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Process surveillance in hydroforming based on machine learning algorithms

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Abstract

The requirements related to production and maintenance have increased significantly. An intelligent surveillance of the machines allows the exploitation of significant optimization potentials. Especially hydroforming processes are subject to workpiece specific adjustments and the process parameters have a strong influence on the quality. Furthermore, the surveillance of components which are prone to wear allows the machine operator to optimize maintenance processes in respect of operating costs, machine health and process quality.
This paper describes an approach which allows machine operators to use automatically learned data of standard processes and their statistic variances to quickly analyze and optimize hydroforming processes. Since unsupervised machine learning approaches are applied, the algorithm needs only a few process runs to learn the data of standard processes. Furthermore, we introduce algorithms which automatically detect and classify workpiece defects, monitor the wear of hydraulic valves and optimize the energy consumption of the hydraulic pumps.

Keywords: Analysis; Productivity; Quality Assurance

1. Introduction

In times where customers and insurance providers of production companies demand a high machine availability, an intelligent concept for maintenance and an effective machine operation are required. Hydroforming is a complex

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process which is dependent on a high number of parameters. These define the quality of the process outcome. However, there are many possibilities for errors. In case one of these errors occurs, experts must search through large amounts of data to find the origin of the error with their knowledge of process dependencies. These searches require time and skilled personal.

A further aspect are process optimizations. These are also time-demanding. Furthermore, common software tools only allow the analysis of single processes. Different discrete processes cannot be overlaid or there is no compact data of the parameter distribution. Thus, the analysis of whole production batches in a suitable way is not possible. But a compact representation of the data would allow the operator to find more valuable information and identify aspects such as process stability and parameter distribution.

Also, the analysis of wear effects based on single process data is quite difficult. Variations of parameters can cause misinterpretations of values. Side effects can cause a different component behavior and thus lead to false conclusions. The expert needs to doublecheck possible effects which again is time consuming. A compact overview comparable over larger time periods which are relevant for wear effects is desirable. In some cases where wear effects result in an identifiable and repeatable behavior of parameters, an automated and even predictive analysis of the system failure is possible.

All in all, a system enabling a flexible analysis and representing the process parameters in a compact manner is desirable. It should furthermore give leads to possible error origins and make wear effects visible or even predict the time frame to a component failure.

2. State of the art

Over the last decades, the hydroforming process has been well established as a forming process for a wide range of parts for industrial applications. Different researchers tried machine learning approaches to optimize production parameters for hydroforming, namely the loading path. Early publications focus on fuzzy logic [1] and artificial neural networks [2] which are not applied in this paper. In a more recent publication, Abdessalem and El-Hami [3] use the support vector regression and the response surface method. However, like in other publications, the approach is only used for the tuning of the hydroforming process. The solution described in this paper is based on an automated learning approach for standard processes based on an already tuned production process [4].

Machine learning approaches have also gained more attention in fault diagnosis in the last years. One key principal is the use of Support Vector Machines. The publications [5-10] for example present approaches based on this principal. Other possibilities are fuzzy clustering methods [11-12]. [13] contains a recent overview of unsupervised machine learning methods for process monitoring and fault analysis.

The market for data analysis tools and machine learning applications for industrial processes has developed very fast recently. The tools cover a wide range, but a standard approach has yet to be established. Several tools only offer basic data acquisition functionalities. Further functionalities contain visualization and basic alarming tools such as threshold values for process surveillance. However, these do not offer intelligent algorithms: experts still need to analyze the results and predictive approaches are not possible. A few software tools with machine learning capabilities are available as well. The focus of these tools are clustering methods. We have shown a statistical representation which enables automatic clustering on the one hand and visualizes valuable and compact statistical data of the production process on the other hand [4]. This paper will show the recent developments of this approach.

3. Detecting errors with control groups

As described above, unsupervised machine learning approaches are a possibility for fault diagnosis. When looking at complex processes like hydroforming with many cross correlations, faults are visible in different sensor values. Furthermore, other side effects might cause sensor deviations which are not necessarily an occurring fault. For example, the temperature of the hydraulic oil leads to a different viscosity and thus to a different system behavior. This will be visible in the data of the valve control but the machine might still operate in its margins. However, different errors cause a clear pattern in the sensor data which experts will find when analyzing the machine data manually. Our approach is based on the idea of combining machine learning approaches to analyze and compress the data on the one hand while on the other hand still allowing experts to review the compressed data and give their knowledge as input for the algorithm.

