Connected, digitalized welding production — Secure, ubiquitous utilization of data across process layers

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Abstract. A connected, digitalized welding production unlocks vast and dynamic potentials: from improving state of the art welding to new business models in production. For this reason, offering frameworks, which are capable of addressing multiple layers of applications on the one hand and providing means of data security and privacy for ubiquitous dataflows on the other hand, is an important step to enable the envisioned advances. In this context, welding production has been introduced from the perspective of interlaced process layers connecting information sources across various entities. Each layer has its own distinct challenges from both a process view and a data perspective. Besides, investigating each layer promises to reveal insight into (currently unknown) process interconnections. This approach has been substantiated by methods for data security and privacy to draw a line between secure handling of data and the need of trustworthy dealing with sensitive data among different parties and therefore partners. In conclusion, the welding production has to develop itself from an accumulation of local and isolated data sources towards a secure industrial collaboration in an Internet of Production.

Keywords: Welding Production· Industrie 4.0· Internet of Production· Data Security· Data Privacy.

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1 Introduction

Utilization of connected information sources has led to a paradigm shift in value chains and society, especially since the beginning of digitalization, but is not yet fully established in the industrial context. Initiatives, such as “Made in China 2015” from China, “Industrie 4.0” from Germany, or the “Industrial Internet Consortium” from the USA, are recent efforts to deliberately access and utilize information sources in industrial environments [12]. Corresponding concepts and platforms emerge therefore also in the field of production technology [11,24,22,25,26] and thus welding technology [23], but are difficult to implement comprehensively. Practical difficulties arise as soon as different subsystems, competencies and parties join in a network of various information providers and stakeholders [17]. These challenges end up in confusion of different time scales in which data are acquired and required as well as in security and privacy concerns. Even though welding production is far from being fully digitalized, significant parts of measurable information is already available in forms of accessible data sources in the established welding production, e.g., in digital testing or welding process data. However, these data sources lack extensive networking while offering huge potential in improving welding production [23].

Core terms of connected, digitalized production systems in the sense of Industrie 4.0 are Cyber-physical systems (CPS) and their interactions in cyber-physical production systems (CPPS) [8,18], vertical and horizontal networking [24], data analytics [11] and digital engineering [4]. These elements are characteristic in connecting mechatronic systems to a connected infrastructure (CPS, CPPS), providing information across different levels of industrial production (vertical and horizontal networking), aggregating and interpreting data (data analytics) and providing a digital representation of real production systems (digital engineering).

In this work, potentials and methods shall be described, which utilize the networking of the established welding production among different entities. These potentials are discussed in the context of data security and privacy to ensure industrial application apart from secure, scientific boundary conditions. Deliberate attention given to data security and privacy provides the prerequisite to access extensive data sources that provide knowledge on the analyzed industrial production. This approach is mandatory for research in data-driven digital engineering. The foundation of this work lays in the understanding of welding production as a collection of different interlaced process layers to resolve the aforementioned potentials and challenges. This work does not focus on the welding process itself in the meaning of actual fusion of two workpieces since this part has already been subject to different studies [23] but rather in its superimposed process layers, namely weld seam process layer, assembly process layer and product process layer.

2 Process Overview

Welding technology and its production environment should first of all be considered in their fundamental essence - and thus as a process. The classical welding process technology understands itself as the actual physical process of permanently joining two joining partners under the influence of pressure and/or heat. The welding process itself, however, is dependent on the process of the workpiece design in which the mechanical-technological requirements of the weld seam are defined. Following the welding process, the quality inspection and thus the assurance of the previously set requirement profile are found especially in the regulated welding production. Welding production in its industrial application is, yet, often part of a chain of other sub-processes such as machining or quality assurance. The focus is therefore no longer on the weld seam itself, but rather on the assembly. Within an even larger distance, the welding process is part of a product and part of the interaction between suppliers, production, service providers and customers. Current applications and concepts under the terms Internet of Production [16] or Industrie 4.0 often do not distinguish between these layers although they have essential peculiarities in the context of welding technology. The term “Internet of Production”, in general, describes the vision to establish an interconnected network for the production domain to utilize information across organizational borders and potentially, even across domains. A connected digitalized welding production opens up new potential in all process layers involved; however, continuous networking can only be achieved if all networked parties and competencies can communicate securely and accountable. Similar advances are also pursued for other production processes (e.g., stamping [5]).

Characteristic are the different time periods in which the respective process layers provide information (Figure 1, left). Occurrences that have a significant influence on the quality of the weld seam can take place in the order of milliseconds, while the interaction between suppliers, production and customers can reach multiple days. The distinction between different time scales has a particular effect on the technical requirements of networked systems w.r.t. latency, data volumes, and connectivity. Therefore, the methods for recording the respective processes differ considerably. Nonetheless, the data processing methods can be transferred to a large extent. Each process can be described by a sequence of different states that allow interpretation and ultimately process control in its common consideration.

Another representative challenge are the parties involved in the production process (Figure 1, right). The welding process itself, and thus the weld seam, lays in the area of conflict between the technical requirements of the design and the downstream quality monitoring. As soon as the use of information across all parties is reliably guaranteed in accordance with the idea of Industrie 4.0 or an Internet of Production [16,23], the question of responsibility and information security must inevitably be asked and answered. Especially when company borders are crossed as part of data exchanges, data security is a crucial aspect to protect sensitive business expertise and to protect the company’s assets [17].

