TECHNICAL UNIVERSITY OF MUNICH

TUM Data Innovation Lab

Advanced Analytics in Metal Forming Processes

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1 Introduction

1.1 Use case description - starting point

As cooperation between the TUM Data Innovation Lab and Bosch Siemens Home Appliances GmbH (BSH), this project focuses on the analysis of a Deep Drawing Process (DDP) for the inner door of a dishwasher at the plant of BSH Dillingen. The latter suffering under sporadically occurring cracks in the metal plates during the DDP, the aim from BSH was to start a data-driven production process, in order to identify the reason behind the crack occurrences (in average 34 cracked parts per month) and reduce waste through cracked parts. Consequently, as preparatory work to this project dedicated sensors were installed on one involved tool in the frame of a bachelor thesis (e.g. measuring forces, distances, room temperature etc.). Afterwards data was gathered based on this bachelor thesis.

Henceforth, an important differentiation between the technological perspective and the sensor data perspective is made, as during this work on one hand a detailed analysis on the root cause of the crack occurrences was conducted (Failure Mode and Effects Analysis (FMEA), see chapter 2), as well as a thorough data analysis of the provided sensor data. From the technological perspective, as pre-knowledge, it is known that the production of dishwashers represents a complex process having a high degree of automatization and requiring a high quality of the final product. The occurrence of cracks during a DDP is therefore not tolerable. The DDP of the inner door takes place on a 36 year old triple-acting hydraulic press, not disposing of capabilities to implement sensors directly within the control system without a high investment cost. No assumptions or ideas on the root cause for the occurrence of cracks exist, neither from operators of the hydraulic press, nor from the involved industrial engineers at the plant. This project systematically investigates patterns for the occurrence of cracks.

1.2 Objective - desired output

As cooperation between the TU Munich and its scientific claim as well as the industrial partner BSH GmbH it is particularly important for the project team to agree on common goals and framework conditions. For this reason, special emphasis was placed on the definition of results at a kick-off event. All the interest groups involved took part in this event. These include the production staff from Dillingen, the data science team from Munich, as well as the interests of the university and the student project team. However, it should be noted that the desired output differs from the realized output. In the further course of this paper we will refer to this and explain what caused this difference. As a template for the definition of the intended goals, the BSH template was used by agile data science projects to create a common understanding of the "Definition of Done". This includes a common understanding of communication channels and tools. Figure [1] illustrates the description of the project goals. Additionally, the "Definition of Done" is completed by the determination of the acceptance criteria. In the present project three criteria were agreed upon, which should be present in the final result:

Use case description	▪ As an engineer/machine operator ▪ I want to know when and why cracks occur ▪ I would like to detect cracks at the drawing-machine in real time (<=1s) and then take countermeasures, e.g. stop the machine or signalize a trend. ▪ During the deep drawing process, sometimes cracks occur in the metal plates, about one per shift. It is not known why this happens. A XDK-sensor has been installed to monitor the machine especially the drawing tool. The produced data shall be used to give a better understanding of the drawing-process itself and give insights about the occurrence of cracks and as well a real time algorithm that triggers an alarm when cracks occur or are likely to occur.
Goal	▪ What is the goal of this prototype? Avoidance of cracks by fast real-time detection of trends, which are leading to cracks, through a developed algorithm (in a high-level programing language) which is evaluating (<=1s) the collected data very close to the machine (i. e. Node-Red on the InnoLab-Server) ▪ Finding the root cause for cracks. What parameters on the "machine"/"tool of the machine" is causing the cracks. Which parameter influences the deep-drawing process in which way. ▪ What is the max. potential? Deep dan detailed understanding of the process
Value	▪ Reduce waste ▪ Understanding and improving the process itself and generate knowledge also applicable for other deep-drawing processes ▪ Knowing the cause for developing cracks and be able to avoid them
ROI	▪ **Estimated benefit _____ €/year**
Data source or systems, where the data reside	▪ XDK sensor ▪ Data is already available in S3 ▪ Labels, ppm ▪ Lightcheck (machine that detects the cracks, S7), data is available in S3
Comments	▪ From factory side we're always willing to support the analytics team in any matters. If there are any wishes (i. e. from the students side) or needs that will help to reach the goals faster or easier, just let us know soon enough. Because the sooner we know, the faster we can trigger the processes to implement new ideas.

Select strategic fit? Please select:	▪ Consume Data ▪ **Automated AI for i4.0** ▪ Data provisioning (Source/Make/Deliver)
Scalable/ reusable?	Similar Machines / Other Factories
Product Division/ Factory	PDC Dillingen
Process	Deep drawing
Machine	
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Figure 1: Project goal and summary

- Algorithm (in a high-level language) close to the machine (i.e. InnoLab server) that is able to determine (¡=1 sec.) with the collected data whether the produced part has cracks or is good.
- Ability of recognizing trends (algorithms).
- Root cause identification of crack occurrence (which parameter influences the DDP in which way).

Due to problems with data quality and interpretability, the first two acceptance criteria were modified by all stakeholders. The project will now be accepted if an error model is established which allows the cracks to be explained and also contains recommendations for action which can be implemented in production.

1.3 Planned approach

The project team decided to work on the whole project in an agile way (using SCRUM), as this development model allows for targeted and fast adaptation in a dynamic environment with uncertainty. New findings could be adapted quickly and efficiently. In order to better understand and apply the still young development methodology, the project team was allowed to participate in an online seminar by SCRUM expert David Cole. He explained the general aspects of the project, but also explained to the team which mistakes have to be avoided (for example the direct communication with the team members when a problem occurs). The applied SCRUM sprints had a duration of 2 weeks and were concluded with a sprint retrospective and a presentation in front of the complete "Sirius data science team" from Munich and Istanbul. In the following the major milestones of the project are briefly described:

- *Starting phase:* At the kick-off all stakeholders met for the first time and the foundation for the project was laid. The first weeks of the project were determined by the setup of all required accesses and authorizations. Furthermore, parallel work was done on the problem, technology, process understanding, among other things by a literature research search.
- *Data preparation, EDA and FMEA:* Data cleaning is a central component, as it is here that decisions are made on how to deal with missing values, outliers, etc.. In order to better understand the influencing factors, questions were asked to the machine operator. An iterative implementation of the FMEA is intended to increase the understanding of the process and also provide explanations for the development of cracks. The implementation of the EDA is also central, as in this case basic patterns and descriptive descriptions have been used to increase understanding of the data set and the information it contains.
- *Excursion to the production plant:* A special event was the visit of the production in Dillingen as it not only increased the process and machine understanding, but also allowed the team to see themselves in reality for the first time.
- *Data labeling and implementation recommendations:* The data labeling was carried out iteratively in two steps. First, an attempt was made to classify the cracks by means of the information email, then by means of the light detection sensor in the production line. It was planned to perform prediction modeling at the end of the project, but this could not be done because central data was missing. This is explicitly discussed in the report. Recommendations for implementation were developed jointly, covering both technical and data scientific aspects.

2 Analysis of deep drawing process (DDP)

2.1 Technical overview

The deep drawing is a mechanical process, which can be assigned to forming technology [DB16]. The process is classified by tension forming according to DIN 8584, whereby the classification is based on the prevailing stress conditions [DB16]. A special feature of this process is that a combination of different forces / stresses can be present. This fact explains the high complexity of the process as well as the high relevance of process experience. Also other studies illustrate how complex the modeling of the behaviour is [Qud+20]. According to Doege and Behrens [DB16] the DDP is characterized by the following three different stresses. Firstly Tensile and pressure stresses prevail in the flange area. Secondly in the floor area, tensile and compression stresses occur. Finally the greatest complexity is found in the run-out of the punch edge, since here there is an obstructed uniaxial tensile stress, which leads to a direct or indirect tensile stress input, neglecting the normal stress. For this project, however, the stresses and associated physical forces in the edge region are particularly important, since this is where the cracks in the metal plate show up. For this reason, it is particularly important to relate the scientific findings presented in the following to this fact. In the following, different technical processes of the DDP will be discussed. Essential for this project are tolerances of the process and the machine. An engineer weighs up how imprecise a component/product can be in order to be able to just fulfil the technical function. Production engineering systems are a product that consists of an interaction of different components and tolerance specifications. In order to be able to make statements for the present project about the causes of the occurring cracks it is essential to better understand the accuracies of the present machine. Forming machines are classified according to [DB16] in two accuracy parameters. The first classification are the geometrical accuracies include achievable deviations from the ideal value on the unloaded machine, which can include movement play of components as well as geometrical deviations. On the other hand, there are elastic yielding points on the moving machine which can lead to deviations from the ideal value due to static or dynamic loads. The deep drawing machine used is 36 years old and for this reason technical documentation of the machine is only available to a limited extent. This fact makes it difficult to find the cause, but the machine operator of the machine has a lot of experience and expertise. On the basis of this experience it is possible to look at the tolerances in the machine. It should be particularly emphasized that even very small deviations from the value considered ideal result in the formation of cracks. In addition, the maintenance of the machines has a great influence on the DDP - this is confirmed by machine operators and literature [DB16].

