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Procedia CIRP 72 (2018) 1079–1083

www.elsevier.com/locate/procedia

51st CIRP Conference on Manufacturing Systems

# Machine learning for detection of anomalies in press-hardening: Selection of efficient methods

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**Abstract**

The paper addresses machine learning methods, utilizing data from industrial control systems, that are suitable for detecting anomalies in the press-hardening process of automotive components. The paper is based on a survey of methods for anomaly detection in various applications. Suitable methods for the press-hardening process are implemented and evaluated. The result shows that it is possible to implement machine learning for anomaly detection by non-machine learning experts utilizing readily available programming libraries/APIs. The three evaluated methods for anomaly detection in the press-hardening process all perform well, with the autoencoder neural network scoring highest in the evaluation.



*Keywords:* Anomaly detection; Machine learning; press-hardening; automotive.

## 1. Introduction

The paper addresses, based on a survey of available methods and empirical test data, machine learning (ML) methods that are suitable for detecting anomalies in the press-hardening process of automotive components. Anomalies are events that are not included in the normal variation of a system or process. They occur rarely and there is often insufficient anomalous data to build reliable detectors for each anomaly [1]. The work builds on previous research presented by Lindström et al. [2], where a combination of online predictive maintenance and continuous quality control was presented.

As the amount of data which is collected and stored increases rapidly in many companies, it is also necessary to be able to use it and get good value out of it. However, this requires competencies, knowledge and an adequate selection of analytical methods suitable for the problem as well as the data. Lee et al. [3] list five categories of issues for smart analytics in an Industry 4.0 and big data environment, whereof more or less all categories are covered in this paper. The desired outcome is to be able to use ML to detect problems caused by unknown issues or to predict the need for maintenance and service of production equipment. Further, if problems/issues are indicated early, i.e. before the production needs to be stopped, due to the risk that the output is outside of specifications or there is a risk that equipment may be damaged, the production schedule may be changed to produce a product which is not affected by the indicated issue. This would enable predictive maintenance, reduce the need for reactive maintenance and in turn increase overall equipment efficiency.

Regarding related work, e.g., Lee et al. [3,4], Monostori [5] and Lindström et al. [2] provide a good background for the various problems and issues to be considered from a high level Industry 4.0-perspective. ML is commonly used for classification problems where numerous examples are available for each class. In contrast, problems dealing with anomaly detection often lack numerous examples of anomalies. Data analysis with the intent to detect anomalies has been employed for a number of applications where disturbances are critical to investigate, such as credit card fraud, cyber-intrusion, medical conditions, terrorism or the breakdown of a system and is related to the techniques of classification, clustering, nearest neighbor, statistical methods, spectral and information theoretics [6,7]. In an industrial setting, anomalies in data (a sensor value, or combination of values) typically occur in a specific context (contextual anomalies) or as an anomalous sequence of observations.

Examples of techniques for detection of faults-frequency in the detection of inner-race bearing faults include artificial neural networks, statistical methods, wavelets, spectral models, and high-frequency-resonance techniques [8]. Li et al. [9] discuss the specific challenges in detection of faults in transient and non-stationary signals, such as a strain signal from metal stamping, as opposed to methods used for detecting faults in stationary signals e.g. bearings.

Recent development in hardware and software have enabled the use of ML through high level APIs, for example Keras [10]

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Peer-review under responsibility of the scientific committee of the 51st CIRP Conference on Manufacturing Systems.
10.1016/j.procir.2018.03.221

and scikit-learn [11]. Modern graphics cards and cloud services allow parallelization of machine learning tasks to significantly speed up and lower the cost of training and evaluating models. This means that non-ML experts can apply ML to problems within their domains.

The problem addressed in the paper concerns the evaluation and selection of one or more efficient ML methods in order to detect anomalies in the data collected from the press-hardening processes. Further, the purpose is to make management and R&D engineers aware of possibilities with ML methods for detecting anomalies in manufacturing processes. The paper is organized such that the research approach follows the introduction. This is followed by sections on detection of anomalies, selection of efficient ML methods, an evaluation and analysis, and finally, the discussion and conclusions section.