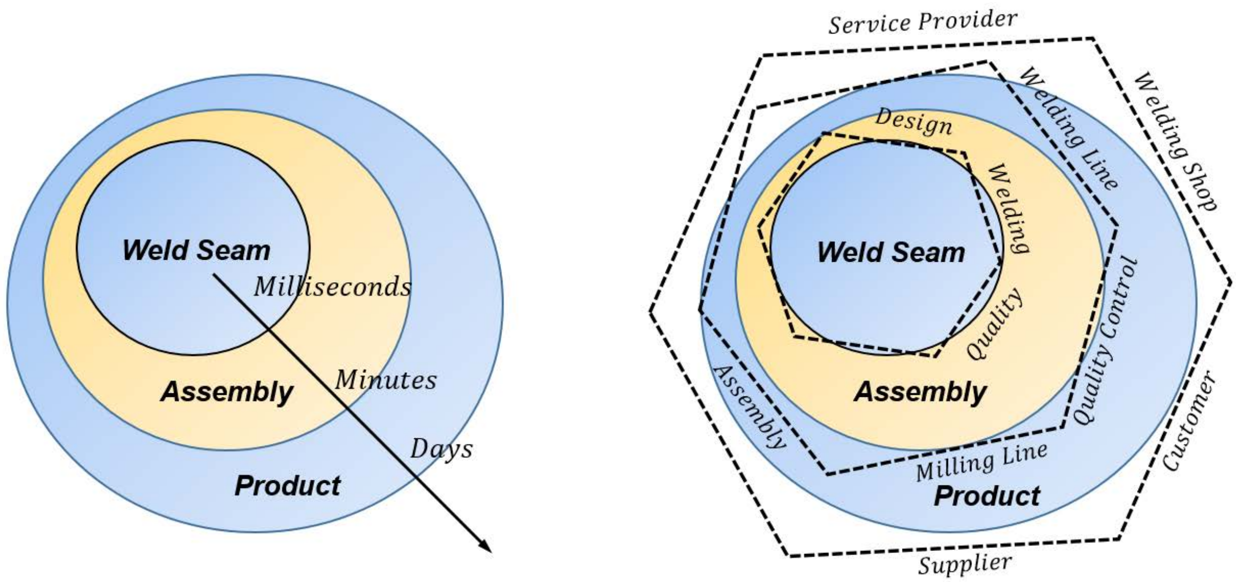


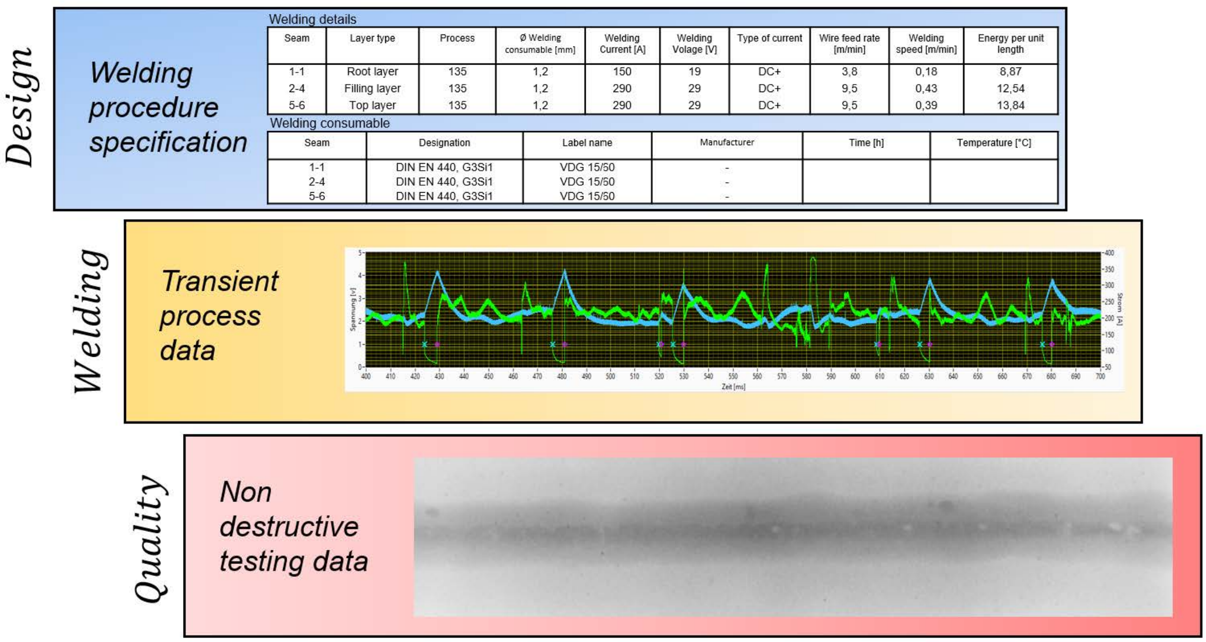
Fig. 1. A visualization of the different process layers of welding: the three process durations (left) range from milliseconds to days and the involved parties (right) differ with each layer.

This paper only considers sensitive process data in the context of a welding production process and leaves the analysis of privacy implications of the workforce for future work.

In the following, technical potentials and methods are described for three process layers that motivate networking across all involved parties. In addition, however, decisive methods are presented that create the important basis for the possibilities described above in the sense of responsibilities, data security and data protection.

3 Weld Seam Process Layer

On the lowest level, the weld seam process itself is described. Figure 2 visualizes three typical process steps that evolve around the weld seam and the essential form in which information on the substeps is available. First, the welding procedure specification (WPS) provides a defined requirement profile for all critical welding parameters (Figure 2, upper bar). The WPS thus defines the mechanically technological weld seam properties and specifies the corresponding parameter spaces for the welding process. This step is followed by the actual welding process (Figure 2, middle bar), which can be mapped using transient process data. The inspection of the weld seam with regard to its mechanical and technological properties is subsequently carried out in quality testing (Figure 2,



Seam	Layer type	Process	Ø Welding consumable [mm]	Welding Current [A]	Welding Volage [V]	Type of current	Wire feed rate [m/min]	Welding speed [m/min]	Energy per unit length
1-1	Root layer	135	1,2	150	19	DC+	3,8	0,18	8,87
2-4	Filling layer	135	1,2	290	29	DC+	9,5	0,43	12,54
5-6	Top layer	135	1,2	290	29	DC+	9,5	0,39	13,84

Seam	Designation	Label name	Manufacturer	Time [h]	Temperature [°C]
1-1	DIN EN 440, G3Si1	VDG 15/50	-		
2-4	DIN EN 440, G3Si1	VDG 15/50	-		
5-6	DIN EN 440, G3Si1	VDG 15/50	-		

Fig. 2. The weld seam process consists of three different substeps: (i) the requirements are set as part of the Design, (ii) the welding process is monitored as part of the Welding, and (iii) the result is tested as part of the Quality component.

lower bar). Here, an example of a digitized X-ray is shown. This approach preserves the workpiece on the one hand and can store data in the form of digital images on the other hand. All described process steps can be linked as described in the following to gain a decisive added value. However, given that these three process steps are often assigned to different operational responsibilities, the issue of data security is already relevant for the lowest level of the production process.