Another very important aspect is the material behaviour of the metals used which has a great influence on the formation of cracks. On the one hand it is important to take a closer look at the type of alloys used and their metallurgical properties. Basically two types of deformation are distinguished, namely reversible/elastic deformation and irreversible/plastic deformation [BS12]. In deep drawing, an irreversible plastic deformation is carried out, which means that the formed workpiece undergoes a permanent change in shape. The deformation behaviour for metallic materials is investigated by means of stress-strain diagrams. These diagrams describe the material behaviour of metallic materials in a homogeneous uniaxial stress state [DB16]. This must be distinguished from dynamic oscillation behaviour, which can be described, for example, by Woehler lines. In the present project, the oscillation behaviour is not considered, since the acting velocity is constant during the whole process [DB16] and no change of force direction affects the material. Central components of a stress-strain diagram are the tensile strength (Rm) as well as the elongation and yield strengths. These characterize the elastic and plastic behavior of materials. For the alloys used in the project, the stress-strain behavior is unknown. However, it can be assumed that only a small gain of information could be achieved by this, since the process itself already works without them. Important factors influencing the forming behaviour are the temperature and the test speed [DB16]. The strength of the material decreases with increasing temperature [DB16]. Strength is a metallurgical property which includes the resistance of a material to deformation and fracture [DB16]. In contrast, ductility is understood to be the malleability of the material and both properties must be combined with each other, whereby an increase in one property results in a decrease in the other. Also a temperature influence results in a reduction of strength but an increase of ductility [DB16]. DDPs can be further subdivided according to the temperature applied [DB16]. In the present project, this is a cold forming process according to DIN 8582 where the workpiece is not heated (room temperature) before. This temperature means that the press has to apply higher forming forces in order to change the shape, but high accuracies can be achieved [DB16]. In addition, it is important that the forming process is usually carried out in several steps.

2.1.1 Cracks

In the present project it is important to deal with the process to be avoided, especially this understanding helps to better consider effects and interrelations. A bad component is characterized by the fact that it does not meet the tolerances to be fulfilled. In the present case, it is a defect pattern which has a crack in the component. A crack is characterized by the fact that the surface of the material is not continuously connected everywhere. As a result, the manufactured component has changed material properties due to the weak point, which are not justifiable from a business point of view. Tears occur when the total force is equal to or greater than the breaking force - this is how Doege and Behrens [DB16] summarize the statements of Melching and Doege [DM77]. It should be noted, that this situation can occur for many reasons (e.g. temperature, speed, ductility/strength, ...). There are also connections with other classifications of errors. In general, there are four types of failure in deep drawing [DB16]. 1) Wrinkle formation of the 1st type is formed in the flange area by tangential tensile stresses of the workpiece. The resulting wrinkles are drawn over the drawing ring into the drawn part and thus change the material properties or the surface. For this project, this type of error is not important because the flange area with its waviness is removed. 2) Wrinkles of the 2nd type are waviness that are formed in free forming zones between the punch and the drawing ring. This error type is to be excluded for this project, because the error patterns do not match. 3) Cracks usually occur in the area of the punch edge run-out or in areas with large plastic deformation, as the forming forces are particularly high in these areas. In the present project, this type of defect is the relevant one and also the location of the defects is the same. 4) Springback is understood to be a deformation behaviour in which elastic components occurring during plastic deformation cause the component to warp. This type of defect is currently only partially detected because the scarring is all matched. The defect is not relevant for the project-specific investigation

2.1.2 Preprocesses

The DDP is integrated into a highly automated production line (VDCD/ GV640A). The central point here is that there are previous processes which have an influence on the DDP. It starts with the production of the metal and the delivery on large coils. These coils are then cut to size and coated with a polymer coating. They are then stacked and individually coated with a continuous oil film. They are then placed in the deep drawing machine and further processed in four stages. At the end of the DDP in the production line, four light sensors are used to determine whether the part produced is defective or not. The machine operator is informed about defective components. Generally, defects always occur in a series. According to the experience of a machine operator, there are usually ca. 6 bad parts in a row. In the following, the individual components of the highly automated production line are described in detail. In particular, the function and then the technology are always discussed first. Each section is concluded with an assessment of why this component is important for this scientific project. All processes that are carried out after the DDP and the transmitted light test can be excluded as influencing factors, as the cracks have already appeared before.

For the DDP a material is needed which should undergo the deformation. This material is produced in steel mills and is delivered to BSH on large rolls which are called coils. The material used is the Ampco 25 centrifugal casting ("Schleuderguss") alloy. Quality checks at both the manufacturer and BSH ensure that the materials have the required material properties. BSH has several suppliers for this. The manufacturing process of the coils is also subject to fluctuations that are within a tolerance range. For example, the material composition of the alloy can vary locally and this can extend over several meters of the coil. This can result in a series of faulty DDPs because the composition of the alloy has different material properties. It is not possible to check this cause because the material properties themselves cannot be measured, but their effects can be observed. A further possibility of influence is the rolling process by which the coils are produced. In this rolling process, varying pressure loads are applied to the hot metal and the shape becomes a very long plate. This sheet is then cut to size and rolled into coils. During the rolling process as well as the cutting process forces are applied to the workpiece. These forces absorbed by the material are called internal stresses. During the rolling process, directional residual compressive stresses are generated. During the DDP, the residual stresses can have a negative influence on the drawing behaviour. Thus, materials subject to residual stresses may fail earlier because the actual resulting stress is composed of residual stress and externally introduced stresses [DB16]. However, it should be noted that compressive loads in the edge areas have a positive effect on the forming process, since the compressive stresses must first be compensated before critical tensile loads (which can lead to cracks) can occur [DB16]. It is also not possible to actively intervene in this process, only the influences on the DDP can be observed. BMW avoids this process by measuring each blank and making it clearly identifiable [BMW].

After the coils have been cut to size at BSH, they are prepared in the feeder and checked for scratches, bends, etc.) and then positioned (machine report). In the coating plant, the polymer "Quaker TF 11" is applied to the metal blanks over the entire surface. The function of the polymer is to protect the metal surface from handling damage, for example from scratches. The applied technique of coating works by applying a spray mist on both sides of the metal plates. The metal plates are then dried, cooled and stacked. The surface loading is measured randomly. There are also specifications for this, for example a coating thickness of 1.4 μm and a permitted tolerance of +0.3/-0.2. The relevance for this project is that an insufficient coating thickness has a negative influence on the subsequent forming process. For example, friction can be increased locally, which can have direct effects on the DDP. Especially this fluctuating coating thickness can manifest itself over several metal plates.

Directly in front of the deep drawing machine an oil film is applied on both sides and flatly covering the metal plates. This oil film is of great importance for the feasibility of the subsequent DDP. According to statements by experienced machine operators, even a small deviation of the oil film leads to cracking of the workpiece. The function of the oil film is to reduce the friction of the material. In addition, the oil film can also prevent metallurgical processes such as oxidation. The oil film is applied on both sides by a continuous spray jet. Coarse contamination of the oil film can be excluded as a cause for crack formation, as marks can be seen in the workpiece. The serial occurrence of cracks is also unlikely in the case of coarse contamination. However, fluctuating oil properties can have an influence on the formation of cracks. For example, oil temperature, consistency and age have a direct influence on the entire process. The relevance for this project is that even small deviations from the ideal oil wetting can have a major impact on crack formation. Even with this cause only the effects can be described/observed, so that an active modeling of the processes is not possible.

2.1.3 Deep drawing process line and machine

The central process which should be better understood by this project work is the DDP in which the forming of the metal plates takes place. There are two production lines in the production in Dillingen which can perform identical processes. It should be noted that only one process line can be equipped with the sensors and also just one tool (8578). Small deviations from the ideal condition of this tools directly manifest themselves in a defective component. The actual forming process takes place in four process steps. It starts with the actual DDP, which is the process with the greatest shape transformation. Then the formed workpiece is cut to size so that the edges are removed. Subsequently, components are removed from the workpiece in a stamping process. The DDP is completed by a bending process. The crack formation is clearly due to the process of the largest forming. This can also be proven by the fact that when a crack is detected, all parts up to and including the DDP are defective. Because a cold DDP is carried out, the forces to be applied by the machine are greater [DB16]. Thus the upper punch (”Oberer Stempel”) can apply a pressure of 80-90 tons (machine report). The hold-down device (”Niederhalter”), on the other hand, can apply the greatest forces, namely between 175 and 200 tons (machine report). The die (”Matrize”) on the other hand can apply a pressure of 110 to 130 tons. The DDP itself works in such a way that the metal plates wetted with oil are placed in the deep drawing machine by a vacuum gripper. Then the die and holding-down device clamp the metal plate and the upper punch moves parallel to the metal plate. The speed of the punch as well as the clamping forces of the die and the hold-down device are adjusted once on the basis of experience. It is important that this clamping holds back material and thus avoids wrinkling [DB16]. As the punch moves downwards at a constant speed, material has to be re-filled which is forged to the mould. This flow is regulated by four drawing bars which limit the flow rate. After the maximum traversing speed is reached, the upper punch, hold-down clamp and die move apart again. The upper punch as well as the lower punch have the shape of a negative image of the workpiece and they fit into each other. The formed workpiece is located between the upper and lower punch.

