potential features for classification.

Following quality control, the product's delivery marks the transition to the service phase. Here, usage data are acquired to trace long-term quality, defects, and customer satisfaction in order to provide assistance and improve the manufacturing life cycle.

Bridge vibrations: This also applies to public infrastructure such as bridges. In a project with a research institute in the domain of structural durability, vibration data of a sensor-equipped bridge were analyzed to identify early signs of damage, aging, or load peaks. The main goal of visualization is to provide an overview of characteristic vibration behaviors and how they are related to external factors like daily and seasonal patterns, intensity of use, or the aging process (Figure 6). This helps to determine a baseline behavior, so that anomalies can be identified as deviations from the known behavior.

RAILING: Another example was explored in this project, where differences in the quality of welding seams on metal parts had to be traced back to different parameter settings in the production process. This allowed process engineers to relate quality issues in the results to process parameters, in which way they could identify faulty or unfavorable settings in the production.

DISCUSSION

In all 13 projects, we identified interactive visualizations and visual analytics as very helpful tools for analyzing data in the manufacturing industry. We experienced that the planning and monitoring of a manufacturing process currently pose the biggest challenges for visualization.

Sector: The selected projects could mainly be assigned to the industry sector *C-Manufacturing*. Two projects also matched the schemes *F-Construction* and *H -Transportation and Storage*.

Phase and focus: The majority of projects (seven) relate to the *operation* phase. Projects in this phase mainly focused on the manufacturing process itself. The rest of the projects were equally distributed among the *design* phase (three) and the *quality control and service* phase (three). These projects mainly focused on the product to be manufactured.

Optimize for: Seven of the projects aimed at optimizing quality, of which three simultaneously aimed at optimizing costs. One project was about directly optimizing costs. The remaining five projects focused on optimizing time. The project details, sorted by the respective phases, are summarized in Table 1.

Data source: The data collected by the industry partners was usually quite large (hundreds to millions of data rows). We noticed a dominance

	Title	Topic	Sector	Foc. (Product, Process)	Opt. (Cost, Time, Quality)	Data Source (Machines, Sensors, Simulation, Environment, Humans, Logging, Other)	Users	Tasks (Multi-Attrib. Choice, Par. Space Analysis, Root Cause Analysis, Forecasting, Inference, Regression, Pattern Search, Other)	Visualization (Basic, ParCoord, Map, VR, SPLOM, Graph, Heatmap)	Int.	Eval.	TRL	Ref.
	Description			Manufacturing Industry		Problem Characterization			Idioms	Info			
Design	PAVED	Design and Optimization of Electric Drives	C.27.11	● ○	● ○ ●	○ ○ ● ○ ○ ○ ○	motor designers	● ○ ○ ○ ○ ○ ○ ○	○ ● ○ ○ ○ ○ ○	●	●	6	[4]
Design	COMPO*SED	Optimization of Multi-Component Systems	C.27.11	● ○	● ○ ●	○ ○ ● ○ ○ ○ ○	motor designers	● ○ ○ ○ ○ ○ ○ ○	○ ● ○ ○ ○ ○ ○	●	●	3-4	
Design	En2VA	Simulation ensemble analysis	C.27.11	● ○	○ ○ ●	○ ○ ● ○ ○ ○ ●	Engine designers	○ ● ○ ○ ○ ○ ○ ○	● ● ○ ○ ○ ○ ○	●	○	7	[12]
Operation	INGRESS	Monitoring the manufacturing process	C.23.32	○ ●	● ○ ●	● ● ○ ○ ○ ○ ●	Process managers	○ ○ ● ○ ○ ○ ● ○	● ● ○ ○ ○ ○ ●	●	○	7	[2]
Operation	InnoFIT	Improvement of forecasting processes and quality	C.15.12, C.24.53, C.29.32, C.28.15	○ ●	○ ● ○	○ ○ ● ○ ● ○ ○	production planners, supply chain and operations managers	○ ○ ○ ● ○ ○ ○ ○	● ○ ○ ○ ○ ○ ●	●	●	3-4	[11]
Operation	AARiP	Auditory Augmented Reality in Production	C.25.73, C.24.33	○ ●	○ ○ ●	● ○ ○ ● ○ ○ ○	workers, production supervisors, operation managers	○ ○ ○ ○ ○ ○ ○ ●	○ ○ ○ ● ○ ○ ○	●	●	3-4	[6]
Operation	Greiner BigDataVis	Machine condition monitoring	C.22.22	○ ●	○ ○ ●	○ ● ○ ○ ○ ● ○	Injection molding technicians	○ ○ ○ ○ ○ ○ ● ○	● ○ ○ ○ ○ ○ ●	●	○	2-3	
Operation	proSVIFT	Probabilistic safety optimization	H.52.10	● ●	○ ● ○	○ ● ○ ○ ● ○ ●	Reliability engineers	○ ○ ○ ○ ● ○ ○ ○	○ ○ ○ ○ ○ ● ○	●	○	1	
Operation	Chassis analysis	Regression analysis of sensor signals	C.26.51	● ○	● ○ ○	○ ● ○ ● ○ ○ ○	Gearing engineers	○ ○ ○ ● ○ ● ○ ○	● ○ ○ ○ ○ ○ ○	●	●	3-4	[5]
Operation	BlueDAT	Asset tracking (products and materials)	C.22.21	● ○	○ ● ○	○ ● ○ ● ○ ○ ○	employees in production	○ ○ ○ ○ ○ ○ ○ ●	○ ○ ● ○ ○ ○ ○	●	●	3	[7]
Quality Control	EoL	Automatic detection of motor defects	C.27.11	○ ●	○ ● ○	○ ● ● ○ ○ ○ ○	motor designers	○ ○ ○ ○ ○ ● ○ ○	● ○ ○ ○ ○ ○ ○	●	○	2	
Quality Control	Bridge vibrations	Detection of damage or load peaks	F.42.13	○ ●	○ ● ○	○ ● ○ ○ ○ ○ ○	Construction/ infrastructure authorities	○ ○ ○ ○ ○ ○ ● ○	● ○ ○ ○ ● ○ ●	●	○	2	
Quality Control	RAILING	Root-cause analysis for metalworks	C.25.61	● ○	○ ○ ●	○ ● ○ ○ ○ ○ ●	Process managers	○ ○ ● ○ ○ ○ ● ○	● ○ ○ ○ ○ ○ ●	●	○	7	