## 2. Research approach

The research approach employed in this study has been based on an in-depth qualitative study using action research within a manufacturing company, Gestamp HardTech AB, located in northern Sweden. The research targeted in this paper is parts of the third phase "taking action", of an action research [12–14] effort where the researchers have had the roles of external expert/consultant and internal expert. Earlier steps are described in [2], where most of the diagnostics and planning was done.

Gestamp HardTech AB is part of the global Gestamp Group, which produces parts for vehicles and is active in 21 countries with 13 R&D centers, more than 100 production plants and over 36,000 employees. Gestamp HardTech AB has an R&D center, press-hardening tool development and manufacturing, as well as a production plant. In addition, Gestamp HardTech AB is the creator of the original patent, SE 7315058-3, concerning the press-hardening technique.

Previous research [2] presented the combination of online predictive maintenance and continuous quality control. The rationale for combining and integrating them is that continuous quality control can provide input to the online predictive maintenance in cases where no signs of maintenance issues have been indicated and inadequate output is produced. Further, often the feedback to the maintenance department is too slow and with too low granularity for engineers to react promptly enough to avoid quality issues when or before they arise.

As part of the action research approach [2], the first initial design criterion for the combination of online predictive maintenance and continuous quality control was that it should be simplistic and have a low implementation cost and be inexpensive to use and maintain over time (in comparison with existing solutions for either of the concepts on the market). Further, the second initial design criterion was that the outcome should be a solution that can operate online close to real-time, i.e., with seconds or parts of seconds in response time, but not in hard real-time mode with requirements on millisecond level. The design criteria will not be formally evaluated (as the action has not yet been fully completed) in this paper, but discussed in the last section of the paper in order to judge if the outcome will lead "towards intelligent and sustainable production" as well as "select efficient data analytic method(s)" during the way.

## 3. Detection of anomalies in press-hardening

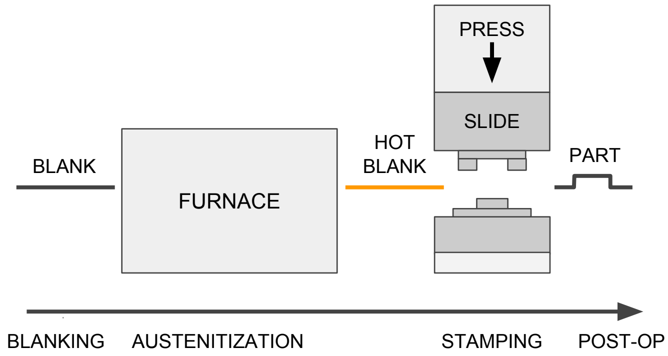


Fig. 1. Illustration of the press-hardening process;

The press-hardening process consists of four major steps, illustrated in Figure 1:

- Blanking: Where the blank for the final product is punched from a sheet metal coil.
- Austenitization: Where the blanks are heated up above their austenitization temperature.
- Stamping: Where the hot blanks are formed and quenched in a cooled pressing tool.
- Post-operation: Where the final shape is achieved by punching/cutting operations.

In this paper the focus is on the stamping step of the press-hardening process and specifically the non-stationary and transient forming stage.

The control system used for the hydraulic press slide provides access to a number of signals. Many of these are captured by sensors that measure pressures, positions or temperatures, such as: the pressures in the hydraulic cylinders that move the slide, the position of the slide, and the temperature of hydraulic oil. From these signals the force and speed of the slide were chosen as signals to be used for analysis due to their impact on the forming process. The force is calculated from the pressure and the speed from the position of the slide. The reason for selecting the force instead of pressure, and speed instead of position was that historical data of these signals was already available.

