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User-Guided Visual Analysis of Cyber-Physical Production Systems

Modern cyber-physical production systems (CPPS) connect different elements like machine tools and workpieces. The constituent elements are often equipped with high-performance sensors as well as information and communication technology, enabling them to interact with each other. This leads to an increasing amount and complexity of data that requires better analysis tools to support system refinement and revision performed by an expert. This paper presents a user-guided visual analysis approach that can answer relevant questions concerning the behavior of cyber-physical systems. The approach generates visualizations of aggregated views that capture an entire production system as well as specific characteristics of individual data features. To show the applicability of the presented methodologies, an exemplary production system is simulated and analyzed. [DOI: 10.1115/1.4034872]

1 Introduction

The "industrial internet" refers to developments triggered by new information and communication technologies (ICT) in industry. Terms like industry 4.0, cyber-physical production systems (CPPS), or smart factory are associated with the same phenomenon of industrial systems using ICT in production by applying cyber-physical methodologies. The most prominent feature of a CPPS is the interconnection of its different manufacturing elements such as machine tools or workpieces and the resulting amount of production data [1].

It is expected that these technologies will make it possible to handle the increasing complexity of production systems and to cope with current trends and challenges [2]. Shorter product life cycles and mass customization are leading to higher numbers of product variants and ever smaller lot sizes, making it necessary to adapt a production system in a fast, efficient way.

With the goal of increasing the flexibility of a production system, decentralized concepts within production planning and control have been discussed in theory [3]. Yet, their application in industry has not been widely spread [4]. The availability of modern ICT, as discussed under the term of industrial internet, is expected to have a highly positive effect on the applicability of such concepts [2].

The enormous amount of data generated by cyber-physical systems makes it necessary to devise approaches for refinement, for the data to become truly helpful to human decision-makers. Also, to identify ways to make machines "intelligent," data analysis and visualization tools are becoming essential. Hence, the effort of this work was driven to a large degree by developing new and more effective ways to analyze and visualize production data, allowing humans to have quick access to just the needed, most relevant information.

This work introduces a visual analysis approach that captures the performance of a production system in an intuitive manner. For example, bottlenecks and excess capacities are identified and visually highlighted, thereby guiding the user in the analysis. The impact of changes applied to a manufacturing system can be analyzed by utilizing the presented visualizations. Additionally, the approach can generate an aggregated view of an entire system or focus on merely the most interesting features captured in a data set. The developed tool supports a performance driven and yet detailed analysis by enabling a highly efficient evaluation of production data and by guiding a user to ask important questions. An exemplary production system is simulated to depict the characteristics of the visualizations and to show the applicability and effectiveness of the presented analysis tool.

This work is structured as follows: Sec. 2 provides an overview of related work and defines requirements for data analysis and visualization tools for complex production systems. Section 3 describes the underlying simulated production system and focuses on the methodologies used in the presented analysis and visualization tool. Finally, this work is concluded by summarizing the main contributions in Sec. 4.

2 Related Work

This section will summarize related work in data analysis and visualization tools for cyber-physical production systems and derive the resulting requirements for a visual analysis tool.

2.1 Data Analysis in Cyber-Physical Production Systems. The data available in a cyber-physical production system can be used to make production systems more flexible. In this context, flexibility can be understood, on the one hand, as the transformability of the system to engineering changes on medium or long term perspective. On the other hand, flexibility can be understood

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as achieved by decentralized production control on a short term view.

It is obvious that the vast amount of data is not useable without refinement. Therefore, user friendly tools for data analysis and visualization are needed [5].

Examples for engineering changes are the reconfiguration, addition, substitution, or removal of production equipment, e.g., machine tools, in a manufacturing system [6]. They usually have extensive impacts on the manufacturing system due to the manifold interrelationships among production objects [7] and hence need careful analysis and planning before implementation. The change in one element might result in the disruption of the process chains, material flow, or information flow. Therefore, tools are required that can analyze the effects of envisaged engineering changes in a fast and comprehensive manner [8].

Tools that support the planning and analysis of changes in manufacturing systems can be found within the concept of the digital factory [9]. Simulation and evaluation software for products and material flows can be applied in order to analyze processes and their changes. However, such software tools require specific know-how and qualified personnel to use them and to keep them up to date, and are not specialized on engineering changes [10].

A framework specialized for analyzing impacts of engineering changes to existing manufacturing systems is proposed by Malak and Aurich [8]. Here, the alternative solutions for engineering changes are visualized in a 3D virtual environment where effects on factory layout and material flow can be seen in a spatial context. Although a three-dimensional virtual environment displays information intuitively and thus gives a realistic feeling of the modeled factory, it shows only partial views of the factory and does not guide the user to the information needed.

For the fast and effective analysis of impacts to engineering changes, both, aggregated and detailed views, are necessary. To enable the overall evaluation of the given situation, e.g., to examine process chain and information flow consistency, the available data need to be visualized in an aggregated manner. On the other hand, scalability of the data is required to allow the user to focus on single products or machines and to well defined time steps of special interest. An essential requirement is to guide the user to the most interesting features of the regarded system and to show critical issues. Therefore, comparative and interactive data highlighting integrated in the spatial context of the factory are needed. Different perspectives focusing on machines, products, and material flows within the visualization tool need to be distinguished and interlinked in an interactive manner.