Table 1: Structured overview and characterization of our practical experience with applied visualization research projects in the manufacturing industry. (Sector according to the statistical classification of economic activities in the European Community (NACE Rev. 2): https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF; ● = fulfilled; ○ = not fulfilled; Foc. = Focus; Opt. = Optimize for; Int. = Interactive; Eval. = Evaluation; TRL = Technology Readiness Level; Ref. = References)

of time-dependent and multivariate data (similar to domains like energy and climate research). In many cases, the data came in the form of simulation ensembles, especially in the *design* phase. In other cases, particularly in the *operation* phase, sensor recordings were most common. In contrast to other domains like cyber security or social sciences, geo-referenced data requiring map-based visualizations or graphs are less often present. The main reason why industry partners started research projects were severe limitations that they experienced with existing solutions (often based on Excel) due to the sheer data volumes and the large solution space.

Visualization and interaction: We mainly applied basic charts (e.g., line charts, box plots, bar charts), parallel coordinates, and some custom charts developed together with the domain experts. All of the charts included interaction techniques and were most often arranged in multiple coordinated view interfaces. One project made use of virtual reality technologies. In many cases, the implementation of the applications was based on web technologies and libraries (e.g., D3.js), while others employed scripting environments like Python and Jupyter. Only two projects involved stand-alone systems based on C++. In one case, the commercial tool Tableau was used for data analysis. Traditional data analysis frameworks often provide the possibility to create basic visualizations that might be enough for domain experts to grasp the main patterns in a dataset. However, creating interactive applications is not trivial and commercial tools like Tableau are not explicitly suited for engineering data. Therefore, there is still a need to support the creation of well-suited interactive visualizations.

Users: The *end users* in our projects had diverse engineering roles and responsibilities. Nevertheless, a commonality is that most of them had only little experience in data visualization.

Tasks: The analysis *tasks* cover different data-driven ambitions to understand the behavior of products and processes along the entire manufacturing life cycle. While confirmatory analyses may occur, open explorations - where engineers cannot explicitly describe the phenomena they are looking for - are more common. Depending on their role, the users' analysis tasks varied from multi-attribute choices through parameter space and root-cause analysis to correlation tasks (forecasting, inference, regression) and pattern exploration. Unlike other domains, engineering activities are largely prescribed by standards. To categorize the tasks in our table, we initially tried to apply a task taxonomy from visualization literature, but soon realized that its granularity did not match the distribution in our projects.

Evaluation and TRL: Nearly half of the projects included a qualitative or quantitative *evaluation* of the developed application. One of their common outcomes was that interfaces with multiple views and additional operators (e.g., filters) require a proper familiarization phase for users without a visualization background. While our projects cover a wide range of Technology Readiness Levels (TRL), we noticed that none of the applications with the highest TRL have been evaluated, mostly due to integration and customer issues that have been prioritized.

In summary, we can confirm that visualization and visual analytics are an essential driver of the digitization in the manufacturing industry. Visualizations are particularly helpful for engineering scenarios that require an understanding of simulation ensembles or an efficient handling of large and/or heterogeneous data sets.