2.1.4 Sensors

In order to be able to analyse the data, it is particularly important to know how they are recorded. For this analysis, different sensor data are available, which are directly attached to one production line and one tool. In the following, the individual sensors used are described. A light detection system is installed in the production line. This checks in absolute darkness whether light can pass through the formed metal. If there is a crack, the light is detected on the other side and the component is classified as defective. In addition, camera shots are taken from different angles. These images are time stamped and stored in the cloud. Additionally, three ultrasonic sensors UFP-400 of the company "Waycon" are installed on one tool. The decision for this type of sensor was made on the basis of the short scanning time of 40 - 60 milliseconds [Gut19]. The ultrasonic sensors measure the travelled path of individual components (hold-down device, upper punch and die) of the deep drawing machine. The path measurement is based on an interpolation of the measured voltage and the stored distances or their voltages between position 1 and position 2 [Gut19]. In addition, resistor circuits (shunts) are installed, which enable the analog - digital converter of the micro-controller to read out the data [Gut19]. It should be noted that it is currently not certain whether the data acquired can record the change in behaviour of a crack. There is a danger that the large mass of the tool will absorb the changes. In order to be able to measure the forces acting, three strain gauges are placed at different locations on the tool. The strain gauges measure changes in the resistance, which are then calculated back to the existing force. Measurements with strain gauges are always characterized by the fact that they have a large tolerance range. To reduce additional sources of interference, strain gauges with a resistance of 350 Ohm are installed [Gut19]). Measurement signals are transmitted to the micro-controller. The micro-controller used in the bachelor thesis is a Bosch XDK "Cross Domain Development Kit". It is mounted on the outside of the tool. The XDK has different inputs which receive the measuring signals of the sensors. In addition, it has its own sensors which can measure temperature, humidity and vibration. The micro-controller processes the signals and then forwards them to the cloud [Gut19]. It is controversial, however, whether the additionally recorded values represent an added value for the analysis. For example, the signals are recorded outside the critical range, and analysis of the recorded data also shows that they naturally fluctuate. The project team comes to the conclusion that only large deviations can be recorded with these additional data. A further uncertainty is the performance of the micro-controller, so it cannot be clearly determined whether the micro-controller is capable of processing all the information. In addition, it might be possible to obtain information about the frictional conditions of the DDP using acoustic sensors [STS98] but for this adjustments of the setup must be made. Since the recorded signals of the sensors also always record interfering signals and these disturb the analysis. For this reason, in the previous bachelor thesis digital filters (e.g. Nyquist-Shannon-Theorem and Alias Effect) and analogue filters (e.g. low pass filters) were applied to the acquired data [Gut19]. The filtering of the signals has been verified by the project team, but it is possible that minimal deviations caused by crack formation are filtered out. However, it should be noted that these would probably not have been detectable/identifiable.

2.2 Failure Mode and Effects Analysis (FMEA)

The objective of this scientific project is to make predictions about the condition of the metal plates and their risk of cracking. A pure prediction without deeper knowledge about the process itself is not useful for the stakeholders of the production, because their incentive is a continuous improvement according to the "Toyota Production System". For this reason it is particularly important for them to better understand the DDP in order to be able to apply preventive measures. At present, a deeper understanding of the sources of errors is not yet available. During the course of the project, the team considers different product development methodologies. These methods (Root Cause Analysis, Petri Nets, ...) allow a systematic investigation of the error sources, causes and influencing factors. With an overall consideration of the required input information as well as the desired results, only an iterative execution of the process FMEA fulfils these requirements. The abbreviation FMEA stands for Failure Mode and Effects Analysis, which provides cross-functional teams with a uniform view of the possible failure modes and their behavior. A FMEA iteration is normally carried out in five process steps [Wer12]. At the end of an iteration there is a first possible modeling of the reality of a process. With each further iteration, the understanding of the prevailing processes and failure mechanisms increases. The first step of FMEA is to consider the product structure. In this process step the physical components of the process are considered and their relationships to each other are shown in a graph. As the complexity of the deep drawing machine at hand is very high and the available technical information is very limited due to the age of the machine. The project team uses abstractions for modeling. In a classical FMEA, a time separation between the modeling of the system components and the corresponding functional modeling. After an extensive investigation, the project team finds that the FMEA process steps 1 and 2 must be combined, since abstraction of the complexity is only possible to a limited extent. Functions in this context are connecting attributes that describe the interaction of system components. The most important process step of each FMEA is the modeling of the failure processes. For this purpose, a failure tree is created for the modeling of the failure chain in two steps. First, the type of failure is described, for example an abrupt change of movement of the control. Afterwards it is considered what the failure consequences are. In the present example these would be the crack formation, a change of the graph will be visible in the data as well as the cracks can show a serial behaviour. The first investigation stage is completed by the investigation of the failure causes. Here it should be mentioned that the flow velocity of the metal would be slower than the required flow velocity required by the change of path. This type of failure cause can be caused by control or measurement processes (e.g. absolute and not relative travel). In the second stage, the actual failure tree is now modelled on the basis of the first stage. Here the modeling is divided into the DDP and the pre-processes. The modeling itself takes place using a color-coded flow chart. Figure [2] shows the Failure Tree for the preprocessing. It was found that the reasons for failure can be very diverse, but the failure itself is always based on the same failure pattern. The flow behaviour of the metal is affected by friction, contamination, temperature, vibration, ... with the result that there is not enough material to handle the deformation forces. After creating the failure tree, a risk priority number is assigned to each failure type in the fourth process step. Based on the literature, points for the characterization of the failure are given. The characterization is carried out on the basis of severity, occurrence and detection. Severity describes how comprehensive the failure is. The occurance describes how probable the presence of the failure is and the detection describes how probable it is to notice the failure. The greater the values assigned on the basis of the literature, the more important it is to investigate and reduce the error. The FMEA is completed by sorting the failures according to the risk priority number and defining activities starting with the highest risk priority number. The FMEA is very comprehensive, only excerpts are included in this report. The complete FMEA is available to BSH and can be viewed upon request.

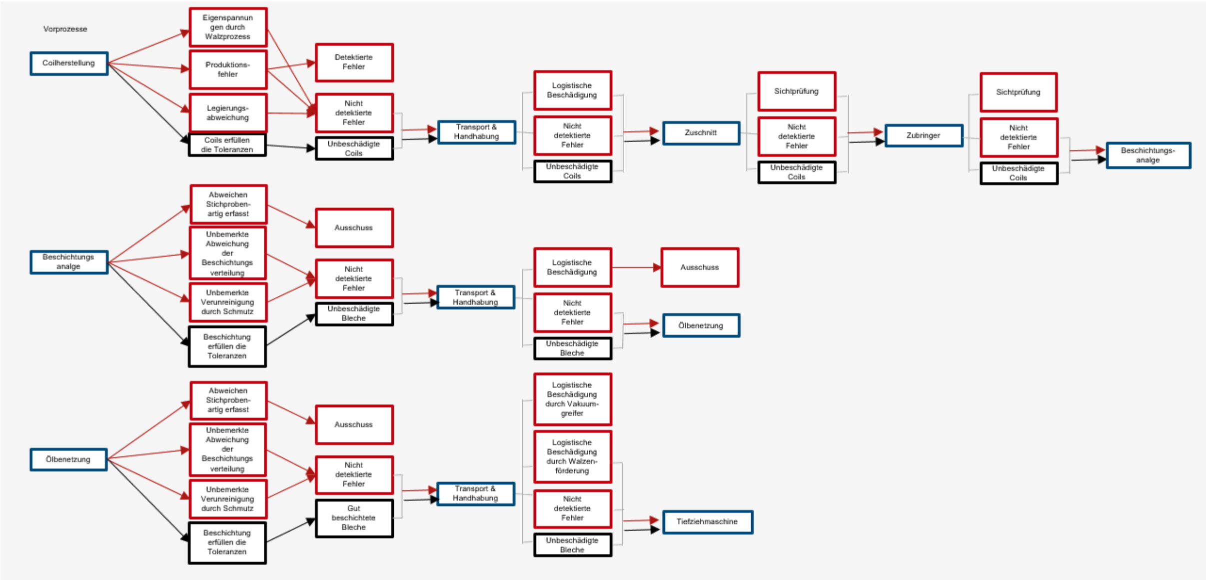

Figure 2: Part of the FMEA failure tree - illustrating the preprocessing

3 Exploratory Data Analysis (EDA)

Within the EDA two main questions were sought to be answered. Are and if so how are cracks represented in the data collected by the installed sensors? How can the cracks be characterized apart from the provided data from the sensors?