In contrast to the planning of engineering changes, decisions in production control need to be taken in real-time with limited information. The concept of self-control in a decentralized production system is based on the ability of several elements of the system (e.g., machine tools or work pieces) to act and decide autonomously. In contrast to that, in the centralized approach, planning is accomplished by a superordinated planning entity. Therefore, especially for decentralized production control with a multitude of decision-makers, a fast recognition of data patterns is necessary to adapt the behavior and decision rules of the acting elements.

The applicability of different self-organization concepts is tested in several research projects by using prototype factories (e.g., Refs. [11–13]). As the implementation of such prototypes with real machinery involves considerable effort and expenses, they are therefore not meant for real scale experiments. Thus, the amount and complexity of data can still be managed manually, so tools for visual evaluation and optimization of the concepts are missing. Ilsen et al. propose a test field based on a multi-agent system to test several self-organization concepts against each other in a real sized but virtual environment [14]. Here, several different decision routines, e.g., for machine tool selection or production order, are possible. This case shows that in the analysis of decentrally controlled production data, the impacts of different decision routines need to be visualized. Further, there is a need to identify patterns on an aggregated data level to derive the system's sensitivity to changes of decision routines. As a consequence, aggregated views displaying the overall performance in a spatial context, and detailed views representing the perspective of single elements, are necessary to understand an entire system.

To summarize, one major issue for data visualization is to be intuitively understandable. Therefore, an interactive guidance for the user is required, which makes it easy to find interesting features in a data set. To get a quick but comprehensive overview of the status of the production system, different perspectives on an aggregated level are needed. These have to be interlinked to navigate through the perspectives. Beside the aggregated views, scalability is a further required functionality that enables to select single hotspots and establish detailed comparisons between machines, products, or time steps. Embedding the data into the spatial context of the factory is needed to give the user a realistic and intuitive understanding of the factory and its performance.

2.2 Visualization Tools in Production Planning. Various approaches [15–18] present tools to visualize the performance of a production system. They mainly consist of strategies on stacking or combining single visualization entities, as workload or production time graphs for different machines or points in time. The main disadvantage of these approaches is that they do not provide spatial context or user guidance, which was identified to be essential for data analysis in cyber-physical production systems.

The visualization of product flows is an important task in the field of production planning. Embedding such flows into an underlying geometric model was already used in other domains like economical trade visualizations [19] and urban traffic visualizations [20]. There, money transfers are embedded into geographical maps and vehicle flows are embedded into traffic maps, respectively. The presented work makes use of this approach and transfers it to the domain of cyber-physical production systems by embedding product flows into virtual factories.

Wu and Acharya [21] present an approach to visualize the workload of a machine with a stacked box representation of the products waiting for this specific machine. Although this representation shows the order and number of waiting products, the approach does not provide a spatial context and only takes a certain point in time into account. Therefore, this work extends the approach of Wu and Acharya by applying it to a whole time window and embedding it into a spatial context for all machines at once.

Doil et al. [22] present an exploration system based on a virtual reality environment that allows users to choose different manufacturing settings. Because this is an intuitive way to handle manufacturing settings, this work also provides a three-dimensional representation of the factory that is compatible with a virtual reality environment. In addition to the approach of Doil et al., important aspects for factory planning like product flows or machine workloads are visualized directly in this spatial context.

The visualization of production times is handled in the work of Zhang [23]. Their approach presents a comparative visualization of production times where the user can examine the production times under certain conditions. Although that is a good representation of the production times, their scatterplot alignment makes it hard to compare different products. In contrast to that, this work visually captures the development of manufacturing time against degree of completion. Here, all products are aligned consistently, enhancing the user to directly compare production times.

Ertek et al. [24] visualize statistical features of production times for different manufacturing settings. Their approach can compare production times resulting from these settings, but no user guidance to find good settings is provided. In addition to that, the visualizations presented in the current work highlight interesting features and thereby guide the user in the analysis of manufacturing settings.

Based on the derived requirements and the found issues in production planning, this work shows the development of a visual analysis tool for virtual manufacturing systems.

3 Methods

This section will describe the production system that is simulated to obtain the data used for analysis, and the methodologies to visually analyze this data and guide the user to interesting features.

3.1 Characterization of the Simulated Production System. In a first step, a simulation is used to acquire production data of a virtual factory. All of the factory's components like the machine tools and the product workpieces are virtual as well. Each machine has a machine type and each product has a product type, so there are different types of virtual products and machines.

The work plan, i.e., the order of operations required to produce a final product, is given externally and cannot be changed (see Table 1). Thus, the product type defines which operations need to be processed sequentially to finish the product, while the machine type defines the operation the machine is capable of.

The ability of machines of a certain type to perform an operation with specific requirements is encoded into the machine type. For example, if the machines of a certain type are able to drill holes, but their accuracy cannot be guaranteed to be high enough for a certain operation, their machine type marks this operation as not performable. Though, other machines might be able to perform this operation with the required accuracy. Thus, the technological capabilities are encoded into the machine types.

The material removal rate (MRR) may vary during operations depending on material type, cutting speed and depth, cutting aids, tool type, or other factors. This leads to different process times, even for operations with the same production technology. The required setup times for each operation are included in the resulting processing times that are given in Table 1.

To finish the production of a product, all of its operations need to be processed in order, while each operation takes a certain time. Since in the presented example no machine is capable of performing all operations, the products have to be processed on different machines sequentially. So the current operation of a product is first finished on one machine, and then the product is transported to another machine. Since this new machine might be busy, the product is enqueued. To do so, each machine has a queue of waiting products that are processed in order of arrival (first in–first out).