The data available in this case was unlabeled, in the sense that data on faults on the products resulting from the forming stage were not available. However, a subset of the data was captured during a time when there existed an hydraulic problem with the press. Product quality is assured by sample measurement of the batch which leads to a low time resolution of detected faults on the products. The assumption is that faults are uncommon and that most of the data represents press strokes that resulted in products without defects.

One approach to deal with the problem of insufficient anomalous data would be to use oversampling. This is however not desirable when the goal is to create a model that also can detect anomalies that are unknown beforehand and are therefore not represented at all in the anomalous data.

To detect faults during the forming stage using the speed and force of the slide as input, a method that can detect anomalies in these signals is required.

## 4. Selection of ML anomaly detection method(s)

Criteria for selecting one or more suitable analysis method(s) to detect anomalies included:

- Known to work well when none or only a few examples of anomalies are available
- Easy to implement. Libraries/API with documentation and examples for the Python programming language.
- Can provide a detection of an anomaly in near real time.
- Can achieve a high level of detection with a very low level of false positives.

Reviewing available methods for ML anomaly detection resulted in three categories: neural networks, support vector machines and ensemble classification. From each of these categories one method that is known to work well when the availability of anomalies to train on is low was selected. Broader surveys of anomaly detection methods can be found in [6,7].

### 4.1. Autoencoder Neural Network (ANN)

An ANN consists of two parts, encoder and decoder [15]. The encoder reduces the dimensionality of the input and the decoder reconstructs the input. The ANN is trained to minimize the reconstruction error of the output compared to the input. When the input to the trained ANN is different from the training data the reconstruction error is large and a limit can be set to classify anomalies. The ANN network was implemented in Keras [10] using 10 layers and a compression of 10x. This architecture was chosen based on testing and still has a large potential for optimization.

### 4.2. One Class Support Vector Machine (OCSVM)

Support Vector Machines (SVM) [16] separates two classes in a dataset by generating a hyperplane. This can be achieved in high dimensional space. In contrast the OCSVM creates a boundary that contains the normal data points and any point outside would be anomalous [17]. We implemented OCSVM using scikit-learn [11]. *RBF* was used as a kernel and all parameters were left to auto, except *nu* which sets the upper limit for training errors. This parameter was set to 1% which gave the highest recall.

### 4.3. Isolation Forest (IF)

Most anomaly detection approaches learn the profile of normal data, then identify data that do not fit the profile as anomalies. In contrast, IF explicitly isolates anomalies [18]. This is achieved by assuming that anomalies are the minority and that they have values that are very different from those of normal instances. This method was implemented in scikit-learn [11] and all parameters were set to auto except *contamination*, which, like *nu* in OCSVM sets the upper limit for training errors and was tuned to maximize the recall which resulted in a value of 1%.

Table 1. Comparison of selected methods.

| Method | Implementation | Training time | Execution time |
|---|---|---|---|
| ANN | Medium | 93 s | $5.7 \times 10^{-5}$ s |
| OCSVM | Easy | 0.2 s | $7.0 \times 10^{-5}$ s |
| IF | Easy | 0.6 s | $1.6 \times 10^{-5}$ s |

### 4.4. Evaluation and analysis

The three selected methods were evaluated based on their ease of implementation, the time it takes to perform training, the execution time needed to predict the class of an instance and their prediction performance. Table 1 and Table 2 present the results from the evaluation.

The methods were trained and evaluated on the data without anomalies that was manually cleaned to remove obvious outliers, resulting in a total of 8399 instances consisting of two channels and 150 points for each channel One instance represents one press stroke. The intances were then randomly separated into 67% training data and 33% test data. The dataset was normalized between 0 and 1. This dataset will be referenced as *Reference dataset*. The ANN was trained using a GPU while the other two methods were trained on CPU.

To evaluate the methods it is desirable to obtain data that is known to include anomalies. Due to a hydraulic problem with the press, the speed and force of the forming was affected during a period creating an offset of the forming sequence. Note that this did not significantly impact the quality of the products but it is still interesting to test the analysis methods with this data since we know that it is faulty. This dataset includes 2905 instances, that all represent anomalous strokes. These instances were also normalized and will be referenced as *Error dataset*.