3.1 Applications and Methods

The very basic type of data acquisition in arc welding is the transient recording of the electrical welding parameters, such as voltage and current. Those parameters need to be measured with a high sample rate (>50 kHz) as arc welding processes and GMA welding in particular are highly dynamic processes. A GMA welding process is presented in Figure 3.

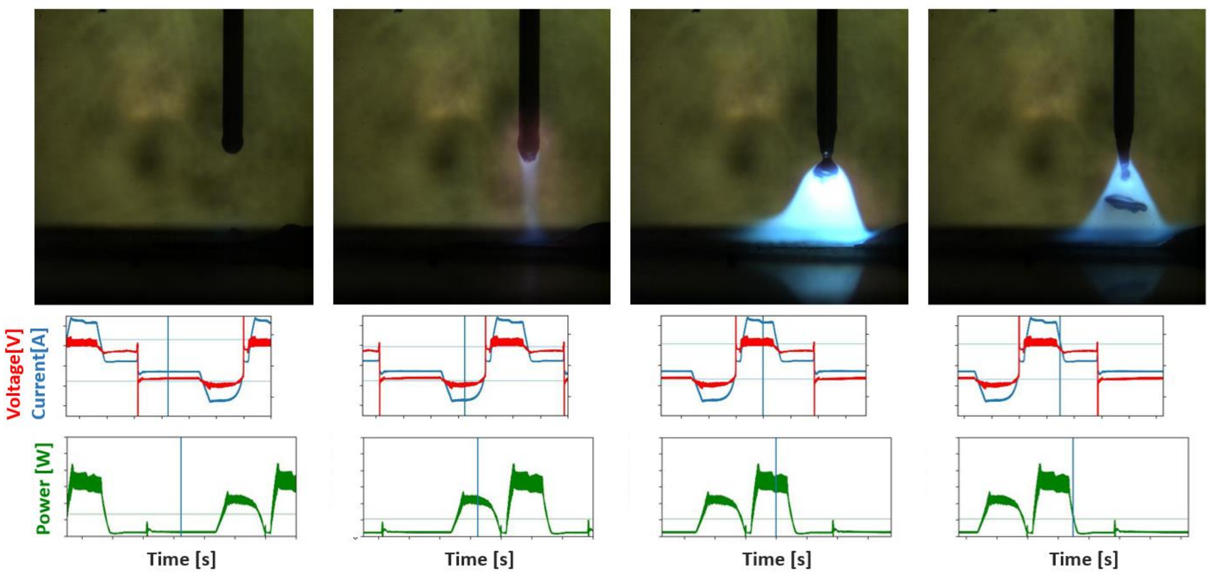


Fig. 3. GMA-AC process droplet detachment: the topside pictures show high speed images of the process, the bottom side pictures detail the acquired electrical signals.

As the droplet detachment happens within a very short period of time, an evaluation of the process quality, as well as the detection of weld defects via the electrical signals generate a high amount of time series data, which is hard to analyze in real time. The measurement data can be acquired using an industrial computer. Other very important welding parameters are, for example, the welding speed or the contact tip to workpiece distance of the welding torch. As those parameters are not changing rapidly, the data acquisition can be conducted with a significantly lower sample rate.

The example shows that for data mining in welding processes, different sets of time series data, acquired with different sample rates need to be aggregated, labeled, and reduced to handable sizes. One possibility of analyzing the time series data may be the shape analysis of 3-dimensional voltage-current process window as shown in Figure 4.

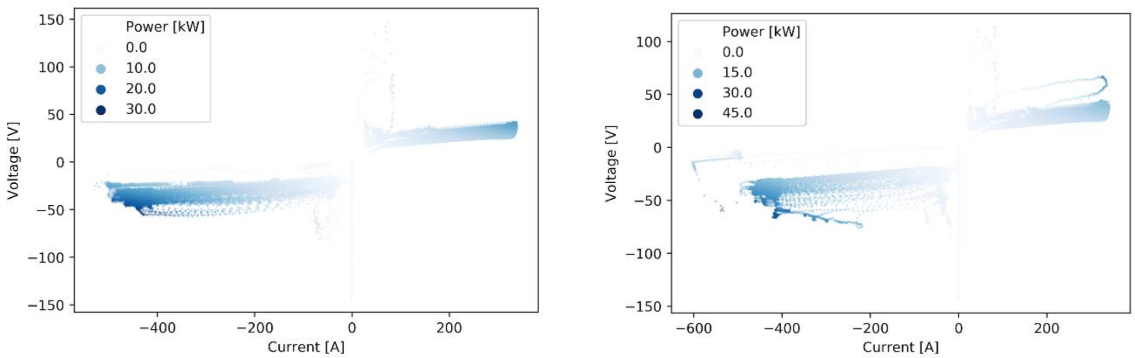


Fig. 4. Visualization of a GMA-AC welding process by plotting the process voltage over process current. The process power is indicated by the color intensity. Left: Stable process, right: unstable process, followed by weld defects.

Besides, Figure 4 shows a possible visualization of a GMA weldment by plotting the transient current measurements over the voltage measurements. At the same time, the calculated process power is indicated by the color intensity. The analysis of the time signal could be reduced by extracting features out of the shape of the correlated voltage-current plot. This approach can give the possibility of describing a weldment by discrete features, aggregated out of a time series signal. The right side of Figure 4 shows a weldment, which was followed by a formation of weld defects. By performing a simple cluster analysis, critical clusters can be identified, and the process can be quantified regarding the amount of data points that belong to a cluster, characterized by an increased chance of weld defects. Thereby the time series measurement of a welding process, recorded with a high sample rate, can be reduced to a simple set of quality key numbers to characterize the process. At that point, a compliance check with the defined WPS data may already hint to undue deviations.