If there are different machines of the same type, the question arises, which of these machines should process a certain product. This question cannot be answered in a perfectly optimal way for real-life sized problems due to its high-computational complexity. So an optimal solution cannot be calculated in a feasible time, but heuristics can be evaluated efficiently to come close to an optimal solution of product distributions. This work uses the heuristic of always choosing the machine that will have processed the product's individual operation first. Other heuristics could be considered as well, but since the choice of heuristic is not important for the demonstration of the presented analysis tool, the described heuristic is chosen out of simplicity reasons.

Table 1 Work plan describing the individual operations performed for each product type and their according processing times

Product type	Operation number	Production technology	Process time (min/pc)
A	1	Milling	52.0
	2	Milling	65.3
	3	Drilling	200.0
	4	Tapping	211.1
B	1	Milling	83.3
	2	Turning	163.9
	3	Drilling	100.0
	4	Tapping	88.9
	5	Turning	16.4
C	1	Turning	185.8
	2	Drilling	300.0
	3	Turning	142.1

Another issue is the optimal arrangement of machines in the factory. This problem is also computationally very expensive and cannot be solved optimally in a feasible time for a larger number of machines. Therefore, the arrangement of machines in the presented example was chosen as demonstrated in Sec. 3.2 by simply distributing groups of identical machines within the factory.

The transportation times of products between the machines depend highly on the arrangement of those machines. Since the production batches in the used example are very large, the resulting transportation times are very small in comparison. Therefore, the transportation times are visually disappearing in this example. Still, the methodologies that are presented in Sec. 3.2 are easily extendable in a straightforward way to also visually include transportation times, as will be seen shortly. In the presented example, a free transportation model is used. Naturally, other simulations could use restricted transportation routes to implement conveyor belts or other transportation methods.

The production data used for the analysis describe which product and which operation are performed on which machine at which point in time. To acquire this data, each product type is virtually produced 30 times in a simulation, while starting with a product of type A, then B and C, and then repeating this loop 30 times with a temporal gap of 10 min in between the products. This means, a new product of a specific type starts its virtual manufacturing every 30 min. To analyze the gathered production data, the visualizations and the methodologies described in the following are used.

3.2 Visualization. Based on the requirements developed in Sec. 2, a tool for the user-guided visual analysis of simulated production data was designed as described below. The tool is a linked view system, visualizing the manufacturing process under different aspects. This means that there are different views, each showing the same data but having a focus on different aspects. The presented tool contains a flow view, a workload view, and a production view.

Additionally, the views are interlinked by transferring user interactions like selection and highlighting of products, product types, or machines from one view to all views. Another user interaction is to choose a time window by manipulating a point in time and an interval size in all views. Then, this time window will be considered for visualization. This enables the user to zoom in and out onto certain interesting points in time.

All of the views of the system only show the data that occur during this chosen time window, thereby treating this window consistently for all views. By doing so, the user is enabled to focus on certain features, while the overall picture is preserved. This helps the user in building a mental map of the production data. Since all views of the presented system always show data for the same time window or selection, a cognitive transition from one view to the others is straightforward.

After the virtual manufacturing system is simulated once, the whole tool and its views work in real-time to provide flexibility of interactions to the user. The presented tool can be used to analyze virtual factories, provide user guidance for later optimization or comparison, and help in decision making.

The overall goal is the optimization of the production process with respect to a diversity of parameters. Still, this optimization cannot be done fully automatically because of its high-computational complexity. This stresses the importance of the presented tool to support users in their analysis tasks. Although the optimal solution is unknown to users, the presented tool can be used to iteratively improve factory settings. By that, users are enabled to approximate an optimal solution, thereby finding a sufficient solution and gain a certain confidence in their production process.

The realization for each view of the tool is presented in the following.

3.2.1 Flow View. The flow view provides the most general and intuitive visualization and helps creating an overview of the virtual manufacturing system by containing different visual elements (see Fig. 1).

The geometric model of the factory and its machines is displayed to form a basis for an embedding into a three-dimensional virtual context. To reduce the visual occlusion of other graphical elements, semitransparency is used for the geometric model. Using a three-dimensional model of a factory as a spatial context is a familiar working environment for analysts and domain experts who are used to these kinds of visualizations and interactions. Also, due to its simplicity and intuitiveness, this embedding is suitable for presentations.

The product flow extends this natural environment to allow the tracking of products throughout the factory as described later. This results in a direct visual feedback on the emergent behavior of the products in combination with the used heuristic method for distributing products onto machines. A user can see what machines individual products were processed on, and how the products are distributed.

In addition to the visualization of the product flow, the presented view contains a visualization for machine workloads. Here, the workload for each machine is displayed by showing the machine's queue for several points in time. These graphical elements are attached to the individual machines, leading to a direct visual feedback on the performance of machines and their queues. Also, the visual embedding into a spatial context supports a higher degree of intuitive understanding.

Combining multiple elements in one view results in a tool that is capable of analyzing factory arrangements and mechanisms. The realization of the product flow and the machine workload is shown in the following.

Product flow. The product flow is the combination of the trajectories formed from all the products moving throughout the factory over time. This is demonstrated in Fig. 1, while the images in Fig. 2 show a more detailed look on the properties of the product flow.

A spline [25] is a piecewise polynomial function of a fixed degree. It can smoothly interpolate a sequence of points without fluctuating too much, so it is well suited to follow a trajectory. These splines are used to represent the product flow by visualizing a spline segment for each moving product.

Instead of visualizing the "real" transportation routes between machines, the spline representations show the topological routes of the products, meaning the order in which machines are visited. If real transportation routes were provided as a model or restrictions in the transportation were known, these real paths could be used instead.

