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Artificial Intelligence in Automotive Production

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Abstract:

Deep Learning (DL), Artificial Intelligence (AI), Machine Learning (ML): Three terms, often used synonymously, that stand for a new kind of intelligent systems. Companies worldwide invest financial and human resources to tap the potential and promises of these technologies for themselves: be it in the establishment of data science departments or of powerful computer clusters. The automotive industry is no exception – thereby, with a prominent media focus on "autonomous driving". However, this is not the only application area for Artificial Intelligence in the automotive domain. The use of machine learning is also researched and applied in automotive production plants: From the use in the body shop all the way to predictive estimations of what proportion of a component is damaged. In this contribution, we discuss the use of Artificial Intelligence in practical examples of automotive production and point out which challenges exist and which approaches are promising. At the same time, we discuss and evaluate the potentials and challenges.

JEL Classification: C88

Keywords: Industrial Machine Learning, Automotive, Predictive Quality, Failure Forecasting, Time Series Data, Sensor Analysis, Soft Sensors

1 Introduction

The digital transformation in the early 21st century has a significant impact on modern society and is accompanied by phenomena like the Internet of Things (IoT) and the fourth industrial revolution (I4.0) (Federal Ministry of Education and Research, 2013). The development and introduction of modern digital technologies – above all artificial intelligence – lead to high expectations among companies in all branches of industry. As one of the most advanced industries in digitizing its production environments, the automotive industry has great potential for value-added approaches based on artificial intelligence (AI) and machine learning (ML) (Exone, 2018). AI and ML have seen great success in domains like computer vision (CV) (Krizhevsky et al., 2012; He et al., 2016) and natural language processing (NLP) (Graves et al., 2013; Cho et al., 2014) and are increasingly exploited for applications in the classical production technology sector, not only, but especially of the automotive industry. Here, manufacturing processes from prototype and series production scenarios, which are generally subject to a number of restrictions imposed by the requirements placed on production machines and manufactured products, demand careful adaptations of today's AI and ML methods for the successful transfer to these complex scenarios. Some relevant challenges of such scenarios regarding data is the assurance of its quality, its security and its accessibility, i.e. the possibility to collect relevant data. Specifically, the limited possibility to interfere with specific process steps and to take the necessary precautions when dealing with the requirements of stable and clocked series production processes is a major concern for the successful transfer of data driven AI and ML methods. Another frequently encountered challenge is the beneficial utilization of domain expert knowledge for AI and ML methods. In many cases, domain experts make decisions based on years of experience and human intuition. Formalizing this experience and intuition often significantly improves the performance of an AI/ML model or even enables its beneficial use.

In this paper, we demonstrate the transferability of AI and ML methods to industrial scale challenges. Therefore, we present and discuss three different scenarios from the automotive industry and the application of AI and ML approaches to contribute to these scenarios. The first use case addresses the task of forecasting sensory time series signals acquired from a deep drawing tool to predict process failures, i.e. cracks in the manufactured metal sheets, in order to react to possible process failures before they actually occur. The second use case addresses the task of predicting the curvature of windshields manufactured along a multi-step production line based on process parameters in order to complement the posterior manual quality control process at the end of the line by a data driven a-priori estimation of the windshield's quality. Last, the third scenario addresses the reconstruction of real-world sensory time series signals from internal control units in a prototype vehicle in order to replace these sensors by soft sensors that provide the same information in series production vehicles without the need of the actual physical hardware. We further discuss the potential to generalize our transferred approaches to other scenarios with similar problem settings and identify some key considerations to be made for a successful use of AI and ML methods in industrial setups.

2 Use Case: Deep Drawing of Car Body Parts

Deep drawing is a sheet metal forming process in which a sheet metal blank is radially drawn into a forming die by the mechanical action of a punch (cf. Figure 1) (DIN 8584-3, 2003-09).