While the first question is referring to potential outliers and anomalies in the sensor data and whether they can be traced back to actual crack occurrences (important for data labeling), the second questions deals with the timely distribution of crack occurrences and their physical variance (different lengths and positions on the metal sheet) based on data generated from a separate light detection sensor.

3.1 Analysis of sensor data

Although all sensor data undergoes preprocessing (see chapter 2) before being visualized within the Production Performance Manager (PPM) it is nevertheless useful to firstly check how consistent the collected data is. As next steps possible outliers can be interpreted in order to decide whether they are caused by faulty sensor data or whether they represent the actual occurrence of cracks.

3.1.1 Identifying and interpreting outliers

In figure [3] two boxplots showing respectively the distances of the inner stamp ("Stempel"), the die ("Matrize") and the hold-down clamp ("Niederhalter"), as well as a density

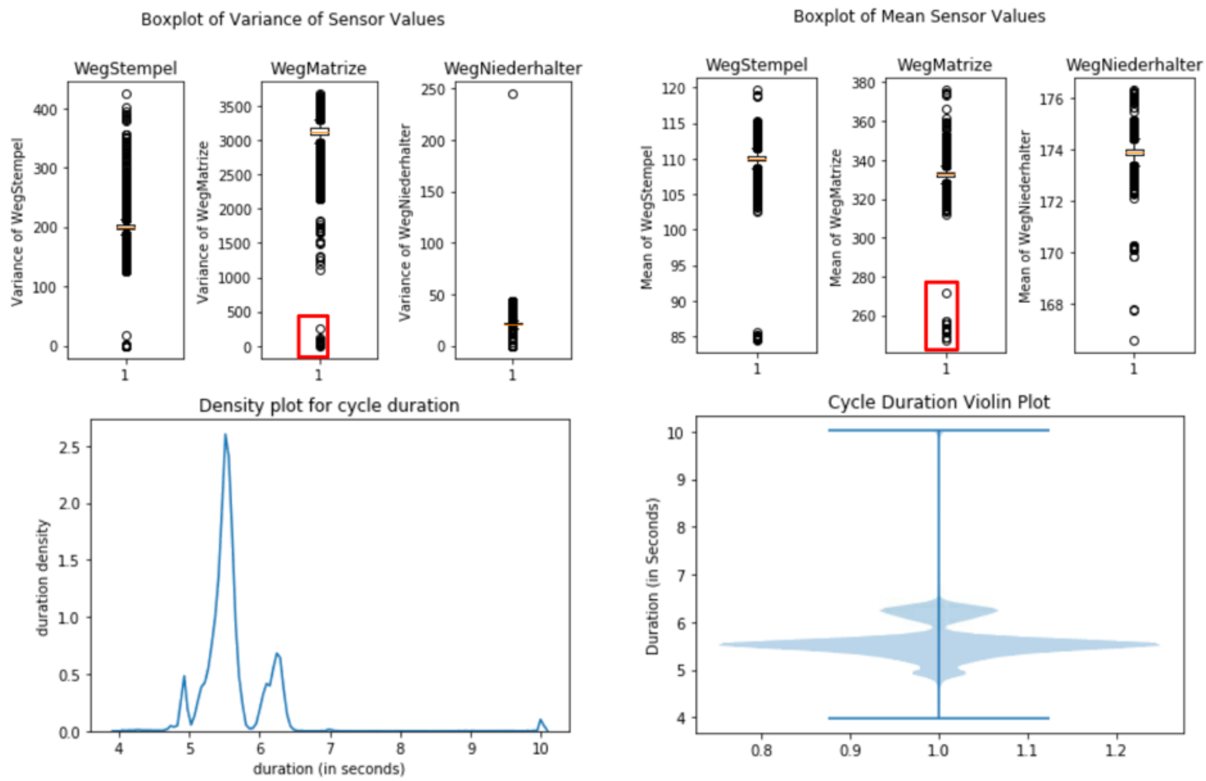

Figure 3: Boxplots of sensor values (mean and variance) and average cycle time duration

plot and a violin plot both displaying a distribution of the cycle duration are visualized. Both the variance and the mean of the distance values (boxplots) are relatively concentrated without a clear occurrence of whiskers. The few outliers, especially for the distances of the die have as next step (see next chapter) to be analyzed to investigate whether they are caused merely by faulty sensor data or related to the actual occurrence of cracks. Both the violin and the density plot show that the majority of cycle times range between five to six seconds. Additionally, however, another peak at over six seconds cycle time can be observed, yet again needing further investigation on its origin.

Apart from the distances traveled by the respective components of the press, the installed sensors (for full overview, see chapter 2) also include strain gauges ("Dehnmessstreifen (DMS)") that should measure the forces applied during the DDP.

As visualized in figure [4] it was ascertained however, that the force values displayed in the PPM remained constant throughout the entire DDP and additionally showed a difference in forces of approximately a factor of a 100. Both observations were considered not plausible with respect to the theory of a DDP (chapter 2)) and after discussion with the industrial engineers on site, it was agreed on neglecting the data gathered from the force sensors.

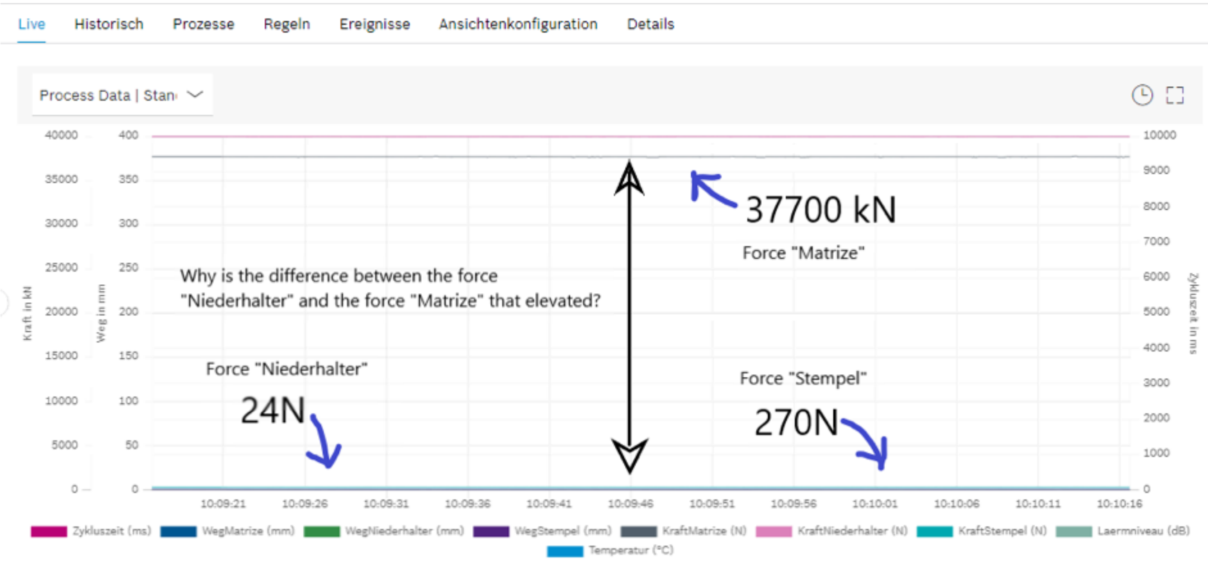

Figure 4: PPM visualization of measured forces for the hold-down clamp ("Niederhalter"), the die ("Matrize") and the stamp ("Stempel")

3.2 Analysis of cracks

In order to identify relevant influencing factors for the occurrence of cracks in the specified DDP, the timely distribution of crack occurrences with a set time frame of e.g. a month might be helpful. Not only can the total number and their timely occurrence be specified but the average number of succeeding "broken parts" (assumed to be ranging from 1-5 at this point) can be verified. This might help identifying trends or patterns and permit more founded assumptions on root causes for the occurrence of cracks.

3.2.1 Using E-Mail error reporting as reference for timely distribution of crack occurrences

The first approach of quantifying the number of crack occurrences per day / month / year and identifying possible trends, was by extracting the respective timestamp of an e-mail error reporting from the so-called Production Performance Manager (PPM). It was assumed that an error notification was send shortly (with a negligible delay) after the actual crack was detected by the light detection.
After thorough investigation of the data gathered from the error reportings it was decided to neglect them because of the following reasons:

1. *Unclear timing:* The error reportings do not allow a precise traceability of the time of the crack occurrences as they are send via the PPM tool and it is unknown whether the sending time represents also the time of the crack occurrence.