The basis of this approach is the automatic unsupervised learning of the standard process. It is learned for each production batch of a specific workpiece. The algorithm needs approximately 30 runs for this task. The input for the algorithm are the sensor values combined with a timestamp. The approach is applicable for different sensors in a hydroforming machine. The following sections will focus on cylinders and hydraulic components directly involved in the forming process. Fig. 1 lists these components and the corresponding recorded values. The hydraulic controller of these components sends the sensor data to our algorithm. The figure shows a schematic drawing of the hydroforming setup. The goal of the approach is that no additional sensors need to be added to the control setup and different sensor and cylinder configurations are still manageable.

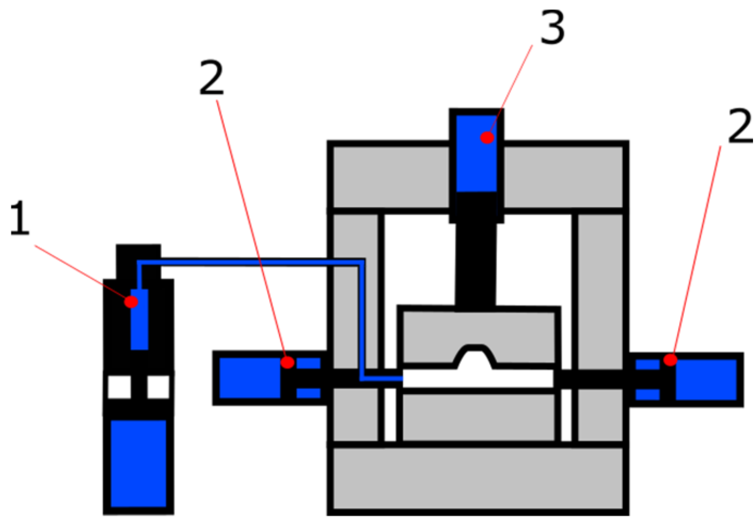

Fig. 1. Schematic drawing of the hydroforming components and the corresponding recorded values: pressure intensifier (1) – intensifier pressure on high pressure side, intensifier position, intensifier velocity and the intensifier valve control value; sealing cylinders (2) – sealing cylinder force, sealing cylinder position, sealing cylinder velocity and sealing cylinder valve control value; ram cylinder (3) – ram cylinder force, ram cylinder position and ram cylinder valve control value

The data for all following figures was collected in a running industrial application. The hydroforming press produces different car parts with up to six workpieces per process run. Thus, the algorithm needed to match these complex tool configurations. To gather the data, we made no changes to the machines hardware setup. We only used the already existing sensors and interfaces. Only minor software modifications in the machine controller were necessary. The single runs of the machine are defined by trigger signals and the software stores it divided in theses runs.

After the cumulation of about 30 runs it is possible to calculate a significant probability density function over each sensor value in respect to the process time. The important values for error detection derived from the probability density function are specified quantiles. They are derived from the cumulated distribution function over the time.

Fig. 2 shows an example of these quantiles for the actual high-pressure value of the intensifier pressure. In the presented example the quantiles define the green and yellow areas. The green area is the statistical estimate for 95 percent of all values. The green and yellow area combined are the estimate for 99 percent. This is also the detection level for the further process. If a sensor is outside these boundaries, the algorithm will detect and document a possible error. However, the percentage values are adaptable for different cases, but 99 percent proofed to be a working surveillance level for the analyzed hydroforming application.

One advantage of this quantile function representation is that the information of process runs of a production batch within the probability parameters can be condensed to only a few curves. In our basic approach we store the quantile curves and the median curve of a production batch. Only if a sensor value exceeds the quantile boundaries for a process run the algorithm stores the raw values of this run as well to further analyze the possible error. Thus, the algorithm achieves a significant compression of the data.

The quantile representation gives a further advantage to the machine user. He can analyze the distribution of different sensor values. If a distribution spreads to far over a process it might be a hint for not optimal process. In the above described industrial application, this helped to detect optimization potential and stabilized a not optimal process with a too high failure rate.