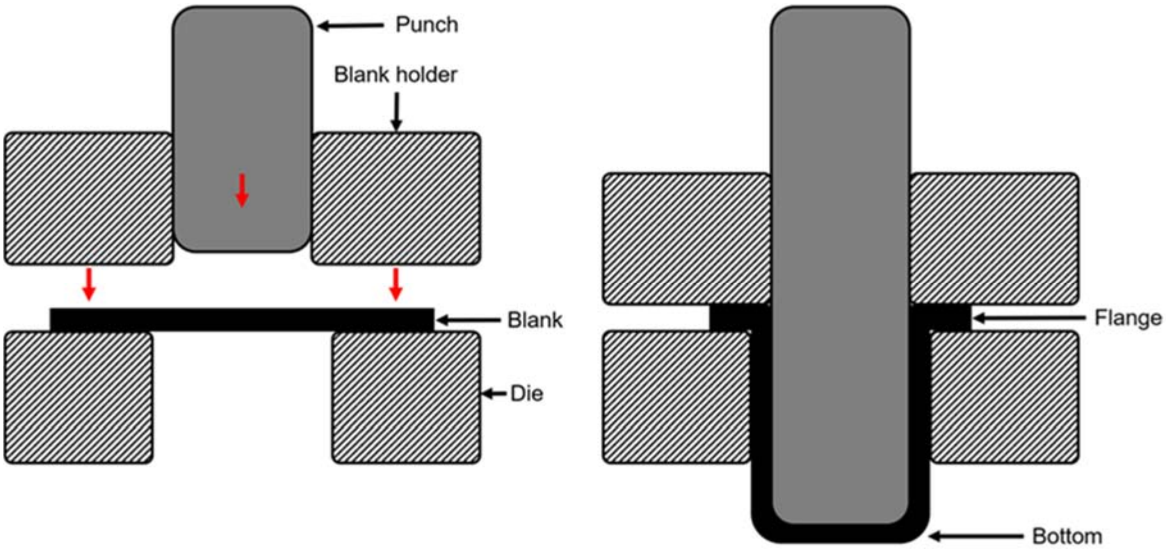

Figure 1: Schematic illustration of the deep drawing manufacturing process. Left: before the deforming process. Right: after the deforming process

The most frequently occurring process failure in deep drawing is the accidental formation of cracks in the metal sheet. Besides economic aspects of producing waste products, such process failures pose the much more critical problem that the deep drawing tool may be damaged in the process. Currently, the quality of the manufactured metal sheets is assessed manually by human workers at the end of the line. If a cracked sheet is identified, it is sorted out and recycled, however, no data about the quality control process is saved and the cause of the crack is not determined. Therefore, the occurrence of cracks in the metal sheets and potentially devastating consequences for the deep drawing tool can only be identified after the actual manufacturing process, however, an a-priori prediction about the likelihood of process failures is required to react to these failures before they happen in order to protect the deep drawing tool from critical damage.

In order to address this issue, first the deep drawing tool was enhanced with strain gauge sensors and flange retraction laser sensors that acquire data during the deep drawing process (cf. Figure 2).