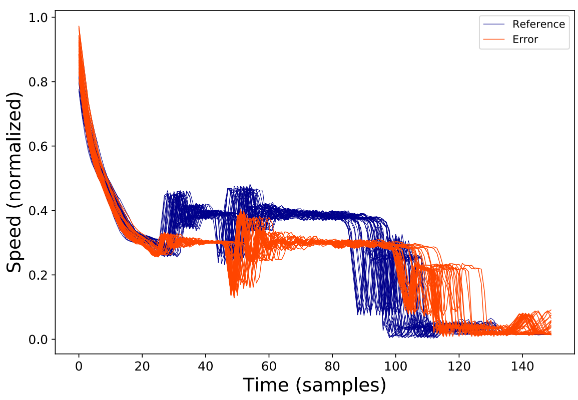


Fig. 2. Slidespeed (normalized)

Figures 2 and 3 show a subset (to make illustration possible) of the Error dataset overlaid in red on a subset of the Reference dataset. In the Error dataset the speed of the slide, after initial impact between the upper tool and the blank, is slower than in the Reference dataset, leading to a slower forming of the blank.

The performance of ML methods can be measured in True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN) using precision, recall and accuracy as

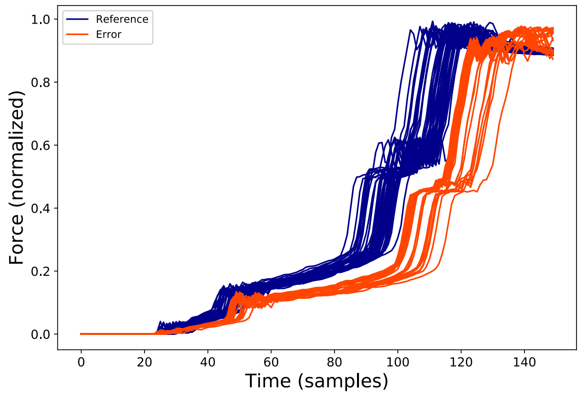


Fig. 3. Slide total force (normalized)

defined in Equation 1. In this case a "positive" is an anomalous instance and a "negative" a non-anomalous instance.

$$\begin{aligned} Precision &= \frac{TP}{TP + FP} \\ Recall &= \frac{TP}{TP + FN} \\ Accuracy &= \frac{TP + TN}{TP + TN + FP + FN} \end{aligned} \quad (1)$$

To detect anomalies using the ANN a threshold for the summed mean square error (MSE) for each point in the sequence of a reconstructed instance was set to 150% of the maximum MSE sum of the training part of the Reference dataset. Using this threshold the Error dataset was evaluated resulting in a recall of 100%, meaning that every instance in the Error dataset was classified as anomalies. The precision was 100%, meaning that none of the instances in the test part of the Reference dataset was classified as anomalies.

Evaluating the two other methods using the same data resulted in a recall of 100% for the OCSVM and a lower precision than ANN at 98.9%. IF also reached a recall of 100% and a slightly higher precision than OCSVM at 99%.

An overview of precision, recall and accuracy can be found in Table 2.

Based on the result from the three ML methods for detecting anomalies we can conclude that all three can detect the hydraulic error that resulted in an offset sequence of the force and speed measurements. ANN has a longer training time and a more complex implementation but on the other hand gives a higher precision. Although differences can seem minuscule it is very desirable to avoid false positives which in this case might lead to a stop in production while it is being investigated. Additionally, false positives can lead to diminished trust in the capabilities of the ML methods. The execution time for either method to perform anomaly detection on one instance/stroke is very short and for this application more than fast enough to automatically sort produced parts where anomalies were detected into a separate flow.