2. *No reliable correlation between error reporting and crack occurrence:* After checking whether at specific times of error reportings anomalies in the gathered sensor data at the machine tool are visible, a significant amount does not show any recorded data at all. The only plausible explanations for lack of data is that either another tool (not having the sensors installed) was in use at this particular time, or that error

reportings were also send while maintenance was conducted. Both interpretations however, lead to an uncertainty whether actual cracks are reported or not, therefore justifying the approach of looking at the timestamps of the actual black and white photos of the light detection cameras.

3.2.2 Using light detection camera photos for characterization of cracks and their occurrences

The advantage of using the timestamps of the light detection photos of cracks is that for every given timestamp the photo can be verified in order to be sure that an actual crack occurred. Therefore, before using the timestamps of the light detection photos they were sorted and reviewed to only include actual crack occurrences. A time shift still exists between the time of origin of a crack in the DDP and its detection. This shift is assumed to be equal for every crack detection and should therefore not distort the distribution of crack occurrences. The light detection station consists of four cameras taking pictures if a crack is detected (through a light sensor). In the following analysis only Camera 3 was taken into account. 262 events were photographed within a time frame from May 2019 to July 2020 and were equated to crack occurrences. From the 262 events however, 83 were disregarded occurring on the 19th of November 2019 and the 23rd of January 2020 and considered as insignificant outliers due to their uncharacteristic high number of crack occurrences in a row. Hence, 179 crack occurrences represent the baseline of the following exploratory data analysis.

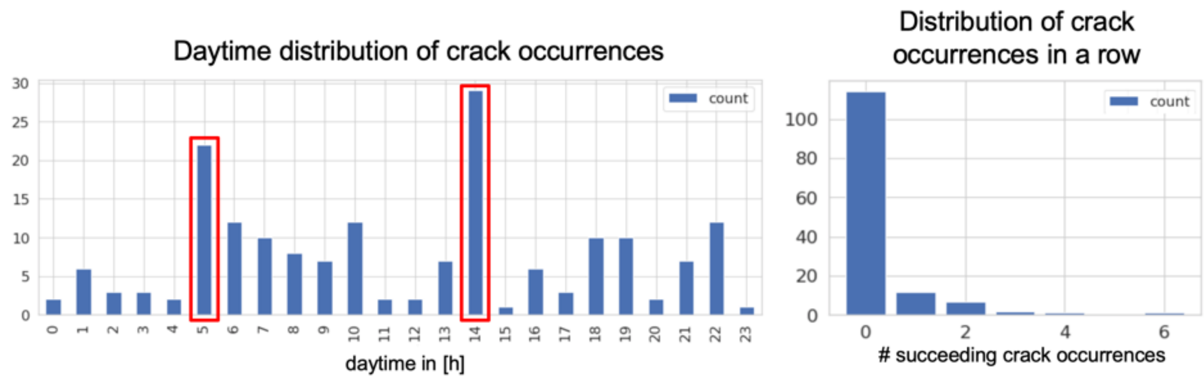

Figure 5: Daytime distribution of crack occurrences and occurrences in direct succession

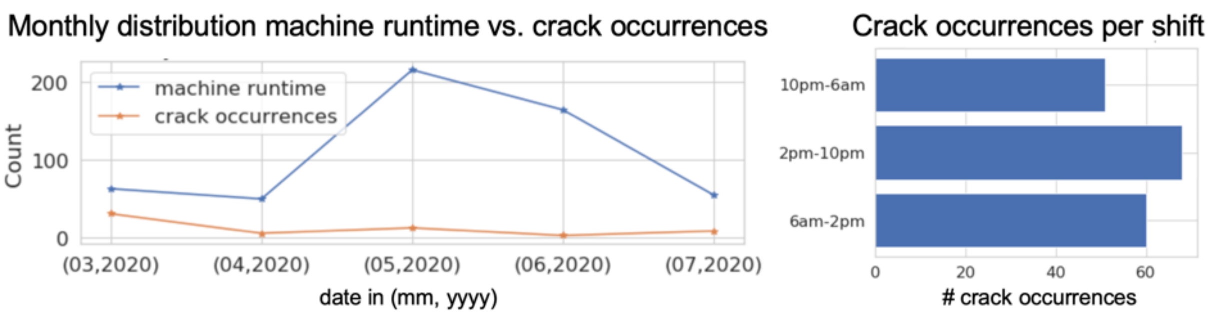

Figure 6: Relation between machine runtime and number of crack occurrences and occurrences per shift)

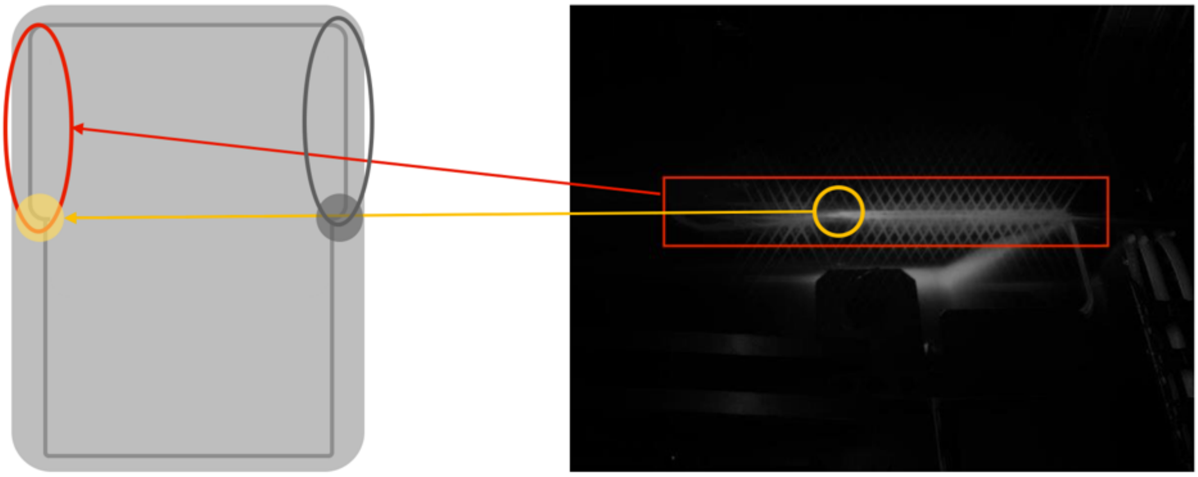

Figure 7: Distribution of positions of crack occurrences on sheet metal

1. **Observations**

    - Figure 5 displays on the left side the daytime distribution of crack occurrences from all the anomaly events of the above-mentioned time frame. In general, no clear pattern is detectable however, peak crack occurrences at 5am and 2pm are visible, clearly in contrast to the remaining daytime hours. On the right the crack occurrences in direct succession is visualized, counting all parts that occurred within less than one-minute difference. Although, one minute is much higher than the cycle time it should also take all kinds of latencies into account, justifying this high threshold. Despite this, in average only 1.23 cracks in a row have been detected in the stated time frame. The average cracks occur with 5.60 hours difference in-between however, with a standard deviation of 7.44 hours.
    - Figure 6 compares (on the left) the monthly distribution from March 2020 to July 2020 of crack occurrences with the overall runtime of the machine. No strict correlation between an increasing machine runtime and crack occurrences is visible. Additionally, the overall runtime is significantly higher than the crack occurrences, only occupying a very small share. Looking at the distribution of crack occurrences per shift, all time periods show similar anomaly events, the afternoon shift having a slight increased number of crack occurrences.
    - Figure 7 makes use of the actual light detection photos corresponding to the previously used timestamps of crack occurrences. On the right side the standard deviation of all light detection photos is visualized. The bright line in the red box displays the detected cracks, which position with regards to the overall sheet metal is visualized on the left. The yellow circle refers to the origin of the cracks on one particular side. Although only one side is considered, it shall be noted that cracks also occur on the mirrored (y-axis) of the sheet metal.