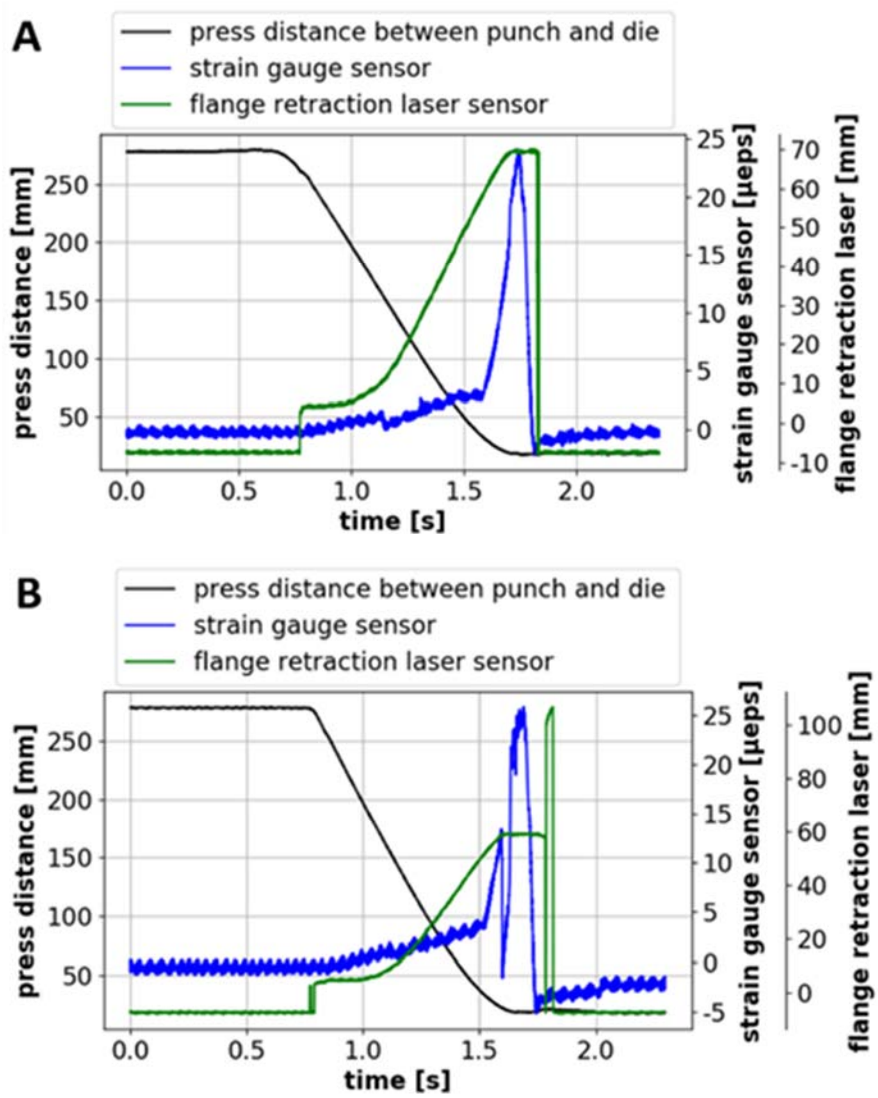

Figure 2: First: exemplary time series data of a good stroke acquired from the deep drawing tool. Second: exemplary time series data of a bad stroke acquired from the deep drawing tool. Note that the sudden decrease of the strain gauge sensor data likely indicates a crack in the metal sheet. Additionally, the distance measured by the flange retraction laser plateaus before the end of the stroke and is much smaller as compared to the good stroke.

The acquired data contains information about whether a crack occurred in the metal sheet and can be used for predictive analysis in order to forecast process failures. Second, we utilized a combination of two Long-Short-Term-Memory (LSTM) neural networks that were trained on the acquired sensory data to estimate whether a deep drawing process will result in a good product or a waste product and to forecast the sensory signals to predict the occurrence of process failures, i.e. cracks in the metal sheet.

2.1 State of the Art

Prominent research fields in the deep learning domain that largely utilize LSTM based neural network architectures to analyze time series data are natural language processing (NLP), computer vision (CV) and anomaly detection. In addition to the successful use of LSTMs for CV and NLP tasks, there is a number of applications using standard LSTMs for industrial use cases. For example, in the field of process control engineering LSTMs are used to predict package signatures of field-devices, detect anomalies in the communication and finally identify problematic processes (Feng et al., 2017). Furthermore, in the field of chemical process control, LSTMs are utilized as a dynamic soft sensor modelling method to deal with complex non-linearities and to predict sensory time series data of coal gasification online (Tsinghua et al., 2017). An example much closer to the field of mechanical engineering and production engineering utilized LSTM based analysis of industrial internet of things equipment for the regression of 33 sensors of a main pump in a power station (Zhang et al., 2018). Despite the numerous applications that utilize LSTMs in different fields, to the best of our knowledge, there are no realizations to transfer bidirectional LSTM networks optimized for frequency-based anomaly detection to manufacturing processes. We adopt the combination of a wavelet transformation-based approach for feature extraction and a bidirectional LSTM based neural network to sensor time series data for anomaly prediction and regression analysis in manufacturing.

2.2 Methods and Results

In a first step, we supported the manual quality control process at the end of the line by an automated and data driven solution to identify cracks right after the deep drawing process preparing the data for further training. We utilized the labeled data to train a supervised learning model to identify cracks and predict their severity and occurrence in time before they actually happen.

label		true		Σ
		good	bad	
predicted	good	604,25	2,4	606.65
	bad	36,75	21,6	58.35
Σ		641	24	665

Table 1: Contingency table containing the averaged results across the threefold cross-validated performance evaluations

Figure 3 shows the analysis workflow starting with preprocessing the raw sensory data from the strain gauges and the flange retraction lasers. The preprocessed data was cut before all the cracks occurred so that the model's input has no information about when a crack occurred or how severe it was. The cut data is fed into a classifier, which estimates the likelihood of a particular stroke to cause a crack in the deformed metal sheet. That estimation is fed together with the preprocessed strain gauge sensory data into a regression model that forecasts the strain gauge time series, thus estimating the point in time and the severity of the predicted crack.

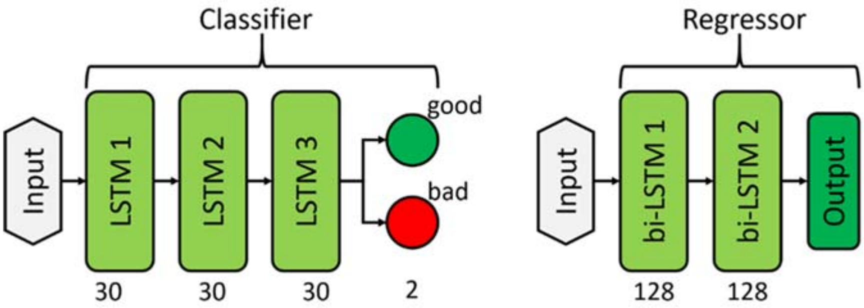

Figure 3: Schematic illustration of the architectures of the classifier model and the regression model

Figure 4 shows the architectures of the LSTM classifier and the LSTM regressor. The classifier contains three LSTM layers with hyperbolic tangent activation and 30 units in each layer and a binary classification output layer with SoftMax activation. The regressor contains two bi-directional LSTM layers with hyperbolic tangent activation with 128 units each and a single output node, which returns 412.5 milliseconds forecast of the strain gauge sensory data. Figure 3 shows the confusion matrix corresponding to the evaluation of the classifier's performance in the test data set which contained 665 strokes in total. The classifier reached an F1 score of 0.9686, indicating a good classification performance despite the strong unbalance of both classes.