The supporting points of a spline are set to the machine positions that perform the respective production steps of a product, with an additional random offset to avoid visual clutter among multiple splines. The smoothness of the splines helps the user to follow the progress of individual products. The splines are visualized using Gouraud shaded [26] tubes. This means that small tubes are used for their geometric models, and that these geometries are lit by a light source to enhance the natural understanding of their shape and progress. Additionally, alpha-blending the spline representations help making them halfway transparent to further distinguish individual spline tubes while preserving an overall picture of all spines. The middle image of Fig. 2 shows a closeup of both milling machines from Fig. 1 that demonstrates these visual effects.

Like all other data mining and visual analysis approaches, this method has its limits. Large numbers of products or product types can lead to visual clutter and increased confusion. Fortunately, for the chosen spline representation, there exist methods like attribute-driven edge bundling [27] or hierarchical clustering of flow maps [28] to compensate or mitigate those effects. In addition to that, general filtering and data aggregation techniques can be used to analyze and compare facets of interest in the production data.

By utilizing these visualizations, an intuitive tool for the examination of properties in the product flow is introduced. By color-coding different properties, the user is guided to interesting events and locations in the simulated production system. The left and right images of Fig. 2 show two examples for different properties. In both visualizations, the lower left dot represents the factory's entrance position for all products, while the lower right dot is the exit position when the products are fully manufactured. Also, for demonstration purposes, both images only feature one drilling machine (top-right dot in each image).

The left image of Fig. 2 shows the overall product flow for three different types of products. Here, each spline has a color given by the respective product's type. This enables the user to follow and distinguish products by their specific type. Also, the user can see how products of the same type are split up and distributed onto different machines for certain production operations. In the example in Fig. 2 (left image), this directly generates inside into the unequal distribution of products.

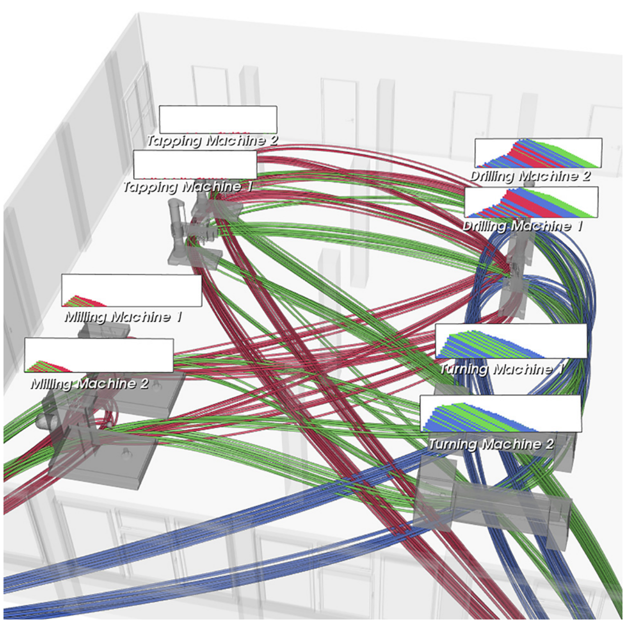

Fig. 1 Flow view of a virtual production system showing the geometric model of the factory and its machines, the product flow for all products color-coded by product type, and the machine workloads for all machines

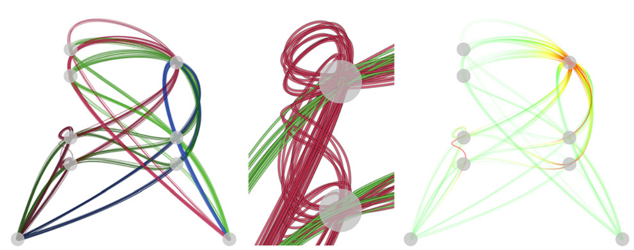

Fig. 2 Detailed views of the product flow demonstrating the visualization of different properties like product types (left image), methods to reduce visual clutter (middle image), and waiting times of the products (right image)

Another alternative to showing product types in the product flow is to visually encode the waiting times of products. In the right image of Fig. 2, the relative waiting time of an operation (in respect to the mean waiting time of all operations of the respective product type) is coded as color. Here, the colors range from a light color to a darker color. For a product of a certain type, a light color means that an operation has a low-waiting time compared to the other operations of the same product type. A medium color represents an average waiting time, while a darker color encodes a high-waiting time. This highly intuitive visualization method guides the user to machines where products have to wait longer than average before being processed, like the single drilling machine in this example.

Besides the presented properties, further attributes like production time can be visualized. By mapping the values of such an attribute directly to colors, bottlenecks of production steps can be seen for the products individually. Mapping relative attribute values, i.e., values set in comparison to the values of all other products of the same type, extends this mechanism and enables the user to visually analyze bottlenecks for an entire product type.

Although this is a powerful tool to locate weaknesses in the factory design, this flow visualization cannot show single product locations and their waiting positions. Therefore, an extension of the overall flow visualization is required.

This issue is tackled by restricting the overall product flow visualization to the user-defined time window. Here, only the positions of a product within this temporal window are displayed. A product is moving within the time window defined by the user, resulting in a path segment of a certain length. If a product moves slowly caused by longer transportation, waiting, or production times, the respective path segment will become shorter. In contrast, if a product moves faster, the respective path segment will become longer, since the product travels a longer distance within the given time interval. Figure 3 shows an example for equally large time windows moving forward in time (left to right image), thereby resulting in products moving through the virtual factory. The user is enabled to see that the overall flow slows down with increasing time, since the single drilling machine in the top-right corner of each frame is a bottleneck.