## 5. Discussion and conclusions

The selected ML methods show that it is possible to detect the maintenance need that resulted in lower slide speed in the Error dataset with a high accuracy. It is reasonable to assume that other anomalies could also be detected by applying these methods.

Table 2. Precision, recall and accuracy.

| Method | Precision | Recall | Accuracy |
|---|---|---|---|
| ANN | 100.0% | 100.0% | 100.0% |
| OCSVM | 98.9% | 100.0% | 99.4% |
| IF | 99.0% | 100.0% | 99.5% |

The performance of evaluated methods is similar using the Error dataset as input but there are still some significant differences. The ANN takes longer to train than the other two methods but since this is done offline with historical data it is not an issue. Updating the weights in a pre-trained ANN model to fit new data would be faster. The prediction time for each of the methods is very fast and they are all well suited to be applied in near real-time. The high precision of the ANN can be very desirable if false positives have a large negative impact. Combined with a recall that is equal to the other two methods and a large potential for configuration and scalability the ANN method for anomaly detection should be the first method to be tested when faced with similar datasets as the one used in this paper. The biggest drawback of the ANN is the implementation and configuration which requires more time and experience than the other two methods.

With access to labeled data on confirmed anomalies that resulted in issues with output quality or maintenance actions, it would be possible to use ML for classification of quality issues or maintenance needs based on signals such as force and speed of the slide. Inline geometrical measurement of each product output from the stamping step would provide the needed labels for quality issues. Maintenance records can be used to mark periods of time where a maintenance need is present as well as the time when maintenance has been conducted.

The reduced price of technology and the increased accessibility and ease of implementation of ML methods makes it feasible to not only investigate the most urgent issues but also to assume a much broader scope and analyze less obvious issues which have the potential to impact output quality and production volume, since such issues have a tendency to be under-investigated in comparison to well-known issues. The ease of implementation on the other hand brings the risk that the methods are used without enough testing and verification of their performance for the problem at hand. It is important when introducing new methods that can have an effect on production that the users, in this case operators, maintenance and quality, trust the methods and perceive them as value adding.

The first and second design criteria for the action research effort have so far been aligned with the overall research in the "taking action" phase. Pertaining to the outcome, i.e., the recommendation of ANN, it also adheres to the initial design criteria below:

- Simplistic, have a low implementation cost and be inexpensive to use and maintain over time
- Can operate online close to real-time

However, during the testing of these ML methods it became obvious that an additional design criteria, performance, should be added, including the measures: Precision, Recall and Accuracy. Thus, the outcome contributes to paving the road "towards intelligent and sustainable production" and gives an example of how to "select efficient data analytic method(s)".

The findings are based on one issue during the forming stage of the press-hardening process. Thus, this is a limitation and the results may be different if the methods were applied to other issues. Future research will investigate a wider range of issues and production scenarios; preferably, issues where sufficient data is available to make classification possible.

## 6. Summary

The paper contributes to literature by selecting a suitable method for anomaly detection in the press-hardening process by evaluating three ML methods based on training time, prediction time, ease of implementation and performance. We concluded based on the results from the evaluation that all three methods can detect the hydraulic error that resulted in an offset sequence of the force and speed measurements. The ANN was selected as the the best performing candidate to apply for anomaly detection in similar datasets as the one used in this paper and false positives have a large negative impact. In the industrial setting the results demonstrate the potential of ML and also point to the limitations, especially the specific challenges in detection of faults in transient and non-stationary signals when fault characteristics are unknown. The presented result is a step in including ML techniques into the operation and management system. This would enable real-time detection of possible maintenance needs and quality issues, which in turn gives the opportunity for a deeper insight into the production equipment and the implication of decisions, which will lead to more informed and effective decisions.

## 7. Acknowledgements

The research has partly been funded by the Swedish Innovation Agency Vinnova's VinnVäxt Centre, ProcessIT Innovations, at Luleå University of Technology, Sweden. The authors would like to thank all participants and the respondent for their time and valuable input.

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