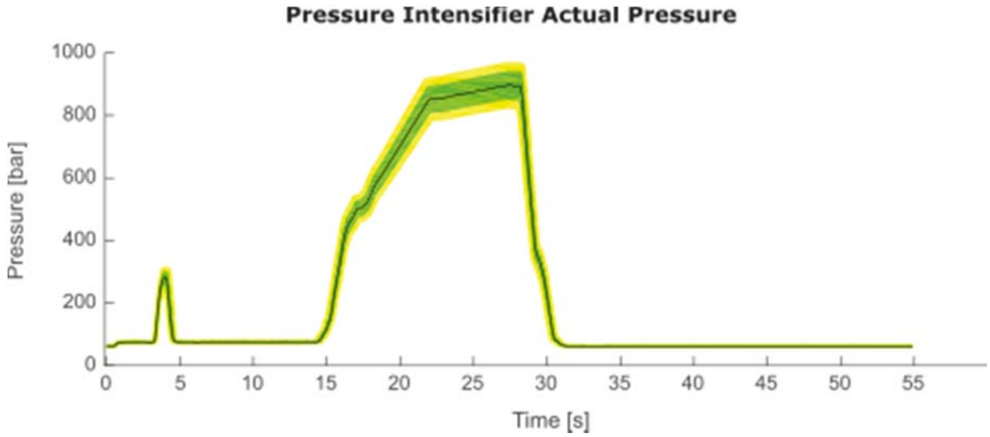

Fig. 2. Example of data visualization for a sensor in a production batch

To get more specific information about the origin of the failure, the analysis of combined sensor values is necessary. It is possible to evaluate the deviations from the norm process for a combination of sensors in a single process run. A value describing the similarity of the value to the norm process gives a compact information about the sensor group performance in run. One possibility for example is to combine all sensors for a specific machine component.

To get a significant feedback from different sensor values, we applied further unsupervised learning techniques. First a normalization of the values is necessary to get a good working basis. The normalized data is the input for a principal component analysis. With the principal component new abstract parameters can be calculated from the original parameters. These give a good description of the overall data distribution.

We used this description of the data to detect process distortions. The data in the new representation forms a cluster with a center. The distance to the center gives a feedback of the overall quality in a process run. If the distance is too high, a possible error occurred. Fig. 3. shows data of different pressure intensifier sensors. Each point represents the distance of a process run. The original values for this figure were the pressure, the position, the velocity and the valve voltage. The control limit in the chart describes the distance of the cluster method. Since the methods are unsupervised methods, it gives an abstract representation of the data values.

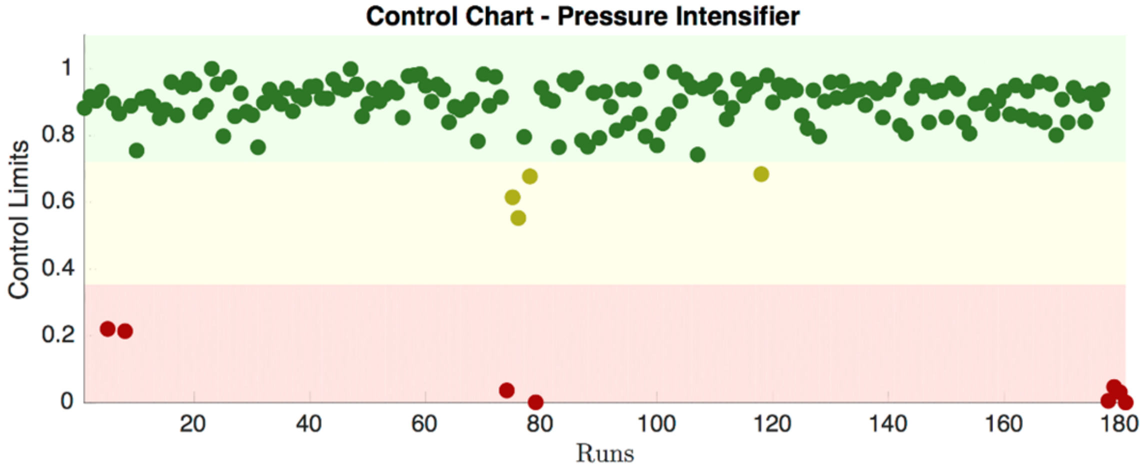

Fig. 3. Example for component control chart

A few values show a significant deviation from the average process runs. This gives good feedback on possible process errors. This combination of sensor values also allows experts to define a group of sensor values which show a distinct error pattern. A workpiece burst for example shows deviations in the high pressure of the pressure intensifier, its position and velocity since there is a loss of fluid volume. Furthermore, the sealing cylinder force will show a difference caused by the internal pressure in the workpiece. Combining these values to a control value for each run shows a large decline when a workpiece burst appears in the production. Fig. 4. shows an example of a production batch where three bursts occurred in the specific control group. We processed the data as described before. In the burst cases, the control values are between 0.34 and 0.42. The runs with control values around zero are false trigger effects of the press. The approach shows promising results for suitable burst detection in a running production without the application of further sensors.