To evaluate the acquired electric signal data and linking it to the weld seam quality, destructive as well as non-destructive testing is essential to generate a valid training dataset. For the initial generation of a usable dataset, the electrical welding data need to be linked to a quality criterion, generated by weld seam testing. The respective approach can be destructive testing, such as cross sections, as well as non-destructive tests, such as offline ultra-sonic tests or online eddy current sensors, etc. Here, anomalies in the electrical sensor signals may give a hint to possible weld defects. Destructive analysis can be conducted by taking cross sections of the weld seams. Automated image analysis can be used to extract features, such as penetration depth, aspect ratio, width and curvature of the weld seam and the heat affected zone, as illustrated in Figure 5.

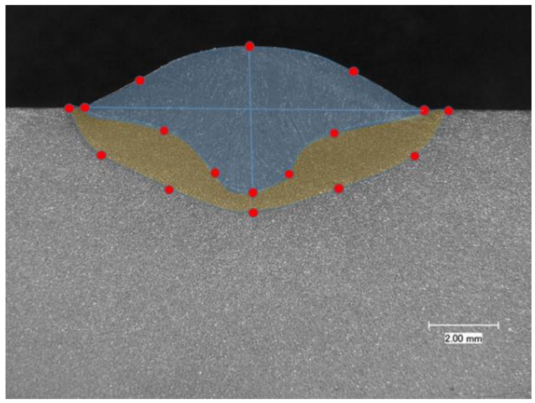


Fig. 5. Example of an automated feature extraction on a cross section. Features, such as penetration depth or weld seam width can be used for labeling welding data.

These tests are used to identify weld defects and therefore critical process parameter fields. Based on this information, labels can be generated for the clusters of the acquired electrical time series data. Similarly, every production step within the process chain emits data, which can be aggregated to a superordinate feature-based dataset, independent of the initial data types. As an aggregated dataset of the production process has been generated, predictive algorithms can be applied to investigate the influence of parameter changes to the efficiency of the process chain.

3.2 Data Security and Data Privacy

The three different substeps of the weld seam process are expected to exchange more information in the future. Consequentially, aspects of data security arise. This challenge is not only limited to company-internal scenarios where information is exchanged between departments as it is especially relevant in scenarios where substeps are outsourced to external parties, i.e., sensitive process information has to cross company borders multiple times [17]. As the data contain much detailed process information, external parties might obtain a deeper insight into the welding process. For example, the processed material or the area of application can be leaked. This scenario is further discussed as part of the product process layer.

In the context of interconnecting the three substeps of a weld seam process (Design, Welding, and Quality), the previously described advances are already expected, based on data sharing between departments. However, concerns regarding accountability by the different departments challenge any adjustments of the process as departments do not want to be held responsible for issues resulting from improper data sharing or the underlying data quality. Hence, mechanisms must be in place to enable verifiability of the data exchanges and data retrieval in situations where deviations from the final workpiece occurred. For this layer, the requirements are less strict because usually no external parties are involved. Hence, each company internally has to agree how to implement accountability and determine the level of security which the respective implementation has to achieve. With such an approach in place, the weld seam process can be improved by utilizing data from other substeps to adjust production in the current substep accordingly without fearing blame or uncertainty in case of production errors.

Following the low-level analysis of the weld seam process layer with detailed process knowledge, the assembly process layer is analyzed in the next section to gain insight into the impact of an IoP-enabled assembly process layer.

4 Assembly Process Layer

The second introduced layer consists of the assembly process.Figure 6 describes the workpiece flow of a corresponding assembly process over different departments and individual steps until the assembly is finalized. All steps are defined according to operational departments and responsibilities with regard to their competence limits. The flow of information follows the workpieces to the assembly and is described by events. In addition to the quality optimization of the weld seam described before, process transparency and optimization are becoming increasingly important at this level. However, the challenges not only result from recording the corresponding events and corresponding workpieces, but also in the interfaces between the various competence limits.

4.1 Applications and Methods

At this process layer, data in form of event-logs is put in the spotlight. Event logs are, in their simplest form, composed of case ids (e.g., for weld seams, workpieces), events, which describe decisive occurrences during production and their according time stamp. This form of data opens up the door to process mining, which may not only be applied in this process layer but even in others due to its universal applications.

Process mining is a young research field which discovers, monitors, and improves real processes by applying techniques utilized to extract knowledge from so-called event logs. Basically, three fundamental types of process mining techniques exist: process discovery, conformance checking, and process enhancement [2], as presented in Figure 4. Process discovery aims at extracting the real process models from underlying event logs, i.e., the real behavior of the processes is acquired, while conformance checking compares the observed behavior obtained from the underlying event log with the behavior recognized by the