To determine the position of a product moving from a machine A to a machine B for a specific time, the route between machine A and B is divided into three parts. The first third of this route represents the operation of the product being processed at machine A. The middle third represents the transportation of the product from machine A to machine B. The last third of the route represents the time the product waits in queue to be processed by machine B. So if the product just finished its waiting period and starts being produced by machine A, the position of this product is the position of machine A. If the product just finished its production period at machine A and starts traveling to machine B, the position of this product is one third of the path from machine A to B. If the product reaches machine B and starts waiting to be processed by machine B, the position of this product is two thirds of the path from machine A to B. And if the product finished its waiting period and starts being produced by machine B, the product's position is the position of machine B.

The advantage of linearly interpolating the position for transportation, waiting, and production phases is that a product's position advances when the product's status is increased. This is the case when either the product's transportation advances, the remaining time the product has to wait in a queue decreases, or when the product's degree of completion increases during production. By that—in addition to spatial processes like transportation—temporal processes like waiting or being produced are transferred into motion, thereby achieving a high level of intuitiveness.

This method forms a visual encoding of the product flow and its efficiency, and allows the user to follow single products over the whole production time. Additionally, it is possible to identify machines with bottlenecks resulting in a high-production time. Furthermore, the user can see the location of the products of different types and the amount of products that are produced within the concerned time window. Also, choosing the time window to be the whole simulated time interval results in Fig. 2 (left image).

Although this is a powerful visualization, it is hard to identify the order in which multiple products line up in queue to wait for a certain machine. This is overcome by the visualization of the machine workload.

Machine workload. To tackle the problem of requiring additional insight into the waiting queue of a machine, the presented approach embeds a suitable visualization for each machine's workload into the three-dimensional factory model (see Fig. 1). By doing that, the spatial context of the virtual factory model is preserved, and hence the intuitiveness is increased.

For each point in time of the time window defined by the user, all products in the waiting queue of a machine are shown in their unique product type's color. For consistency reasons, this is the same color as used in the flow view.

The waiting products are visualized as stacked boxes. Each box has a black frame to distinguish successive products of the same color, meaning the same product type. For each particular product, the height of the respective box corresponds to the remaining production time this product will need at the machine it is waiting for. The product a machine is currently working on is located at the bottom of the stack, while recently enqueued products are added at the top.

A single stack represents the waiting queue of a machine at a certain point in time. The height of the stack equals the accumulated height of all boxes, thereby visualizing the workload of the machine. Instead of limiting this visualization to a single point in time, a stack for each point in time of the user-defined time window is visualized. This is consistent with the flow visualization. Additionally, the current point in time is marked for better orientation. This results in a visualization that is able to provide visual feedback on the development of a machine's workload in contrast to showing only a single point in time.

The result is a visualization for each machine's workload, representing the exact amount of waiting products and their production time and order for each specific point in time. Figure 4 visualizes the workload of the first drilling machine from the example shown in Fig. 1. Figure 4 shows that the products waiting in the machine's queue are quite unordered. This indicates that

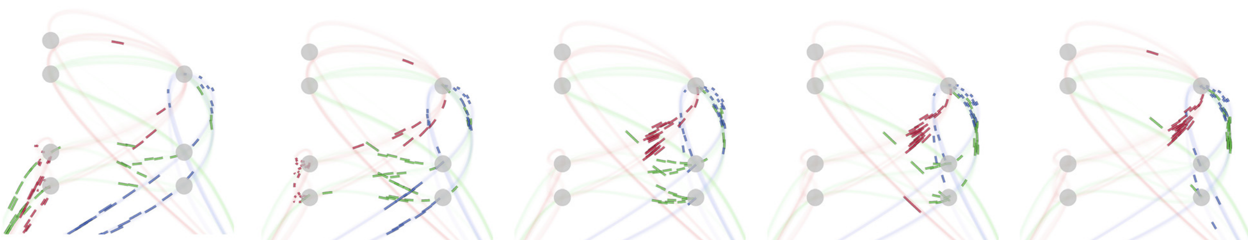

Fig. 3 Sequence of product flows for a short temporal window moving forward in time (left to right image), resulting in products moving through the virtual factory

rearranging the products in the machine's queue into blocks of the same product type might have a high potential in minimizing time losses due to tool changes within the machine. When considering setup times, this could speed up the average production time by decreasing the overall setup time. As this example shows, the user can intuitively analyze machine queues with respect to the number or types of products, their workloads, and even trends over time.

In addition to showing the real order of products in a machine's queue, the user is provided with the possibility to sort the individual stacks of the visualization by product type. By doing that, the insight into the order of the products in the queue is lost, but instead, a more direct visual feedback on the number and the accumulated production time is gained for all the products of a certain type, as the bottom image of Fig. 4 shows.

Although the flow view is a suitable tool to review several aspects of the manufacturing process, it is not able to compare the workloads of different machines or the influence of design changes in the factory layout on production times, e.g., for identifying bottlenecks in the production. This is tackled by further views that are introduced in the following.

3.2.2 Workload View. The flow view lacks the ability to directly compare the workload of the machines in the virtual factory. Therefore, a workload view is provided as shown in Fig. 5 for the example used in Sec. 3.2.1. This view consists of a workload graph for each machine, visualizing the different graphs positioned on top of each other. To make the workloads comparable, the same coordinate system is used for all graphs, meaning that the workloads of all the machines have the same x-coordinate for an arbitrary point in time.