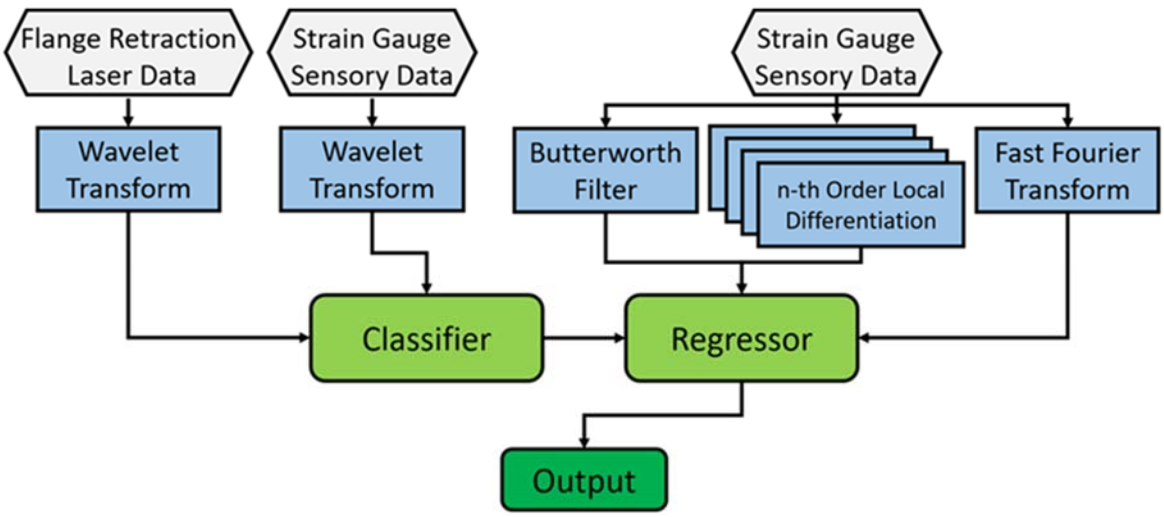

Figure 4: Schematic illustration of the data analysis workflow to forecast the occurrence of cracks in the manufactured metal sheets

Figure 5 shows two examples for the prediction of the learning models. The model accurately forecasts the ime series of the strain gauge signals allowing to reliably estimate whether a stroke is likely going to produce a good sheet or a cracked sheet.