LESSONS LEARNED

To explicitly share our experiences, we derived several *best practices* for applying visualizations in industry and put them in context with existing related work on visualization applications. Performing visualization research in the industry strongly relates to conducting design studies. Our collection emphasizes, but also extends, the practical considerations and pitfalls that Sedlmair and colleagues proposed in this context [15]. Where appropriate, we refer to the stages and pitfalls of their methodological framework (*text in brackets*). We anticipate that both visualization researchers and industrial engineers will find this collection of lessons learned helpful.

We found applied visualization research in the manufacturing industry to be likely successful if...

... partners are interested and committed.

This is what makes a collaboration fun and drives productivity. We believe that a positive rapport between researchers and domain experts is a prerequisite to achieve a project flow that comes with deep focus, mutual understanding, mental clarity, and promising ideas (*PF-11, winnow*). It can also lead to desirable long-term effects beyond the project, e.g. when it comes to software maintenance, consulting, or follow-up initiatives. This is particularly important in manufacturing, where companies typically do not start research projects with external partners easily.

... engineers see the value of visualization.

A knowledge gap regarding the potential of visualization is a natural aspect of visualization-industry cooperations. This applies even more to the manufacturing domain, where the digital transformation draws the attention to fast results from automated processes. Confirming known insights by visualizing test data is a common advice, but it particularly helps to draw the engineers' focus from automated towards visual-interactive analysis. Companies are dealing with different digitization technologies and visualization is just one of them. Market competition is driven by time, quality, and cost benefits, which visualization rarely quantifies at first sight. Engineers should not hold visualization projects responsible for short-time profit, but rather consider them a part of their digitization strategy. Industry experts need to be open and patient when it comes to applying visualization in their fields.

... high-quality data are available. Interestingly, despite the focus being on visualization and visual analytics, the main challenge in many projects was not providing a novel visualization technique, but rather getting the right *data* in proper quality and in a specific format. Companies are sometimes reserved about real data leaving their internal space. At the beginning of a collaborative project, in many cases only test data sets are available. This problem was also discussed by Walny et al. [18] and named *C1–Adapting to Data Changes*. We can confirm that we also had this problem in our projects. The data is often scattered across different platforms (e.g. systems, notes, and logs). The effort required for data merging and wrangling to achieve a structured format is often underestimated (*PF-4, winnow*). It is further complicated by data formats being proprietary or poorly documented. This particularly regards the semantics of parameters, which are often named using cryptic abbreviations. Data consistency and availability are common data problems when implementing visualization projects [14, 18]. Very few companies include data quality measures in their processes, resulting in data often being messy (i.e., missing or faulty values) and sometimes not covering important measurement periods. This was especially the case for the projects BlueDAT, INGRESS, and RAILING. It was interesting to see that our company partners were not aware of their data provision problems until the implementation of the described research projects.

... artifacts fit the technical environment. Most projects included the development of new visualization software. A decisive criterion regarding the further usage of the developed techniques was whether they fit into the existing environment of data interfaces and tools. In the proSVIFT project, we kept hearing that a novel solution can only be established if it connects to existing tools with the highest market share. This was similar in the RAILING project. We experienced the requirement of new tools to fit into existing environments in manufacturing companies to go beyond what is mentioned as challenge *C3–Understanding Technical Constraints* by Walny et al. [18]. From a technological perspective, an integration requires a detailed analysis of the environment and how users are going to access the tools (e.g., directly, via a web browser, via cloud services, or other client interfaces). Reina et al. suggest to have building blocks of visualization artifacts available to support the development process of new tools [14]. We can confirm that visualization modules, and also open source libraries, facilitate the development process.

... visualization embraces domain practices. The development of new visualization approaches required a user-centered approach that involved constant communication to understand the application setting, collect requirements, validate assumptions, and evaluate design options (*discover, design, reflect*). Researchers should also detail how the visualization is intended to blend in with the engineers' current practices (similar to *C5–Communicating Data Mappings)* [18]). Ideally, a project considers these needs, while at the same time inspiring engineers to think differently about their tasks and approaches.

... the topic is already well-understood. Pushing the frontiers forward requires a fundamental understanding of the targeted problem. Scientifically interesting problems and innovative solutions are not found at the surface but can only be identified during long-term collaborations, where increasingly complex problems are uncovered over time. As an example, it was not until the evaluation of PAVED that we encountered an even more challenging research problem leading to the follow-up COMPO*SED project.

... the ideas of engineers are acknowledged. To avoid focusing on visualization solutions prior to having understood the problem, researchers should ask what engineers want to learn during an analysis rather than what they want to see (*PF-17, discover*). However, in the PAVED project, we found that even if it is not their responsibility, engineers might have an accurate vision of meaningful visualization solutions. Although, we tended to neglect their suggestions at first, they contributed significantly to the final visualization design. We therefore recommend that even if researchers might feel that their expertise is underrated, they should acknowledge the ideas of their collaborators despite the engineers' likely limited visualization background.