Consistent to previous visualizations, not only a single workload for a single point in time is shown per machine but also the workloads for all points in time of the user-defined time window are displayed. This provides insight into the development of a machine's workload over time and offers the possibility to temporally zoom in onto interesting features. Since the workload graphs for all machines are linked, they always remain comparable. Additionally, the current point in time is highlighted for better orientation.

Here, the focus lies on the magnitude of a machine's workload, meaning the accumulated production times of all products in the machine's queue (compare to height of graph in Fig. 4). To not overload the visualization, only important information is included. Thus, all information about the individual products forming this workload is neglected.

The workload of a machine is shown in the foreground as the height of the respective graph. At each point in time, the highest workload of all machines is calculated and displayed in the background as a second graph with a light gray color. So the background is the same for all graphs. This helps in comparing the workload of different machines.

The color of the graph in the foreground representing a machine's actual workload ranges from white to dark, thereby encoding the ratio of the machine's workload to the globally highest workload by color. This means that a high-relative workload results in a darker color, whereas in contrast, a low-relative workload results in a white color. This enables the user to relate the workload of individual machines to the globally worst workload, thereby intuitively identifying critical machines dependent on time.

Multiple machines of the same type with a high workload may indicate a need for more machines of this type, while multiple machines of the same type with a low workload may indicate redundant machines. If both occurs for different points in time, the user may want to redistribute the workloads. Because of that, the introduced visualization is a good basis for analyzing machine workloads.

It is not necessary to optimize a machine in general, but at specific points in time, when bottlenecks occur. The presented visualization helps identifying these interesting points in time and the corresponding critical machines, which then can be investigated and optimized further. As the visualization is intentionally not embedded into the three-dimensional factory model, it also provides a good overview of machine workloads and their critical features.

3.2.3 Production View. A missing feature of the previous views is to examine the production times for all products of a specific type. This is done in the production view. The specific product type can be chosen by the user, or an instance of the production view can be displayed for each product type in parallel. Figure 6 shows the production view for product type C with its three production operations (compare Table 1).

The top image of Fig. 6 shows that each individual product is visualized as one slice. Although the manufacturing of different products starts at different points in time, they are shown aligned in the production view to ensure comparability. This allows the user to visually analyze production times.

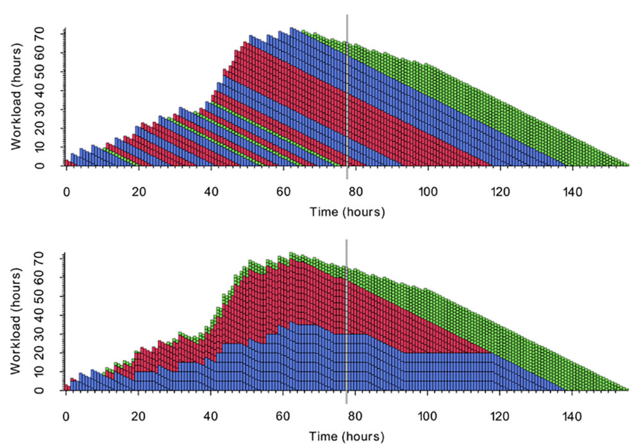

Fig. 4 Unsorted (top image) and sorted (bottom image) workload of the first drilling machine showing the development of the machine's queue with its individual products waiting to be processed

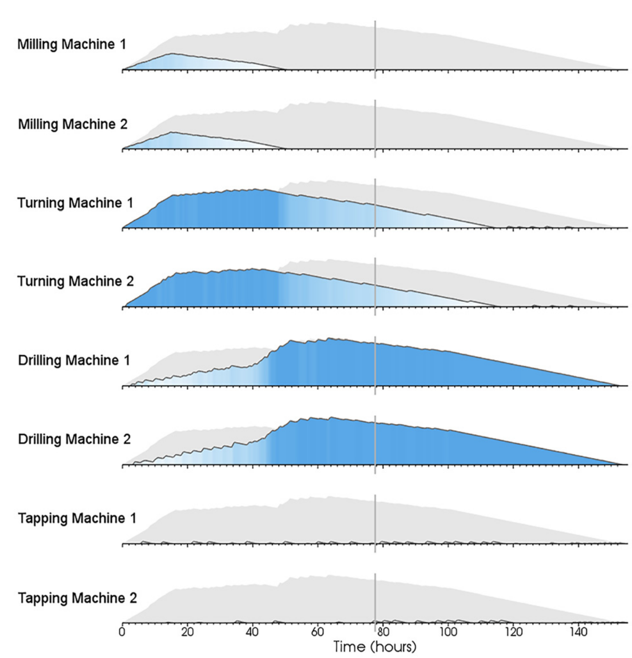

Fig. 5 Workload view showing a workload for each machine in the virtual factory, thereby guiding the user to machines potentially being overloaded or redundant at certain interesting points in time

A time against degree of completion graph is shown per product on its individual slice. This means that the x-axis measures the time since the start of the manufacturing of the individual product. The y-axis measures the degree of completion for each product.

Since each product's slice is parallel to the xy-plane, the remaining z-axis measures the individual products themselves. As all products of the same type start their manufacturing at different points in time, the z-axis can also measure this temporal offset.

With increasing manufacturing time (x-axis), each product's degree of completion (y-axis) increases from zero (darker color) until it reaches a value of one (brighter color), meaning a fully manufactured product. The level of completion is calculated by dividing the elapsed process time through the overall process time of a product. Here, halfway completed operations are taken into account by interpolating their relative level of completion linearly.