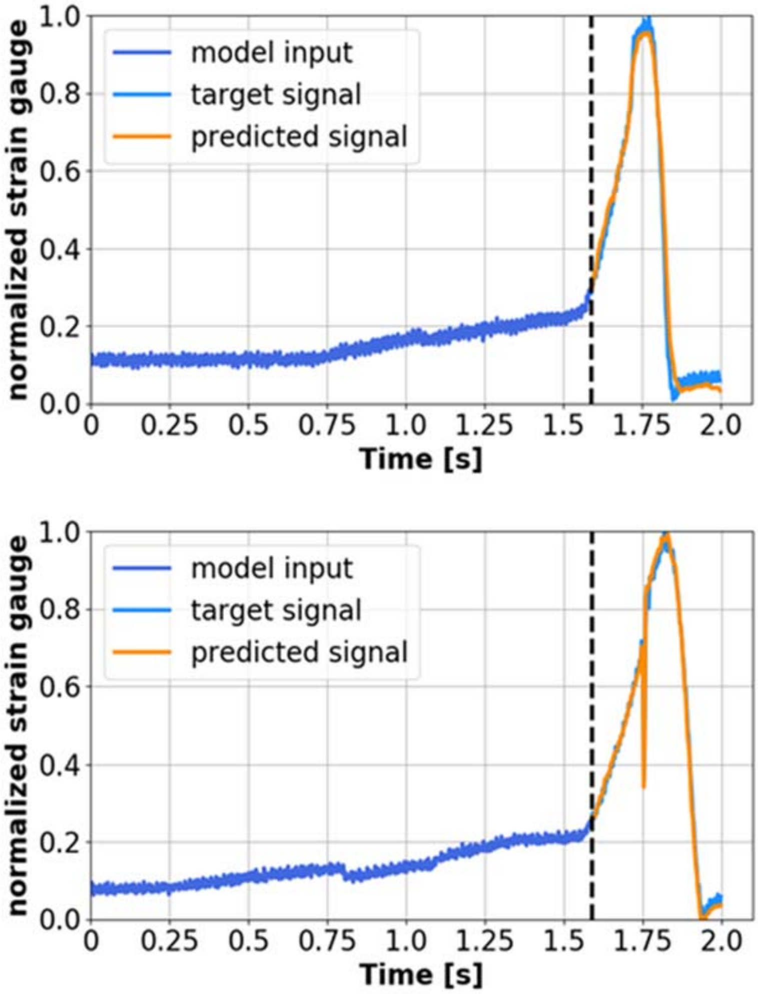

Figure 5: Two exemplary prediction results of the LSTM model. First: a good stroke. Second: a bad stroke, which caused a crack in the metal sheet. The occurrence of the crack is correctly predicted by the regression model.

3 Use Case: Windshield Production for Automobiles

The production of windshields for automobiles is a multi-step production process that comprises highly different and complex processes such as glass pre-processing (e.g. cutting, grinding), glass forming in a high temperature furnace, and the assembly of windshields. The very last step involves the quality control procedure where process experts manually measure quality-related criteria such as geometry deviations or optical reflection of the windshields. Due to the complex nature of the production process and the fact that quality criteria are measured at the end of the process, quality assurance is a challenging factor in the windshield production. In addition, the domain is facing constantly increasing requirements: latest trends such as Head-Up-Displays (HUD) require both higher qualities and lower manufacturing tolerances. In order to meet these challenges, we present a state-of-the-art machine learning based solution to support the control of the windshield forming process. Based on data gathered by sensors in the process (e.g. furnace temperatures), prediction models are used to identify correlations between process variables and to make inline predictions of the much later windshield quality (here: geometry deviations) while the windshields are being produced.

The presented approach lies in the field of predictive analytics, which aims at creating empirical predictions by means of statistical or empirical models (Galit, Koppius, 2001). In the field of production and manufacturing, predictive models are gaining increasing attention and related work has shown their effectiveness when applied to machining processes (Seung-Jun et al., 2014). One application domain of predictive modeling is predictive quality, where the aim is to use data driven methods for the prediction and optimization of processes with respect to certain quality related criteria (Siam et al., 2013). While most of the state-of-the-art solutions lie in the field of control engineering and optimal control theory, new techniques based on machine learning are arising. Especially supervised machine learning models such as decision trees, support vector machines or artificial neural networks have been proven successful to predict quality criteria of manufacturing processes based on process parameters (Choudhary et al., 2009; Hansson et al., 2016; Tercan et al., 2017). In the following, we present a similar approach for predictive quality based on sensory and control data in a windshield forming process.

3.1 Methods and Results

We aimed to predict geometry deviations of windshields (measured at the end of the forming process) during the bending phase based on sensory and control data. For this purpose, at first the data of over 40 quantities relating to the quality of the windshield in an unknown fashion are collected, cleaned and aggregated. These quantities include measured temperatures (furnace chambers, shop floor), parameterizations of the process (pressure settings, cycle times) as well as the windshield temperature in the furnace (measured by an infrared thermal line-scanner). Additionally, we collected geometry deviation measurements of hundreds of windshields during several production campaigns over the course of a month. Figure 6 shows the geometry deviations for two selected campaigns in a box plot, each with approx. 250 windshields.

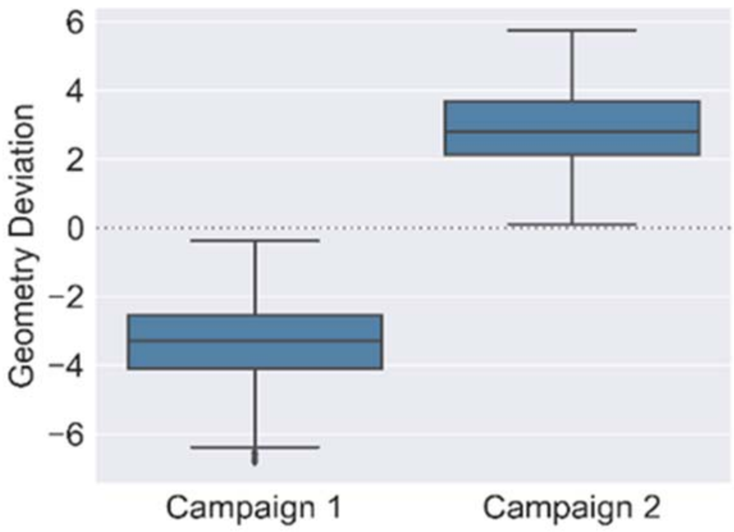

Figure 6: Box plot of geometry deviations from two production campaigns

A significant difference in the distribution of the collected data between the campaigns (positive vs. negative deviations) is evident. One of the main questions is whether this variation between windshields can be depicted in the process data as well. Thus, we subsequently conducted correlation analyses (pearson correlation) to identify relationships between process and quality data. Figure 7 depicts scatterplots between four selected variables that are highly correlated to the geometry deviation. It clearly shows basic principles and phenomena of the glass forming process: the higher the temperature of the windshield in the furnace becomes the more it bends (positive deviation). Based on these findings, uncorrelated variables are removed from the data basis, whereas the most correlated ones serve as the basis for prediction.