2. **Findings**

   - Having an even distribution over the entire stated time frame (05.19 - 07.20), 5am and 2pm seem to continuously have the highest crack occurrences. The majority of cracks seem to occur isolated, meaning not in a row. It shall be noted however, that the low succession rate could also partly be related to the operator removing all succeeding bad parts, directly after the first one is detected by the light detection (light detection and deep drawing press being several seconds apart). The general succession time can be considered to a great extend as random, regarding the high standard deviation stated in the observation section.
   - A slight connection between the machine runtime and the occurrence of cracks can be suggested however, in general only no significant influence can be detected, partly also due to the limited time frame of only five months (03.20-07.20). The night shift (10pm-6am) has the least crack occurrences, followed by the morning shift (6am-2pm) and the afternoon shift (2pm-10pm) having the highest number of crack occurrences.
   - All cracks originate from the identical starting point, being the yellow area visualized in figure 7 (identifiable in the pictures as the brightest point), coinciding with the position of the highest deformation. This corresponds directly to the theory of the DDP (chapter 2), stating that cracks occur most likely at positions of high deformation. The majority of cracks occur always either on the upper left (red ellipsis) or on the right upper side (grey ellipsis), however generally not simultaneously.

3. **Assumptions**

   - The high crack occurrences at 5am coincide with generally the starting of the machine according to the industrial engineer on-site, representing a possible lead to the relevance of the temperature of the machine that can be assumed to increase with a longer operation time and being lowest at the starting point. As no set direct succession length of crack occurrences is detectable (most of them being single-anomaly events) it can be assumed that the anomalies are cause by a combination of influencing factors that occur randomly without a clear recurring pattern.
   - Crack occurrences seem not to be particular dependent on different shifts. Especially as all operators spend equal time on all three shifts (morning, afternoon and night) no definite statement can be made on the influence the operators might have one the occurrence of cracks. Tool-changes, maintenance or other activities conducted during changes of shifts (morning to afternoon shift) could have an impact on the occurrence of cracks (see highest crack occurrences at 2pm). The runtime of the machine does not seem to increase the probability of crack occurrences, despite an intuitive thinking of “if the machine is more used then the chance of cracks should also increase”.
   - The position of the occurring cracks corresponds to the theory of the DDP, allowing the assumption that the forming process itself is functioning normally

and not excluding material failures as an influencing factor for the crack occurrence.

Characterization in one sentence: We have a continuous crack occurrence over the past year, mainly consisting of single-anomaly events, occurring independently of the machine time however, most frequently in a time frame from 5am to 2pm (with respective peaks at these times). They originate always from the same sector of the metal plate.

4 Data modeling

4.1 Raw data model

The data of a set of DDPs consist of measured points of the time-dependent process $\rho(t) = (\rho_1(t), \rho_2(t), \rho_3(t), c(t)) \in R^4$ for $t \in [0, T)$ at the times t_s for $s = 1, ..., S$, where $\rho_1(t), \rho_2(t), \rho_3(t)$ corresponds to 3 sensor data and $c(t)$ corresponds to counting time of each DDP.

The whole process can be divided into N small processes such that each process corresponds to a single DDP. This is done by considering the starting time τ_n of the n-th DDP until the next DDP starts, where $\tau_1 = 0$, $\tau_{N+1} = T$ and $\tau_n < \tau_{n+1}$ for all $n = 1, ..., N$.

Hence, the n-th DDP is described by $\rho(t)$ for $t \in [\tau_n, \tau_{n+1})$ and its measuring times are t_s for $s = \sigma_n, ..., \sigma_{n+1} - 1$, where σ_n is the first s for which $t_s \geq \tau_n$, i.e. $\sigma_n = \min\{s \in \{1, ..., N\} \mid t_s \geq \tau_n\}$.

The description of the DDPs can be simplified by defining the n-th DDP by $\rho^{(n)}(t) = \rho(t + \tau_n)$ for $t \in [0, T_n)$ where $T_n = \tau_{n+1} - \tau_n$ and its measuring times are $t_s^{(n)} = t_{s+\sigma_n-1}$ for $s = 1, ..., S_n$ where $S_n = \sigma_{n+1} - \sigma_n$.

In total, our model results in:
Model 1 The n-th DDP is modeled by a time-dependent three-dimensional process $\rho^{(n)}(t) = \left(\rho_1^{(n)}(t), \rho_2^{(n)}(t), \rho_3^{(n)}(t), c^{(n)}(t)\right) \in R^4$ for $t \in [0, T_n)$. The collected data $\left(\rho^{(n)}(t_s^{(n)})\right)_{s=1}^{S_n}$ consist of the measurements of the DDP $\rho^{(n)}$ at the times $t_s^{(n)}$ for $s = 1, ..., S_n$.

Generally, $t_1^{(m)} \neq t_1^{(n)}$ for $m \neq n$ and hence the "n-dependence" of the measuring time is needed. Also $T_m \neq T_n$ for $m \neq n$ does not hold in general since the total time of a DDP can vary.

4.2 Data preparation

The goal of data preparation is to provide well-structured data for further analysis.
Due to network delay and limit of the microprocessor, some data do not arrive at the expected time. By looking at the raw data, there are three types of points needed to be dealt with: some data come in the wrong order; some data are measured with wrong time step; some data are missing. Besides, it is not necessary to include all data during the DDP, meaning some transformation can help reduce the size. Finally, since there is no correct label (cracked or not) provided for each DDP, we need to do it manually.

4.2.1 Identify DDPs

Motivation: Identifying each DDP in raw data is crucial for further analysis. Also, labeling is done for each DDP. However, the raw data does not contain any identifier for each independent DDP. We have to do it manually.
Approach: As is designed, *cycle time* is reset to 0 when n-th DDP is finished, after which there's a period of time when nothing happens. During this period *cycle time* is set to 0. When (n+1)-th DDP begins, *cycle time* starts to count again. Figure [8] shows the result of dividing a series where red dash lines are separators.

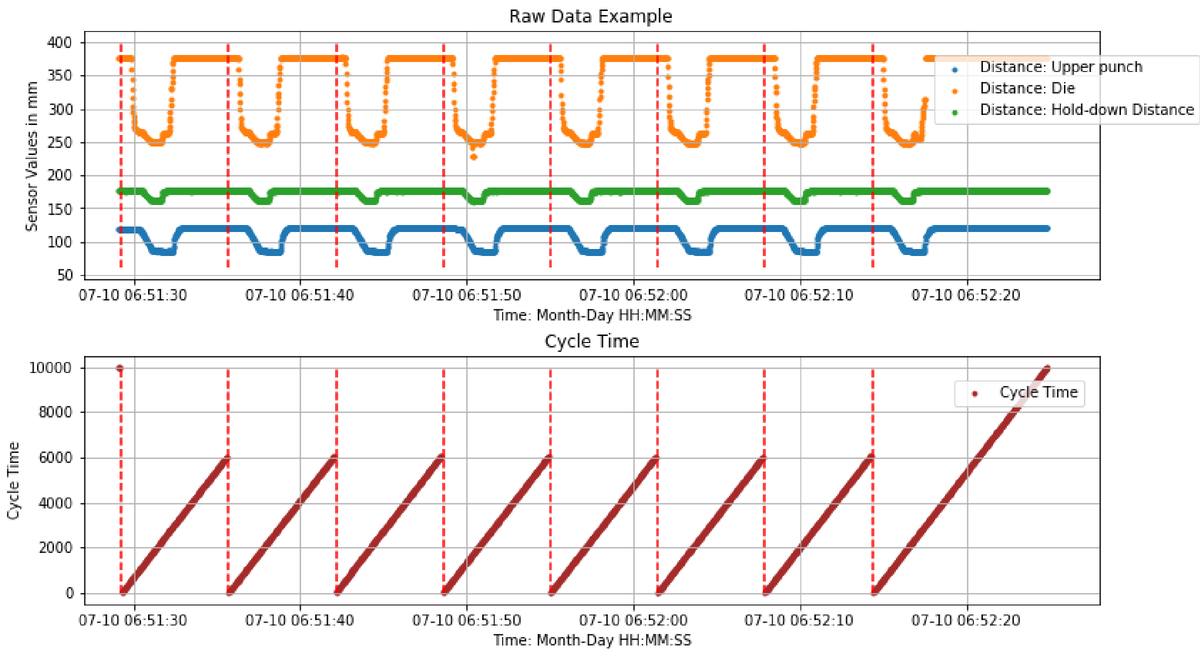

Figure 8: Divide data and identify DDPs

Based on this behaviour, the following conditions are important to identify DPPs:
1. *cycle time* at *separator* is non-zero and it is relatively small;
2. *cycle time* at the time before *separator* is zero;
3. before these *cycle time* of zero values, there is *cycle time* of relatively large value;
4. using *separator*, we cut the whole series and get a set of sub-series, where each element is an independent DDP;
5. assign each DDP to an unique identifier, e.g. incremental integer.

Formally, in order to identify each DDP, it is necessary to determine τ_n for all n. Let $\Delta_1 c(t_i) = c(t_{i+1}) - c(t_i)$, $\Delta_2 c(t_i) = c(t_{i+1}) - c(t_{j^*(i)})$, where $j^*(i) = \max_{j<i}\{j \mid c(t_j) \neq 0\}$. Let $A, B > 0$ and $I(A, B) = \{k \in \{1, ..., S\} \mid \Delta_1 c(t_k) > A,\ c(t_{k-1}) = 0,\ \Delta_2 c(t_k) < -B\}$. W.l.o.g. we assume $k_1 < k_2 < \cdots < k_{|I|}$ for $k_i \in I$. Then, by definition, we know t_{k_n} is the starting point of n-th DDP, thus, $\tau_n = t_{k_n}$.