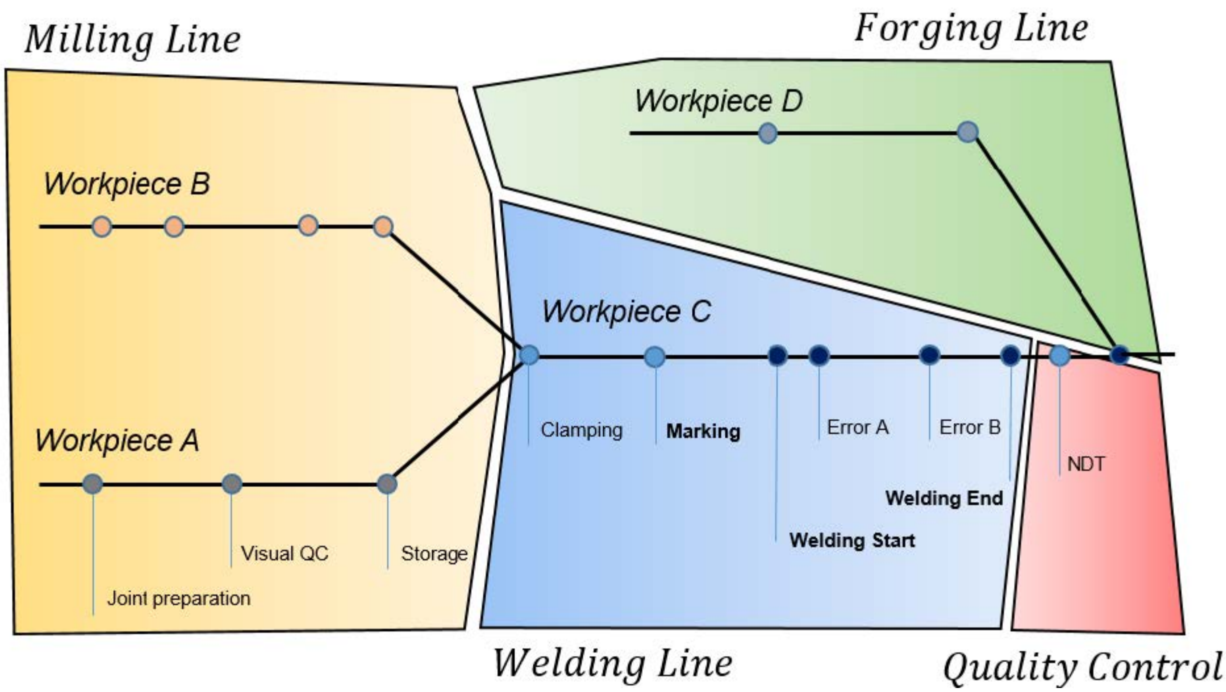


Fig. 6. The assembly process maps the workpiece flow to all departments (e.g., milling-, forging-, welding-line and quality control) that are involved during production from start to end.

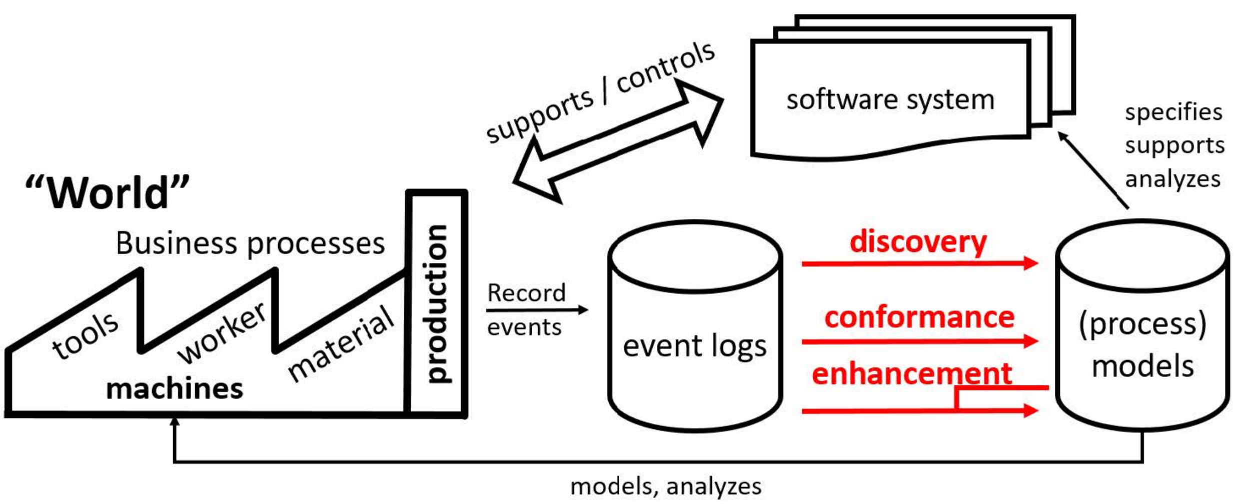


Fig. 7. Overview of the three types of process mining: process discovery, conformance checking, and process enhancement.

model. The goal of process enhancement is to improve the model at hand by exposing the information gathered from the event log. Discovering real processes and checking compliance between observed and allowed behavior, process mining uncovers and quantifies deviations, finds root causes for process variations and delays, and finds bottlenecks in the extracted process models. Furthermore, process mining provides the opportunity to predict process outcomes [19,20], foresee deviations and bottlenecks, and compare processes w.r.t. various time periods, products, and organizations. In the context of welding processes, process mining can be applied at different levels by utilizing various techniques applicable to the process layers weld seam, assembly, and product, as presented in Figure 1 before. In a weld seam process, for example, operators and welding engineers specify the required parameters in the welding procedure specification which typically includes various important parameters, such as material specification (e.g., wall thickness, size / diameter, yield / tensile strength, metallurgical concerns), welding process type, welding direction, position, preheating temperature, filler, polarity, and process parameters (e.g., travel direction, polarity, wire welding transfer mode, number of passes, number of welders, and electrodes). The required parameter studies are time consuming and revealing the relationships and correlations among the input parameter values of the welding process and the corresponding quality results is of high interest. For instance, decreasing the lapse time between passing and filling activities, and changing the number of passes may end up with better coating removal, affecting the overall quality assurance positively. Another example is to reveal the bottlenecks and failure of the welding process, such as extracting the information about the circumstances (at which input parameters' values) in which the output material suffers lack of fusion and penetration, residing out of the tolerance range specified by the welding experts.

Process mining provides methods that are capable to create an integrated view of the welding production process based on data recorded in logs where each recording corresponds to an event. Each of these events comprises an activity, e.g., joint preparation for workpiece A (cf. Figure 6), a timestamp, e.g., 15th February 2019, and optional resources, such as the worker involved in this production step. Furthermore, each event contains a unique case id which identifies an associated case. In the context of the welding process, the assignment of case ids might not be unique. Considering Figure 6, on the one hand, each of the workpieces A and B might constitute its own unique case which spans its production until they are welded together yielding workpiece C. Thus, process mining would reveal models based on an independence assumption on the workpieces, therefore possibly lacking important dependencies. On the other hand, the id of workpiece C could be used for all events related to the workpieces A and B introducing dependencies and relations between events which correspond to, until the timestamp of the event, unrelated workpieces. This relation might then distract the models from the important behavior. In this context, a hierarchical view on the process that enables investigation on different levels of granularity (workpieces A and B as different cases or summarized under the id of workpiece C) would be an interesting opportunity.