Since the target variable geometry deviation is a numerical measurement, we make use of supervised machine learning in terms of regression models. The models are trained on approximately 400 data records, each representing a windshield with twelve variables (e.g. chamber temperature, the windshield temperature). The evaluated methods are: an artificial neural network (Nasrabadi, 2007), a 3rd degree Bayesian polynomial regression (James et al., 2013), a random forest (Liaw, Wiener, 2002) and a gradient boosted regression tree (Tianqi, Guestrin, 2016). All methods are evaluated with 10-fold-cross-validation by calculating the coefficient of determination (R^2) from their predictions.

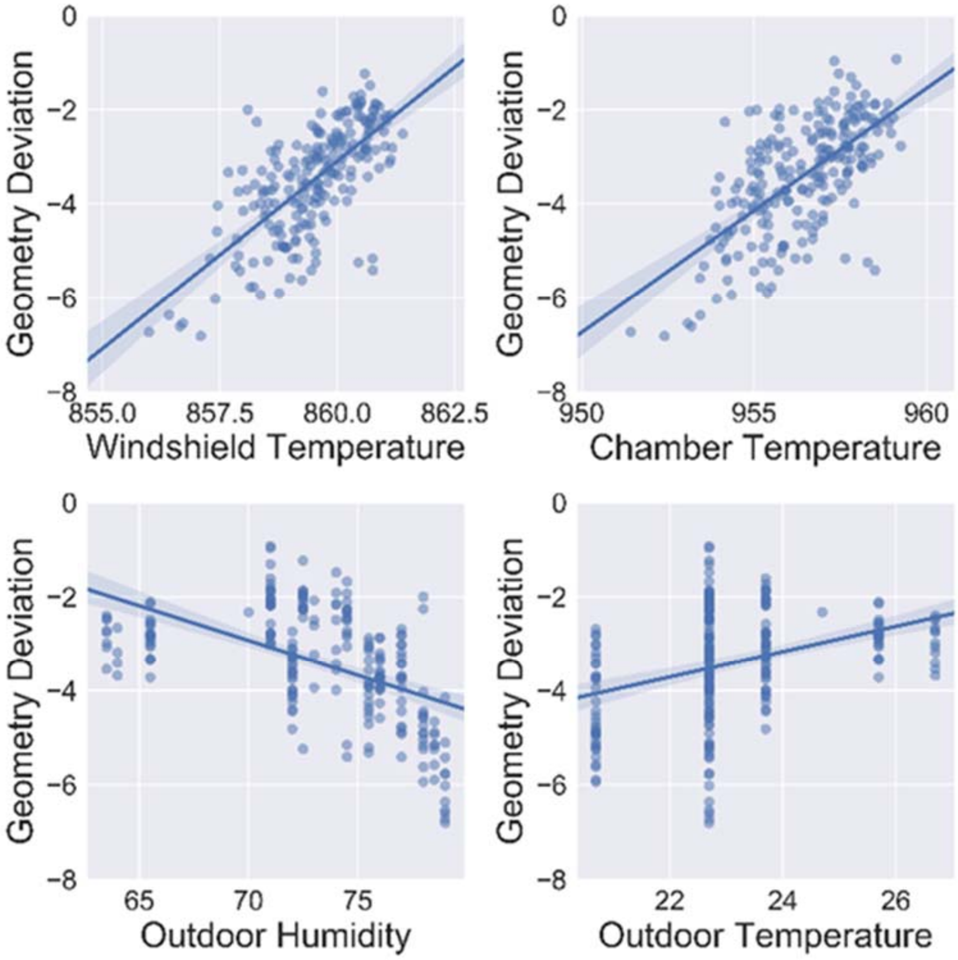

Figure 7: Scatterplots with linear regression curve of different process variables (chamber temperature, glass temperature in furnace, outdoor temperature and humidity) with corresponding geometry deviations. The plots represent windshields over a single campaign

R^2 is defined as follows (Tianqi, Guestrin, 2016):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where n is the number of observations in the test set, y the real output value (geometry deviation) of an observation, $\bar{y}$ the mean of these values, and $\hat{y}$ the predicted output from a model. The best possible score is 1.0, whereas negative values can also occur.

Table 2 shows that the predictions of the geometry deviations yield high accuracies.