4.2.2 Reordering

Ideally, for nth-DDP, we have $c^{(n)}(t_j^{(n)}) < c^{(n)}(t_{j+1}^{(n)})$, meaning *cycle time* $c^{(n)}(t^{(n)})$ is monotonously increasing. However, due to network delay and hardware limit, some data points come in wrong order, i.e. $\exists i_0$, s.t. $c^{(n)}(t_{i_0}^{(n)}) > c^{(n)}(t_{i_0+1}^{(n)})$. We first have to decide $c^{(n)}(t_{i_0}^{(n)})$ actually belongs to which DDP. It belongs to (n-1)th DDP if data of $t_{i_0}^{(n)}$ comes very late. It also possibly belongs to n-th DDP if the data before time $t_{i_0}^{(n)}$ come late after this time. Once it is determined, we can simply reorder data by *cycle time* for each DDP.

Thus, given a time t_{i_0} when *cycle time* is in wrong order, the following route is designed:
Reordering Algorithm
1. find the nearest time t_{i_1} before t_{i_0}, s.t. $c(t_{i_0})$ is close to $c(t_{i_1})$;
2. find the nearest time t_{i_2} after t_{i_0}, s.t. $c(t_{i_0})$ is close to $c(t_{i_2})$;
3. choose the time closer to t_{i_0} and assign the DDP identifier of it to t_{i_0};
4. Once all DDP identifiers are modified, we reorder by *cycle time* for each DDP.

In practice t_{i_0} is very close to t_{i_1} or t_{i_2}. But for t_{i_0} that is almost equally close to both t_{i_1} and t_{i_2}, it can not be decided confidently, thus we delete it. Figure [9] shows two examples that needs reordering.

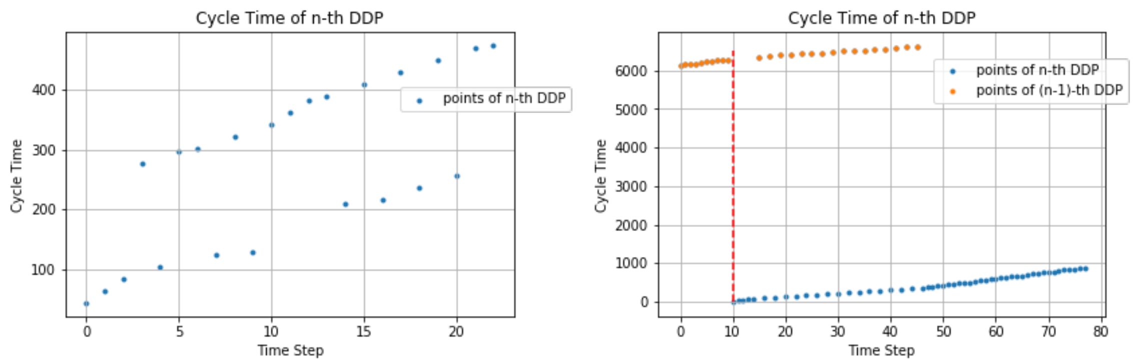

Figure 9: Examples of reordering points

Formally, if $\exists\ n, i_0, p > 0$, s.t. $\min_{j=0,\ldots,p}\{c^{(n)}(t_{i_0+j}^{(n)})\} > \max\{c^{(n)}(t_{i_0-1}^{(n)}), c^{(n)}(t_{i_0+p+1}^{(n)})\}$, $t_{i_0}^{(n)}$ is in wrong order. For n-th DDP $\left(\rho^{(n)}(t_s^{(n)})\right)_{s=1}^{S_n}$, we add a point $\left(0,0,0,c^{(n)}(t_{S_n+1}^{(n)})\right)$ where $t_{S_n+1}^{(n)} = t_{S_n}^{(n)} + 10\ ms$ and $c^{(n)}(t_{S_n+1}^{(n)}) = 10010\ ms$, indicating the end of this DDP as cycle time is always less than 10000. Then, we map $t_{i_0}^{(n)}$ back to t_a (global time before separation into DDPs) and let $m_l(a) = \max\{l \in \{1,...,a\} \mid c(t_{l-1}) \le c(t_a) \le c(t_{l+1})\}$, $m_r(a) = \min\{r \in \{a,...,S\} \mid c(t_{r-1}) \le c(t_a) \le c(t_{r+1})\}$, let the function $DDP\_ID(k)$ output the DDP identifier of t_k, thus

$$DDP\_ID(a) = \begin{cases} DDP\_ID(m_r(a)) & if\ |t_a - t_{m_l(a)}| > 3|t_a - t_{m_r(a)}| \\ DDP\_ID(m_l(a)) & if\ |t_a - t_{m_r(a)}| > 3|t_a - t_{m_l(a)}| \\ drop\ data\ at\ a & else \end{cases}$$

Once it is done, we delete all points whose cycle time equal to 10010 since they are added manually by algorithm.

4.2.3 Uniform steps and impute data

As is designed, the time interval between two measurements is fixed as 20 ms. Once a DDP process starts, data should be measured every 20 ms. However, in real cases, intervals of a small part of data vary differently due to reasons like microprocessor crash. Some intervals are even larger than 40 ms, meaning there's a measurement missing. To make sure that time steps of data are uniform, we have to manually create some data. Here we choose linear interpolation to do imputation because most parts of the curve are like a line for a single DDP.

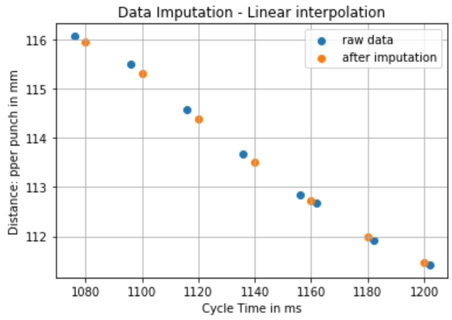

Figure 10: Example of data imputation

Formally: let $\Delta c_0 = 20\ ms$ be the standard time interval. Construct a new series of time for the n-th DDP $\{t_i'^{(n)}\}_{i=1}^{S_n}$, where $t_i'^{(n)} = t_1^{(n)} + \Delta c_0(i-1)$, thus $c(t_i'^{(n)}) = c^{(n)}(t_1^{(n)}) + \Delta c_0(i-1)$ For all i, if $\nexists\ j$, s.t. $t_j^{(n)} = t_i'^{(n)}$, imputation for $t_i'^{(n)}$ is needed.

Linear interpolation [Noo+15] for $t_i'^{(n)}$: given i, let $j_1^*(i) = \max\{j \in \{0, ..., i\} \mid t_j^{(n)} < t_i^{(n)}\}$, $j_2^*(i) = \min\{j \in \{i, ..., S\} \mid t_j^{(n)} > t_i^{(n)}\}$

$$\rho^{(n)}(t_i'^{(n)}) = \frac{\rho^{(n)}(t_{j_2}^{(n)}) - \rho^{(n)}(t_{j_1}^{(n)})}{c^{(n)}(t_{j_2}^{(n)}) - c^{(n)}(t_{j_1}^{(n)})}(c^{(n)}(t_i'^{(n)}) - c^{(n)}(t_{j_2}^{(n)})) + \rho^{(n)}(t_{j_2}^{(n)})$$

4.2.4 Data transformation

By looking at the data, we find that the duration, as well as the starting point of each DDP, is different. Moreover, the cycle time when the main part of DDP takes place is also not fixed. Practically, each DDP takes for nearly 7 seconds. But the primary part of a DDP takes place after the matrix part touches the hold-down part of the machine and before these 2 parts leave each other. Specifically, we can select the period when the distance of the die is less than 165 mm as figure [11] shows.
Formally, n-th DDP becomes $\left(\rho^{(n)}(t_i'^{(n)})\right)_{i=p_n}^{q_n}$, where $\rho_1(t_i'^{(n)}) < 165$, $\forall i \in [p_n, q_n]$. Therefore, all DDPs have the same meaningful starting and ending point. But it still leaves the problem that the length of each DDP is different.