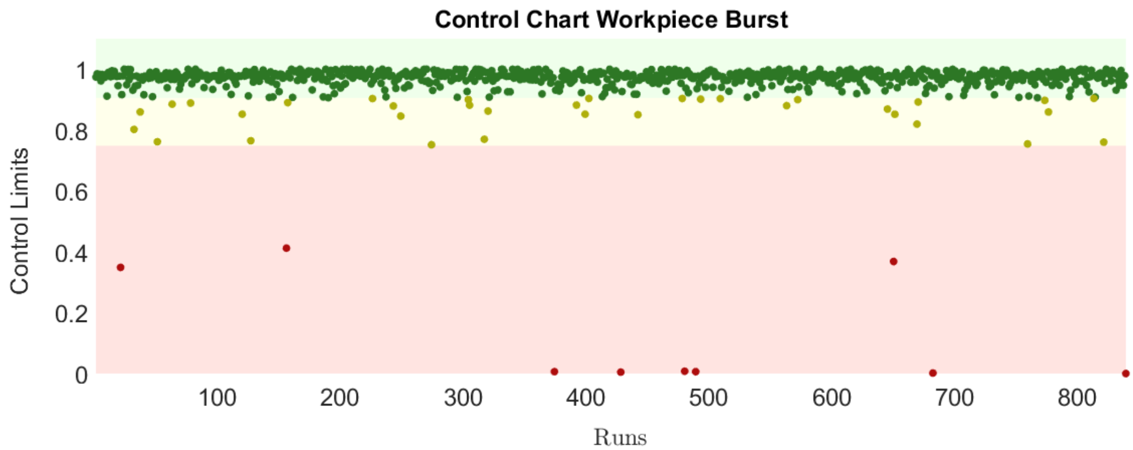

Fig. 4. Example for a workpiece burst control chart

A burst of a workpiece is one example for a control group. Since the definition of a control group is possible without detailed statistical or machine learning knowledge, experts can transfer their machine and process knowledge into an automated analysis in a simple manner. Thus, the approach is also adaptable to machine specific or process specific behavior.

4. Optimize pump pressures

In complex hydraulic machines such as hydroforming presses, different machine components need different hydraulic pressures throughout the whole forming process. The hydraulic pumps supply the machine components with these pressure levels. However, when the pumps work in combination with control valves, they usually run with their full pressure and the control valves reduce the pressure to the necessary value for the machine's hydraulic loads. This leads to an inefficient operation of the machine since the surplus causes an energy dissipation at the control valve.

If the pumps only supply the necessary pressure with a small safety surplus the machine operation is more efficient. One possibility is that experts analyze the whole process and set the pressure values manually. However, this is time consuming and individual for every workpiece and its corresponding production process. The statistical data collected with the presented approach enables an automatic analysis of the pressure data and thus an automatic optimization of the pump setting. The statistical data makes the analysis more robust towards distortions in the pressure.

The algorithm can analyze the individual process steps and the pump assignment to the machine components in the process. Furthermore, in case of bidirectional components such as differential cylinders the algorithm needs to analyze the moving direction. Fig. 5. shows the example of the pressure intensifier pressure. In addition to this, the area ratio leads to different pressure requirements. The maximum pressure value of the components supplied by one pump is the relevant value for the setting.