Model	R^2-Score
Artificial Neural Network	0.932
Bayesian Regression	0.924
Random Forest	0.919
Boosted Tree	0.916

Table 1: Comparison of different prediction models with respect to the final test score.

The best performing model is a neural network that consists of one hidden layer with 50 neurons with the hyperbolic tangent activation function. It obtains a R^2-Score of 0.932, which shows that the network can predict the (future) geometry deviations of windshields based on the process data. In fact, the high score as well as Figure 6 indicate that the model captures the geometric variations very well. The figure illustrates the predictions by comparing the real geometry deviations as well as the predicted ones in a test set of 75 randomly selected windshields. Interestingly, there exist also some major false predictions (e.g. test data point 38 in Figure 6) where the model itself predicts an overbending (positive deviation) of the windshield while the real outcome was just the opposite. The correct prediction of the bending direction is critical, since the prediction itself founds the basis for an automated control in later process phases. Nonetheless, in 95 % of all cases the model correctly predicts this direction.

We conclude that the quality of automotive windshields can be predicted within the production process by means of supervised machine learning models (i.e. artificial neural networks). The results provide a basis for an autonomous online regulation of the process, i.e. the predictions will be fed back to the regulation system automatically, which can react to predicted failures and immediately compensate fluctuations by adjusting process parameters such as furnace temperatures to minimize upcoming quality deviations in a targeted manner.

4 Use Case: Soft Sensors for Series Production Vehicles

Modern car prototypes are equipped with a large number of sensors that acquire data during various test runs under different test conditions and on different test tracks. The acquired data yields information about the state of the car during its operation and specifically about the strain on particular components that are enhanced with e.g. strain gauge sensors. The live data bears great potential and extends the accessibility of information during the lifecycle of specific components from periodic maintenance appointments to their daily use. However, due to the large number of single components in modern cars, transferring this approach to series production vehicles would require considerable changes of the production lines with new production steps and additional quality control measures. In order to harness the potential of such sensors and avoid additional hardware in series production vehicles at the same time, we propose to replace the real sensors with virtual sensors or soft sensors that reconstruct the real-world signals from the internal control units.

4.1 State of the Art

The concept of soft sensors is widely used in chemical industrial scenarios where their most frequent case of application is due to the lack of possibility to place real sensors within some area of interest of an experimental setup, e.g. within a tank filled with acid liquid. For similar reasons, soft sensors are also widely used for the system control of combustion processes in power plants (Kugler et al., 2014). A domain closer to the domain of mechanical engineering is the domain of plastics processing, where soft sensors based on artificial neural networks are used for online adjustment of process parameters to improve energy consumption, and product quality (Kugler et al., 2013; Kugler et al., 2012). To the best of our knowledge, there is no realization of soft sensors to acquire live data from prototype vehicles to gain more detailed insights about the lifecycle of specific kinematic components and how these components are stressed during the use of the vehicle.

4.2 Methods and Results

We propose an approach that reconstructs the sensor signals from internal control units that are installed in every series production vehicle. We utilize extreme gradient boosting (XGBoost) (Liaw, Wiener, 2002), a popular machine learning algorithm that has been proven to be an excellent solution for many learning problems winning a number of highly decorated Kaggle challenges, to reconstruct the force and the torque that is exerted on specific components of a vehicle's axle kinematics. Figure 9 shows the sensory time series data that poses the basis for the learning problem. The black signals stem from different internal control units while the blue signal is an example of an external signal that needs to be reconstructed. All timeseries are plotted on the same time scale and in most cases show a periodic course, which comes from the periodicity of the test track on which the data was acquired. The darker grey areas correspond to the first five rounds on the test track and are used as training data while the lighter dark area is the test data, i.e. the learning model is supposed to learn from five rounds on the test track how the torque on the drive shaft in the sixth round unfolds. The prototype vehicle with which the data was acquired provided 79 internal control units, which form the basis for the reconstruction task. Figure 8 shows a schematic illustration of the analysis workflow.