4.2.5 Labeling

Our goal of labeling is to assign each DDP a class 0/1, representing it's a cracked DDP or not, i.e. set the class y_n of n-th DDP:

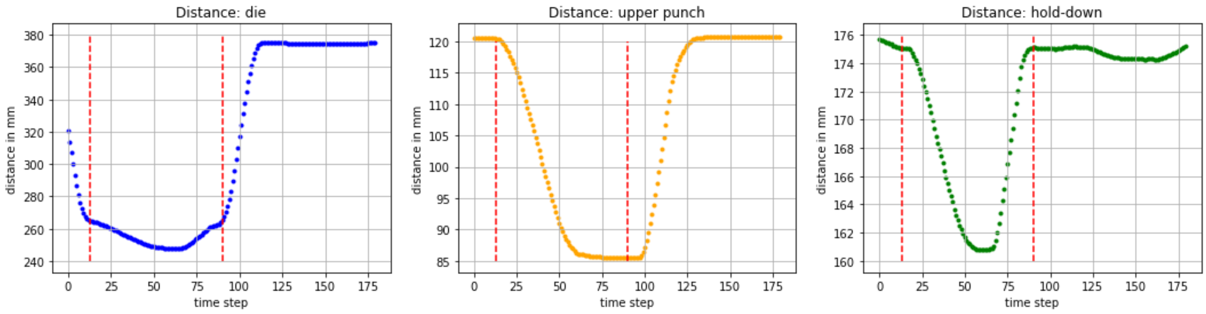

Figure 11: Primary part of a DDP(between red dash lines)

However, we only get the timestamps when cracks were detected. There are stations in the factory to detect cracks, from which we get failure reports. As is measured by the factory, it exactly takes 58 seconds for a metal plate to be transferred from the machine to the test station. Therefore we have the following route to label:

Let the function $M : t \mapsto n$ map an arbitrary time t to the identifier n of the corresponding DDP. Let $\{a_i\}_{i=1}^{N_{crack}}$ be a set of timestamps when cracks are detected. The set of identifiers of cracked DDPs is thus $\{M(a_i - \Delta T)\}_{i=1}^{N_{crack}}$, where $\Delta T = 58 + 6 = 64\ s$.

4.3 Analysis for data of cracks

In practice, only 5 cracked DDPs are found in collected data from 1st May to 15 July 2020. Factory also manually produced 8 cracked metal plate for us, resulting in 13 cracked DDPs in total. Usually, in an imbalanced scenario, some data augmentation algorithms are helpful. However, it is almost impossible in this project because the mechanical reasons for producing cracks are unknown so that we cannot ensure that a small change in data still keeps the original class of a DDP. So we focus on those cracked DDPs.

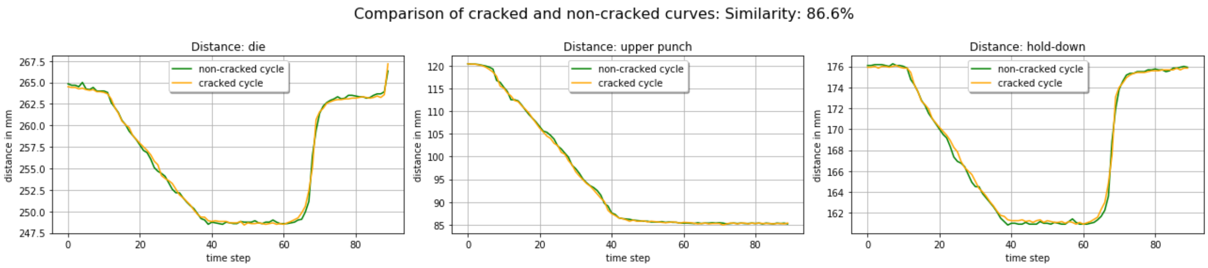

Figure 12: Similarity comparison

4.3.1 Similarity comparison

To get insights of cracked DDPs, we compared similarities of data between cracked and non-cracked DDPs. Here we use Gaussian radial basis function kernel $sim(x, x') = \exp(-\gamma \cdot ||x - x'||^2)$. Since the length of each DDP is not equal, we are not able to use distances requiring fixed size. Therefore, we use Dynamic Time Wrap [Cat+10] to calculate distances, making similarity $sim(x, x') = \exp(-\gamma \cdot dtw(x, x')^2)$, where we set $\gamma = 0.006$.

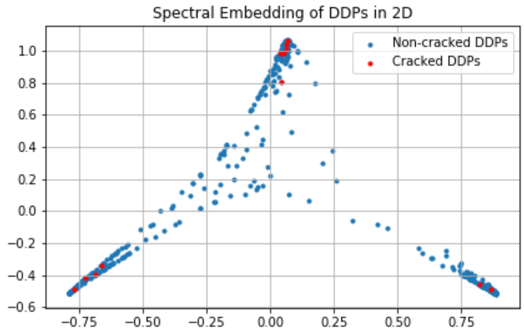

Figure 13: Spectral Embedding of DDPs in 2D

Figure [12] shows the similarities between a randomly sampled cracked DDP and 2 DDPs selected from 500 randomly sampled non-cracked DDPs. The DDPs in the diagram have a similarity of 86.6 %. and the shapes almost overlap. We cannot even make sure if the difference results from noise because at every point the difference is very tiny.

In fact, there are 5 % of DDPs with similarities larger than 86.6 % in the 500 sampled DDPs, meaning a large proportion of non-cracked DDPs are highly similar to cracked ones. Figure [13] shows the spectral embedding results where DDPs are transformed into 2D points. There are many normal points near cracked ones and the overall distribution of cracked points seems random.

Next, We try to see if cracked DDPs tend to "gather" in some particular patterns. Therefore we did spectral clustering for different number of clusters. Then we compare the proportion of cracked and normal DDPs over different clusters for each clustering. Figure [14] shows the comparison of 2, 3, 4, 6 clusters. Despite some fluctuations, the distributions look very similar. Based on this fact, it is difficult to apply an algorithm to distinguish cracked and non-cracked DDPs.

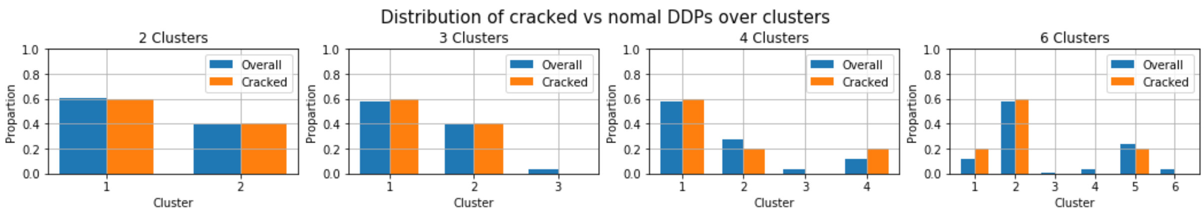

Figure 14: Proportions of cracked vs non-cracked DDPs over clusters

5 Conclusion and outlook

In the following, the conclusion of the TUM Data Innovation Project at BSH is discussed. In particular, the most important findings are addressed and possible recommendations for action are also discussed. These findings are divided into three areas.
We start with the findings of the FMEA. It is important to note that the failure consequences always follow the same pattern. Thus, the change in movement required in the DDP is greater than the flow speed of the alloy. This discrepancy then leads to crack formation in the metal. The failure causes for this are very variable and cannot be narrowed down on the basis of the available data. For the further technical production investigation, the failure tree as well as the process activity table is a value-adding instrument. For example, it is important to know that the last part of the graph should contain the crack behaviour, as this is where the actual DDP takes place. It should be noted that the definition was established to the best current knowledge. For the causes with the highest risk priority number, recommendations for action are given in the following. Metal plate properties must be recorded in order to be able to make statements about the metal properties (e.g. material thickness). In addition, the coating properties must be recorded so that, for example, statements can be made about the distribution of the oil film on the sheet metal or the coating itself. Possibly suitable sensors are the measuring systems of MeSys GmbH, because they allow a continuous data acquisition in a μ-meter range. The additional findings can be obtained from the FMEA.

The second important area of discovery is data acquisition. The project team concludes from the findings of the entire report that the currently collected data is not suitable for the detection of cracks. The installed strain gauges record data that cannot be interpreted mechanically. For the displacement measurement using the ultrasonic sensors, it is assumed that the mass of the tools absorbs the vibrations caused by the crack. For this purpose, it is recommended to carry out impact tests and to see whether data can be recorded. The measured values obtained by the Bosch XDK sensor only capture very large influencing factors, but the relevant data is not currently being collected. It is recommended to track the individual components and assign the recorded values to a unique product ID.

The third part is about data. We still think the data of cracks are not enough for analysis. So far we were only provided with data of five “natural” cracks and eight “artificially induced” (manually) cracks. It is hard to get a significant mathematical conclusion with only 13 cases. The lack of data may result from the fact that only one tool-set is used to collect data. Therefore, in order to get more data, more tool-sets could be equipped with sensors. Though the method we use for labelling seems to work, there are still concerns about the correctness of time shifts from machine to test station. For example metal plates may stop for a while, making it very hard to find the correpsonding DDP in the data.

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