The resulting horizontal lines that can be seen in Fig. 6 represent periods of time in which the individual product is not processed. Instead, the product is waiting in a queue for the respective machine to start producing the next operation of this product. Several products with the same degree of completion lead to visual plateaus. This is caused by equal operations being finished for several products. Since plateaus are caused by a number of products waiting for the next operation to begin, the vanishing of a plateau indicates that there are no more waiting products for the upcoming operation. In general, transitions between neighboring plateaus represent processing phases, while the plateaus themselves represent inactive phases, i.e., transportation or waiting phases.

The two lower images in Fig. 6 show the same data as the top image but without possible occlusion problems. Here, the lower left image clearly shows the different process phases, while the completion ratio is visualized by color analog to the top image. The begin and end of process phases are highlighted by thin black lines. It becomes clear why optimizing machine workloads and thereby inactive phases is that important for optimizing the overall manufacturing times by comparing the time intervals of process versus inactive phases.

The lower right image shows an overview of the amount of products that have exceeded a certain completion ratio after a given manufacturing time, ranging from none (white color) to all products (darker color). This visualization focuses more on the temporal trend of the products' completion, thereby enabling the user to identify interesting features based on the distribution the product's completion ratios during the manufacturing process.

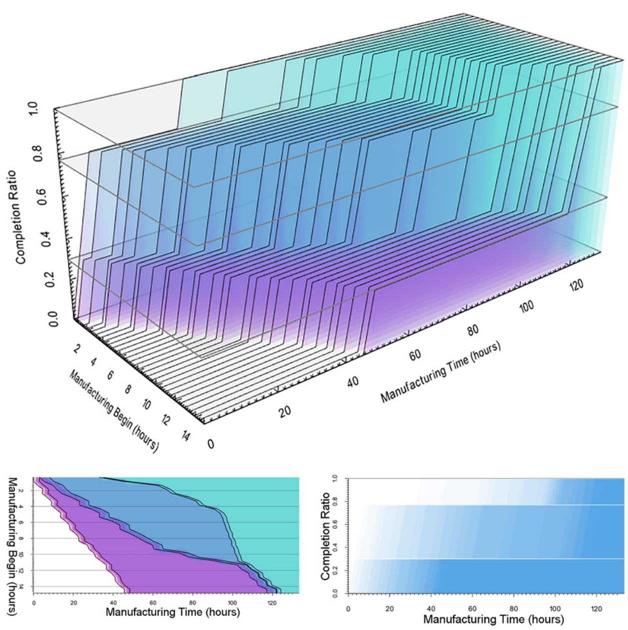

Fig. 6 Production view for all products of type C showing inactive and processing phases of their three operations under different aspects of manufacturing time, manufacturing begin, and degree of completion

In contrast to displaying only two-dimensional graphs for the minimum, the maximum, or the average production times for all products of the same type, the presented visualizations are capable of providing trend analyzes over the whole manufacturing time, while still preserving a high level of intuitiveness. The views are also able to show interesting features like drastic changes in manufacturing time. This is not only possible for the overall production time of a product but also for each individual operation. Yet, the user is enabled to get an overview over all products of the same type. Furthermore, the user is visually guided to operations that take longest or increase the production time most. At last, a visual exploration of changes in production times is possible by comparing the resulting production views based on different factory setups.

The presented flow view, workload view, and production view focus on different aspects and form a combined system of interlinked views allowing the user to examine production properties and factory performance.

4 Conclusions

This work introduced a tool for analysis and visualization of manufacturing data generated by cyber-physical production systems. The tool displays manufacturing data in an intuitive format that communicates relevant information to a human expert. To enable an overall understanding of a manufacturing system's state and process, aggregated views were generated. In addition, the visualizations can focus on individual machines or products and zoom in onto interesting time steps. The user is guided between the interlinked views showing machine workloads, state of workpieces being manufactured, or material flows. Bottlenecks or excess machining capacities can visually be highlighted, thus guiding the user to interesting locations and events. The influence of changes of the factory setup, e.g., addition, removal, or reconfiguration of machining tools, can be simulated, analyzed, and evaluated.

To support more realistic analysis and visualization of process chains, properties like machine accuracies and criteria like costs or lead times are a natural and straightforward extension of the presented manufacturing system.

The presented visual analytics tool can be used to show the impact when using different decision rules for production planning and control. Thus, this tool is suitable for the analysis of the behavior of self-controlled production environments. Here, the presented tool provides access to and visualizations of the detailed, underlying data, and its patterns.

Considering the ever increasing size and complexity of data created by today's production systems, opportunities exist to greatly increase the flexibility of production systems with a focus on time or cost reduction, rapid adaptation to new manufacturing demands, and product quality control. The presented approach holds the potential to evaluate these opportunities by mining production data and analyzing different engineering changes, thereby adding value to the decision-making process.

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References

[1] Monostori, L., 2014, "Cyber-Physical Production Systems: Roots, Expectations and R&D Challenges," Procedia CIRP, **17**, pp. 9–13.

[2] Kagermann, H., Wahlster, W., and Helbig, J., 2013, "Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0: Final Report of the Industrie 4.0 Working Group," acatech—National Academy of Science and Engineering, Munich, Germany.

[3] Leitão, P., 2009, "Agent-Based Distributed Manufacturing Control: A State-of-the-Art Survey," Eng. Appl. Artif. Intell., **22**(7), pp. 979–991.

[4] Monostori, L., Váncza, J., and Kumara, S., 2006, "Agent-Based Systems for Manufacturing," Ann. CIRP, **55**(2), pp. 697–720.