The discovered models can further be a subject of conformance checking, i.e., a set of techniques which assess the compliance between the behavior described by the model and behavior comprised in the event log [3]. Therefore, conformance checking can be applied to discover deviations or anomalies of the production process, thus contributing to its transparency and efficiency.

Process Comparison. Any important characteristic of the underlying processes can be considered as an individual dimension for the process comparisons. In the context of welding production processes, there are different aspects, such as products, time, and resources. Based on these dimensions, a welding process cube can be built whose structure is similar to that of the Online Analytical Processing (OLAP). In a process cube, events are organized by using different dimensions [1]. The cells of a process cube can be analyzed by using different process mining techniques. Slicing and dicing are common operations in process cubes [1]. By slicing based on resources, the events related to a specific resource are removed. By dicing based on resource and time, the activities associated with a specific resource in the particular duration are filtered. Using correlation methods in different slices and dices allows companies to find correlations between the workload and performance. The comparison of these correlations in different slices and dices can provide beneficial information for process owners and engineers. This approach enables investigations of the effect of the workload on production performance of a specific user and also investigations of the impact of the workload on the performance of all users. This investigation can be performed in different slices or dices of the cube, depending on the focus.

Moreover, process mining may provide tools for detecting and monitoring changes in the assembly process termed concept drift. Aside from concept drift detection on the control flow level [6,14], process specific attributes can also be incorporated [10] to gain insight into the assembly process development exploiting welding specific domain knowledge. This may further be a starting point for a following analysis, e.g., regarding causality detection or inter-process/intra-process comparison.

4.2 Data Security and Data Privacy

The field of responsible data science is concerned with the different issues regarding publishing, accessing, and using data in data science techniques. Process mining as a set of techniques that directly deals with the data of the organizations should also address these concerns. The information on the level of events including the resource information should be secured in a way that only responsible people would be able to access and perform analysis while preserving security and privacy issues. Recently, a general framework has been proposed [21] which ensures confidentiality in process mining techniques. In production processes, different stakeholders and levels of the event information, e.g., human resources working on the production processes, machines and sensors, exist.

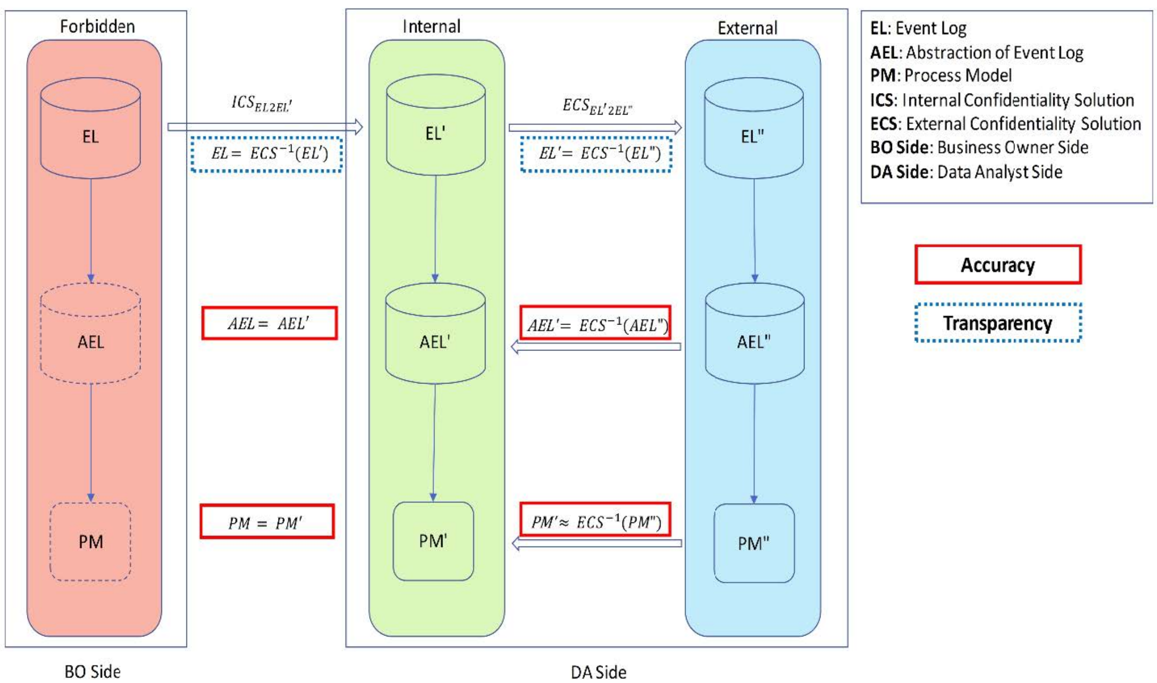


Fig. 8. The framework for confidentiality in process mining protects sensitive information during the analysis [21].

The framework shown in Figure 8 provides the confidentiality in process mining techniques, especially in the context of our focus, i.e., production process. This framework can be customized in the production process context. Two (internal and external) confidentiality solutions along with three different environments, namely the forbidden, internal and external environment, exist. Therefore, event logs can be transformed using the abstraction technique. Moreover, based on the different users in different environments either of the internal and external confidentiality solutions can be used.