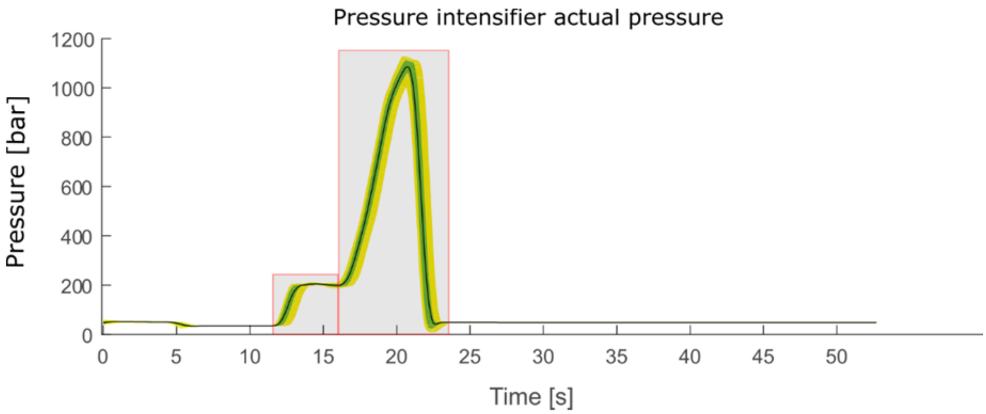

Fig. 5. Pressure analysis example of a pressure intensifier high pressure value

An automatic learning of a new production process can look like this: The pumps start with the full pressure and the user runs a few processes to gather the necessary data. The algorithm will estimate the necessary pump pressure and returns the values to be checked by the user and set for the further machine operation.

5. Detect and estimate wear effects

The collected data also is the basis for the detection and estimation of wear effects. In the following, we will present a detection example which we have developed. The ram of a hydroforming press has different operation phases. It closes the die, builds up force, holds the force and, after releasing the force, opens the die again. In the pressure holding phase, the valve controls the pressure. If the valve's control edge wears off it is not able to hold the pressure as precisely as before. This results in more control movements of the valve and is visible in the data of the control value. Fig. 6. shows the example of two valve curves. The orange curve is from a worn valve and the blue one from a new valve. Over the valve's lifetime, the movement magnitude will increase until fails. The algorithm measures the magnitude. It is further possible to estimate the increase in respect to the movement cycle and thus make a prediction of the valve's life span.

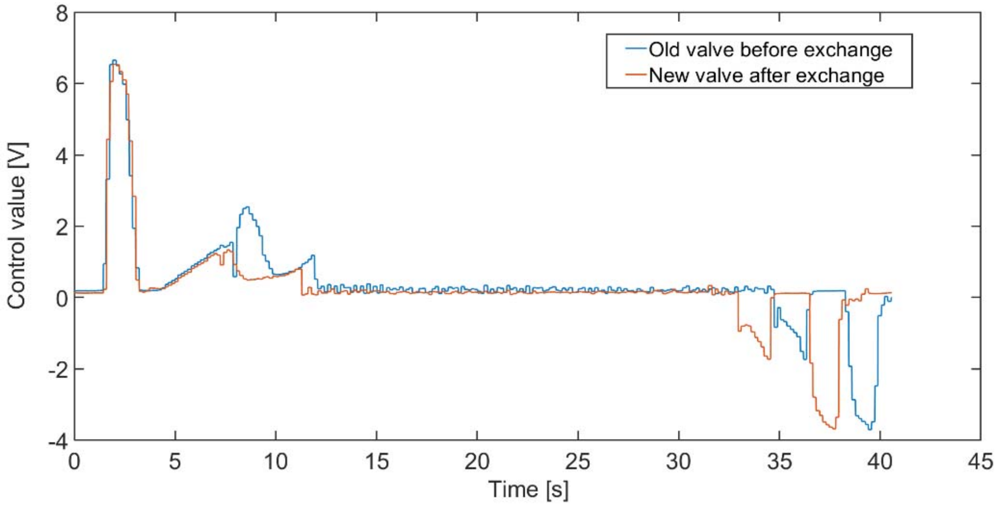

Fig. 6. Comparison of a new and an old ram valve

When looking at other cylinders and their valves, one must notice that they have different duty cycles. Therefore, the control behavior is different and other effects such as oil temperature might cause stronger effects on the control behavior. Therefore, other valves are still subject to further developments.

6. Conclusion

We presented an approach which can address different aspects like quality control, energy optimization and predictive maintenance. Its basic idea is the unsupervised learning of standard processes and their statistic evaluation. The algorithm not only returns information on deviations from the norm process but also the distribution of the values. On the one hand this information allows experts to optimize the process and on the other hand enables further automatic analyses and optimizations. The paper presented three applications for the approach. The first was the definition of control groups to detect specific failures. The second was the estimation of necessary pump pressures. The third was the surveillance of the ram cylinder valve. In all three cases the algorithm can optimize the machine operation.

Further steps of our work will include the definition and test of further control groups and the surveillance of other cylinder valves. Other machine components such as the filters are an interesting aspect as well.

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