[5] Sendler, U., ed., 2013, *Industrie 4.0: Beherrschung der industriellen Komplexität mit SysLM*. *Xpert.press*, Springer, Berlin.

[6] Reinhart, G., Schindler, S., Pohl, J., and Rimpau, C., 2009, "Cycle-Oriented Manufacturing Technology Chain Planning," Third International Conference on Changeable, Agile, Reconfigurable and Virtual Production (CARV).

[7] Malak, R. C., Yang, X., and Aurich, J. C., 2011, "Analysing and Planning of Engineering Changes in Manufacturing Systems," 44th CIRP Conference on Manufacturing Systems, N. A. Duffie, and M. F. DeVries, eds., Page number(s) not provided.

[8] Malak, R. C., and Aurich, J. C., 2013, "Software Tool for Planning and Analyzing Engineering Changes in Manufacturing Systems," Procedia CIRP, **12**, pp. 348–353.

[9] Dorozhkin, D. V., Vance, J. M., Rehn, G. D., and Lemessi, M., 2012, "Coupling of Interactive Manufacturing Operations Simulation and Immersive Virtual Reality," Virtual Reality, **16**(1), pp. 15–23.

[10] Sacco, M., Dal Maso, G., Milella, F., Pedrazzoli, P., Rovere, D., and Terkaj, W., 2011, "Virtual Factory Manager," *Virtual and Mixed Reality* (LNCS Sublibrary. SL 3, Information Systems and Applications, Vol. 6773–6774), R. Shumaker, ed., Springer, Heidelberg, Germany, pp. 397–406.

[11] Chemnitz, M., Krüger, J., Patzlaff, M., and Tuguldur, E.-O., 2010, "SOPRO—Advancements in the Self-Organising Production," IEEE Conference on Emerging Technologies and Factory Automation (ETFA 2010), Sept. 13–16.

[12] Zühlke, D., 2009, "Smartfactory—A Vision Becomes Reality," IFAC Proc. Vol., **42**(4), pp. 31–39.

[13] Leitão, P., and Restivo, F., 2006, "ADACOR: A Holonic Architecture for Agile and Adaptive Manufacturing Control," Comput. Ind., **57**(2), pp. 121–130.

[14] Ilsen, R., Meissner, H., and Aurich, J. C., 2015, "Virtual Test Field for Sustainability Assessment of Cybertronic Production Systems," ASME Paper No. MSEC2015-9232.

[15] Plonka, D., 2000, "FlowScan: A Network Traffic Flow Reporting and Visualization Tool," 14th USENIX Conference on System Administration, USENIX Association, pp. 305–318.

[16] Potter, K., Wilson, A., Bremer, P.-T., Williams, D., Doutriaux, C., Pascucci, V., and Johhson, C. R., 2009, "Ensemble-Vis: A Framework for the Statistical Visualization of Ensemble Data," IEEE Workshop on Knowledge Discovery from Climate Data: Prediction, Extremes, Dec. 6, pp. 233–240.

[17] Lu, C.-T., Boedihardjo, A. P., and Zheng, J., 2006, "AITVS: Advanced Interactive Traffic Visualization System," IEEE Computer Society, Apr. 3–7, p. 167.

[18] Taylor, T., Paterson, D., Glanfield, J., Gates, C., Brooks, S., and McHugh, J., 2009, "FloVis: Flow Visualization System," CATCH, Mar. 3–4, pp. 186–198.

[19] The World Bank, 2011, "Trademap Visualizer," World Bank, Washington, DC.

[20] Klosterman, R. E., and Brail, R. K., eds., 2001, *Planning Support Systems: Integrating Geographic Information Systems, Models, and Visualization Tools*, 1st ed., Esri Press, Redlands, CA.

[21] Wu, P. Y., and Acharya, S., 2011, "Visualizing Capacity and Load: A Production Planning Information System for Metal Ingot Casting," CONISAR Proc., **4**(1823).

[22] Doil, F., Schreiber, W., Alt, T., and Patron, C., 2003, "Augmented Reality for Manufacturing Planning," Workshop on Virtual Environments 2003, ACM, pp. 71–76.

[23] Zhang, P., 1996, "Visualizing Production Planning Data," IEEE, Computer Graphics and Applications, Vol. 16(5), pp. 7–10.

[24] Ertek, G., Kuruca, C., Aydin, C., Erel, B. F., Dogan, H., Duman, M., MeteOcal, and Ok, Z. D., 2004, "Visual and Analytical Mining of Transactions Data for Production Planning and Marketing," Intelligent Manufacturing Systems, pp. 848–859.

[25] Farin, G., ed., 2001, *Curves and Surfaces for CAGD: A Practical Guide*, 5th ed. (Morgan Kaufmann Series in Computer Graphics and Geometric Modelling), Morgan Kaufmann, San Francisco, CA, pp. 119–146.

[26] Gouraud, H., 1971, "Continuous Shading of Curved Surfaces," IEEE Trans. Computer, **C-20**(6), pp. 623–629.

[27] Peysakhovich, V., Hurter, C., and Telea, A., 2015, "Attribute-Driven Edge Bundling for General Graphs With Applications in Trail Analysis," 2015 IEEE Pacific Visualization Symposium (PacificVis), Apr. 14–17, pp. 39–46.

[28] Phan, D., Xiao, L., Yeh, R., Hanrahan, P., and Winograd, T., 2005, "Flow Map Layout," IEEE Information Visualization (InfoVis), Oct. 23–25, pp. 219–224.