Regardless of such a solution, all involved parties can also agree to collaboratively analyze the process. Unfortunately, sharing their process data can reveal a lot of inside information with other stakeholders. However, given that the different parties are (at least partially) in existing business relationships, a certain level of trust is already established. As an alternative, they can also appoint a trusted third party to conduct the analysis for them. From a security perspective, both of these approaches introduce at least a single point which has access to all data, i.e., a valuable target for data theft. Hence, process mining solutions which provide confidentiality are more beneficial in this context. Analyzing the process data without exchanging it is not a realistic option as most advances can only be achieved by collaboration between the different entities of the assembly process. Otherwise, changes to the process can only be implemented locally with a limited impact on the overall assembly layer.

Similar to the weld seam layer, the assembly layer also deals with internal departments in most cases. While an outsourcing of substeps to external parties is a potential future development for these two layers, it is already a reality in the context of the overall product process. Consequentially, as a next step we analyze this layer in the context of digitalized welding production. All security findings can also be applied to the previous two layers when external parties are involved.

5 Product Process Layer

The third layer defines the overall product process. Figure 9 describes the respective movement of different products from involved parties to a final good from the welding production point of view. In addition to the established interconnection of suppliers and customers, the IoP Service Provider also stands out, which will play an increasingly important role in a connected, digitalized welding production. The borders of different companies reveal the issues of data security and privacy more prominently than before. Nevertheless, the envisioned potential of data exchanges should make up for most of the associated risks as outlined in the following, i.e., the benefits should outweigh the risks perceived by the different companies. The flow of information follows the produced products. However, the result may be added value for any involved party due to insight gained at another party.

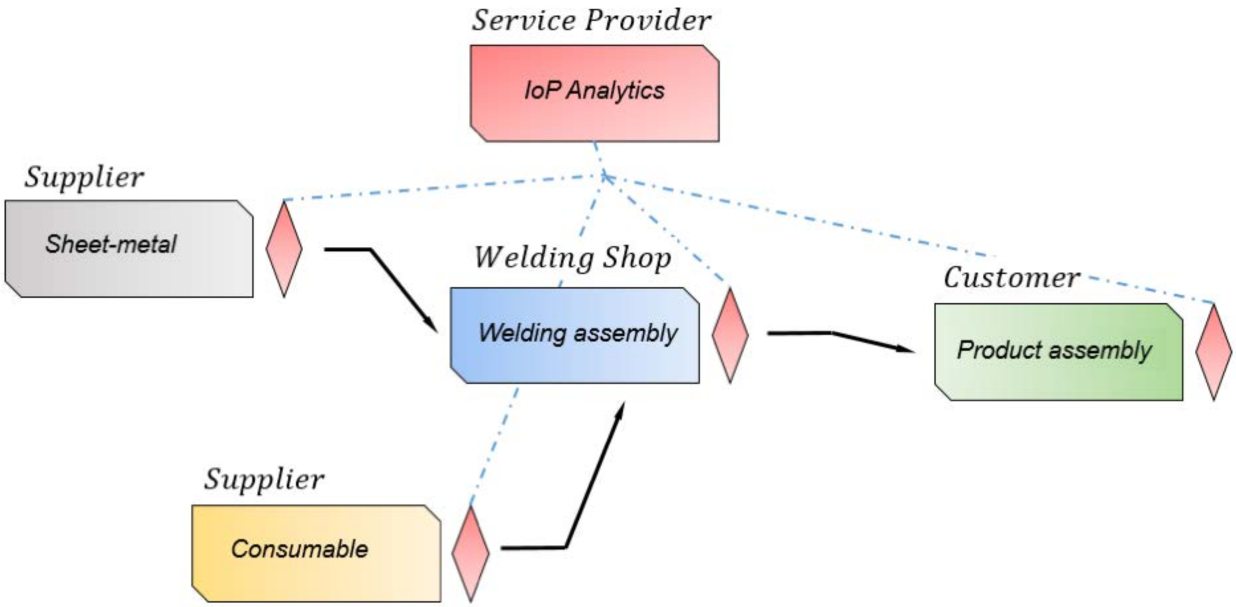


Fig. 9. The product process entails different parties (supplier, welding shop, service provider and customer) and their products until the final good is produced.

5.1 Applications and Methods

The concept of networked product quality was introduced [23] to show which information sources can be used directly to describe product quality in the context of welding. An essential component here is the acquisition of welding process data, but also the integration of decisive boundary conditions such as information about the workpiece-material. The latter information is available to the supplier, but is not part of the inherent process data acquisition in welding production. If this information is utilized in the sense of the networked product quality, the welding shop is dependent on limited quality certificates on arrival or in need of dedicated in-house material analysis. In this context, accessing inherent process data from the material supplier directly in welding production is significantly more useful. The casting production is working towards comprehensive simulation and monitoring of the material microstructure [13,27] which is a crucial property for welding. The competences and process data for extracting microstructural information of individual workpieces are therefore located at the production site rather than at the welding production. Nevertheless, knowledge about where and how microstructural properties are distributed in a casted workpiece are mandatory for successful welding. Adding spatially resolved data to the workpiece would eventually reduce testing efforts to find specific parameter settings and the overall weld quality.

Besides, in the interest of the welding shop customer, new added value is opened up with correspondingly aggregated data on the welding assembly. The description of product quality between customer and supplier is often limited to two simple states: OK and NOK. The boundary between both states is defined by the violation of defined quality characteristics. However, as soon as the customer of the welding assembly has a reliable, higher resolution quality description from the welding production, the products could be used more specifically according to their quality condition. Thus, assemblies that would otherwise fall below the NOK limit remain viable in less stressed products. This measure could especially benefit welding productions with an inherently high-quality fluctuation due to process uncertainties.

Apart from the established partners in welding production, a realistic assumption is that an IoP service provider will also have an increasingly important role in welding production. Cloud services for cross-location data communication are often considered a security risk in today's industry and therefore valuable data are commonly retained and processed locally [16]. If the service provider remains a pure infrastructure provider, without having access to the content of the data themselves, information security mandates properly implemented data confidentiality. However, the supported operations are limited in such a scenario and considering, information from different parties is hard to achieve due to a challenging key management [17].