These lessons learned reflect our personal observations related to conducting application-oriented projects in interdisciplinary teams and dealing with external requirements. They mainly relate to the precondition and early core phase of the nine-stage framework [15]. This does not mean that the remaining stages have been irrelevant for our projects. We can confirm the framework as being a helpful guideline for carrying out applied visualization research projects in industry. In this sense, working with company partners from the manufacturing industry shows commonalities with visualization research projects in other domains (e.g., medicine, biology, physics). We also identified some issues that were not emphasized by existing approaches. As one important insight, we would like to mention the demands placed on visualization systems to fit into existing environments. Furthermore, the availability of data in the required quality turned out to be a recurring and prominent problem when working with industry partners.

RESEARCH CHALLENGES

The *interactive visualization gap* [3], although diminishing in general, still exists when we talk about manufacturing applications. Visualization and visual analytics tools are not recognized as essential assets to be integrated into daily workflows. We particularly need to be aware of the fact that this application domain is largely driven by the ”time is money” principle. We need to find new ways of demonstrating how visualization can serve the common KPIs in manufacturing. In particular, we need to put engineers in the position to recognize analysis problems that cannot be solved by an automated data analysis only.

User Guidance & Onboarding

We often heard from domain experts that highly flexible and interactive visualization frameworks with many views on the screen tend to overwhelm novice users. This calls for guidance in visual analytics, a forward-oriented process that aims to help users in carrying out analytical work. However, some engineers are also hesitant to fully rely on guidance because they assume that inaccuracies might lead to interesting regions being overlooked. In this case, onboarding approaches can help users develop a general understanding of how to read, interact with, and interpret the visual representations [16]. More research efforts on how to design onboarding and guidance would lower the entry barrier for engineers to work with visualizations.

Data Wrangling

Many data infrastructures in industry companies have grown historically and consist of multiple, often incompatible, data silos. Therefore, a significant challenge in any data-based project is to collect and join the necessary data elements. Along the manufacturing life cycle, this particularly involves the combination of heterogeneous items like time series, logs, and audio recordings. Visual analytics could help to get an overview of the data sources, judge the quality of the collected data, and identify suitable interfaces for joining the data (e.g., by timestamp or machine number). In this way, the startup time of projects could be reduced and more effort could be put into the actual support of the users' analytical workflow.

Integration Into Existing Environments

Data visualization and analytics are not completely new to engineers. Over the last years, they already established data workflows using different environments and tools (e.g., Python scripts or BI systems). The acceptance of new applications strongly depends on their ability to blend in with existing workflows and standards. Such an integration can involve providing extensions to well-known visualization packages or command-line support for existing environments.

As data elements are often tied to physical locations in a plant, a better integration of visualization into the physical realm of users in their work environment appears to be a promising research direction. Particularly, approaches beyond classical desktop interfaces can lead to a more seamless integration. This includes visualization on mobile devices such as smartphones, tablets, or smartwatches; multimodal interfaces that combine visual representations with other modalities such as sonification or natural language interfaces; as well as immersive analytics approaches that make use of stereoscopic display technologies such as AR headsets.

Future Application Topics

The *service* phase has rarely been addressed by visualization approaches so far. Besides, the *design* and *operation* phases still pose exciting challenges for future visualization research. This is also reflected in the publications that originated from the 13 projects. We particularly identified engineering design as a promising direction to apply visualization in manufacturing. It requires an analysis of multivariate simulation or sensor data to inform multi-criteria decision-making. Both the analysis of multivariate and time-oriented data as well as the decision support are active fields in visualization research. Yet, research ambitions have not been dedicated to the particular characteristics and requirements of engineering design so far.

CONCLUSION

Visualization and visual analytics are essential techniques for making data from industrial manufacturing processes usable and understandable. In this paper, we characterize and classify our experiences with visualization research projects in the manufacturing industry and summarize our findings. The main insight is that a good understanding of the application domain and an iterative development with domain experts are crucial to achieve the acceptance of end users. Pitfalls were rather related to getting the right data in sufficient quality than to providing a suitable visualization. The paper is based on our involvement in 13 visualization projects that were conducted over the last four years in Austria and Germany. We analyzed our projects along the four phases *design*, *operation*, *quality control*, and *service* of a manufacturing production process. Although each phase is represented in our collection, most of the visualization projects so far have been conducted in the *design* and *operation* phases. From a visualization research perspective, open research questions address the support for data quality monitoring and data wrangling, the integration of visualization solutions into existing workflows, and guidance for novice users. It might also be beneficial to complement our visualization research point of view with the collaboration perspectives of our domain experts.

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