On the contrary, the methods described in the previous paragraphs can hardly be carried out locally by the welding manufacturer. IoP service providers and research institutions can make use of their information technology know-how as well as the corresponding powerful computing hardware, which is indispensable for data-based methods of machine learning. At this point, however, the question of how data can be abstracted to such an extent that sensitive information can be protected without decimating its content comes to the fore. The main challenge is that the value of specific process information is currently unknown as new process dependencies first have to be uncovered.

5.2 Data Security and Data Privacy

In contrast to the individual steps as discussed before, in this context, information of the manufacturing and production steps must be shared in detail to utilize further advances. Proposing a global solution is unlikely as the value of information differs between the different parties of the production process. Hence, the exact implementation must be defined depending on the use case. Furthermore, this categorization can only be made by domain experts, i.e., it requires joint efforts by computer scientists and mechanical engineers alike, to also protect intellectual properties and process know-how. Thus, the individual angles of improving the overall production process have to be analyzed in detail before abstracting too much or too little information. The access of external parties, who are part of the process, should be restricted to the minimum [15], i.e., they may only retrieve information that is required to (a) work on their subprocess and (b) improve the overall process. Respective measures must be taken to obfuscate sensitive data. Time series recordings of arc welding voltage and current can e.g. not only tell which arc welding process is used. Such data can also describe process parameters, process variants or even reveal the deployed welding power source manufacturer.

In the future, newly collected information might become more valuable as it can be combined with a large stash of past production data [9], i.e., future data mining to improve the production process can rely on a large set of existing past process data. By integrating data sources of external parties, the significance of the available information can be further extended and improved. To still fulfill data security aspects that are mandated in today's production process, the respective information can be protected by different concepts, such as secure multiparty computation [17], secure offloading [28], privacy-preserving queries [7], or differential privacy [17]. The individual data collected during the weld seam process are utilized here again on a different level and by a larger set of different parties. Regardless, similar considerations regarding information security hold. In the following, the concepts are briefly put into perspective w.r.t. the considered welding process.

Secure Multiparty Computation. In a setting with valuable process data that should not be shared with external parties, communication protocols based on secure multiparty computation can help to enable collaborations between distrusting parties. The general concept is to retain the input locally while the participants jointly compute a function. During the computation, no information is leaked and eventually both parties receive the result of the function. In the context of welding, participating parties could, for example, jointly compute whether offered material properties match the requirements of the weld seam process without revealing the respective properties and requirements.

Secure Offloading. To utilize (powerful) resources in the cloud obliviously, a welding assembly could encrypt their process data and conduct computations on the encrypted data. When designing a privacy-preserving protocol, the cloud cannot learn anything about the processed data. For example, a welding assembly can check whether they measured the same electrical subtraces in the past to then draw further conclusions about the expected quality of the weld seam. Depending on the level of established collaborations, even multiple parties could send their encrypted data to the cloud to receive the joint result. However, in this case, the cloud must be trusted to not share the input data with the other parties.

Privacy-preserving Queries. In scenarios with an IoP service provider, a welding assembly might be interested to receive insight into a certain welding operation without revealing the properties of the measured weld seam. Similarly, the IoP service providers want to keep their knowledge base private. In such a setting, privacy-preserving database queries can be used to allow a welding assembly to receive insights from a service provider without either party gaining access to the submitted query.

Differential Privacy. While individual data points are valuable from a business perspective, they might also help to identify the concrete order of a weld seam. Consequentially, parties of a product process have an incentive to hide these identifying characteristics. Differential privacy describes a concept how to protect private information in a larger set of data. After application, no private information can be identified as the data have been generalized, i.e., the individual privacy is protected. In the context of welding, process data could be processed before being handed over to the IoP service provider for further analysis.

Overall, the chosen concept depends on the concrete use case and the requirements w.r.t. information leakage. Unfortunately, the overhead for deploying them is far from negligible as they must be carefully tailored to the use case. Once, approaches to improve the product process are widely established and collaborating with external parties is a usual part of production, further advances can be implemented by collaborating securely even with entities that have no direct influence on the production process [17] (this situation is not yet captured in Figure 9). An easy approach is to rely on the IoP service provider to link the product processes of different welding-related processes with the previously considered welding process. However, such advances require trust into both the intermediate party and the utilized data sources underlying any propositions to improve the process.

6 Conclusion

Envisioned by advances, such as Industrie 4.0 or the IoP, process changes are likely to also affect the production of welding workpieces. In particular, companies hope to realize process improvements by connecting, digitalized welding processes to utilize ubiquitous data securely even across entities. In this work, several applications have been presented which motivate to connect well-established welding production entities among different process layers while taking into account aspects of data security and privacy. Weld seam process layer. The connection of transient welding process data with testing data can be utilized to learn how to preemptively detect weld defects and improve the overall weld quality. In addition, simple compliance checks can be introduced by including WPS parameters to mentioned data sets. As currently no company borders are overstepped, each company internally has to agree how to implement accountability and determine the level of security the respective implementation has to achieve. Assembly process layer. The data shape of event-logs has been introduced, opening up the door to process mining. Three established techniques, namely process discovery, conformance and enhancement have been described in the context of welding production to model, analyze and improve corresponding processes. These methods are nevertheless not only applicable to the assembly process layer but even to other processes, describing their universal character. Security and privacy concerns have been addressed with a framework for confidentiality in process mining. This framework allows the secure access to event logs of data analysts by means of anonymizing and encryption without violating the privacy of the production site.

Product process layer. Several use cases of interlinking data among different entities, here even companies, have been described, motivating advantages for each party involved. As security and privacy concerns rise especially to the fore, deliberate methods, namely Secure Multiparty Computation, Secure Offloading, Privacy-preserving Queries and Differential Privacy have been showcased.

Overall, an interconnection of different entities who are part of the production process can help to realize the envisioned welding advances in manifold ways. The structure of process layers is oriented towards the established welding production and prepares therefore the deliberate utilization of diverse information sources without confusing different applications and their stakeholders. To this end, the production landscape has to shift from a setting with locally retained data silos to a scenario with secure industrial collaboration as part of an Internet of Production.

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