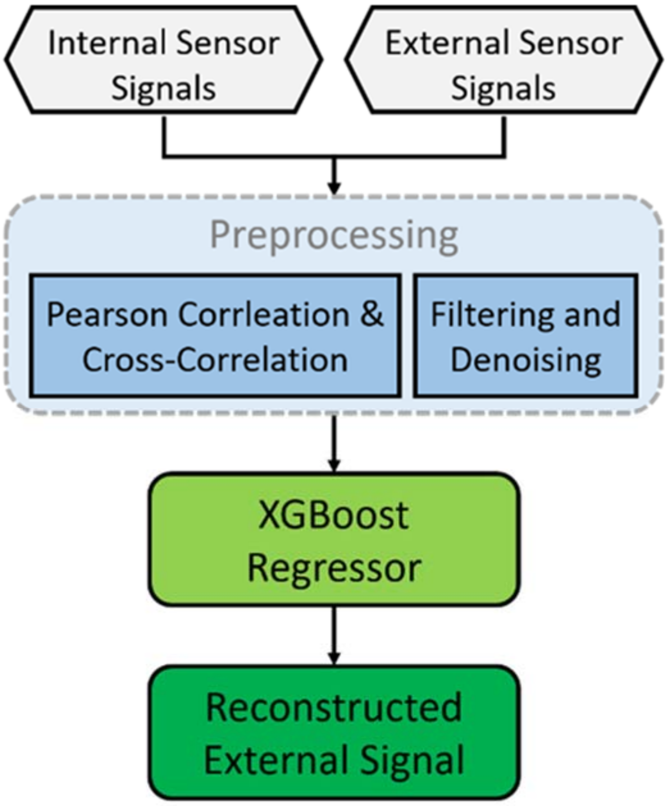

Figure 8: Schematic illustration of the data analysis workflow.

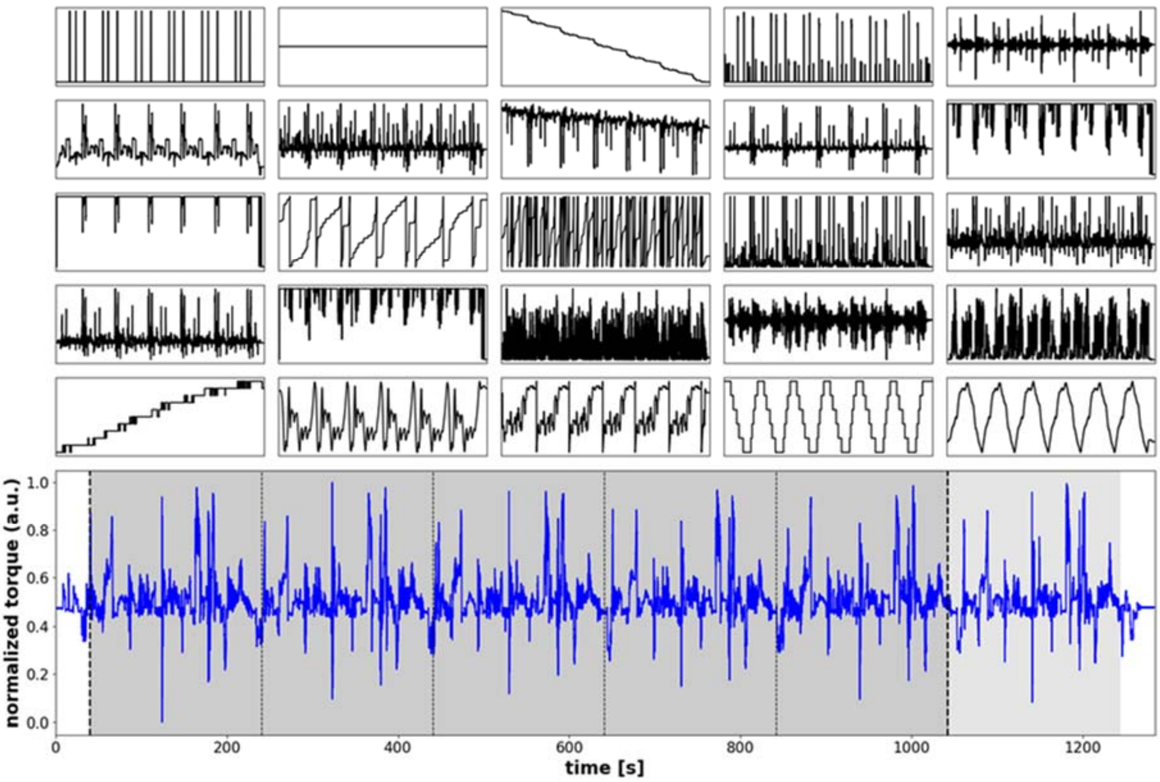

Figure 9: Illustration of the sensory data that is the basis for the learning problem.

In a first step, we selected a subset of these 79 signals based on the significance of the correlation between the internal signals and the external signal. Furthermore, we considered temporal delay between the signals by calculating the cross-correlation and removing any possible time lag. Thus, every external signal is reconstructed from a specifically chosen subset of internal signals. In a second step, the data was cleaned from electrical noise in order to extract frequency components in the data relating to oscillations of the vehicle's chassis. Figure 10 shows an example of the model's prediction for two different test tracks. While the overall trend and most of the different frequency components of the original signal can be reconstructed reliably, there are some minor features contained that are not properly fit by the learning model. This is likely due to the lack of information contained in the correlation between the original control unit signals and the external sensor signal that is reconstructed.

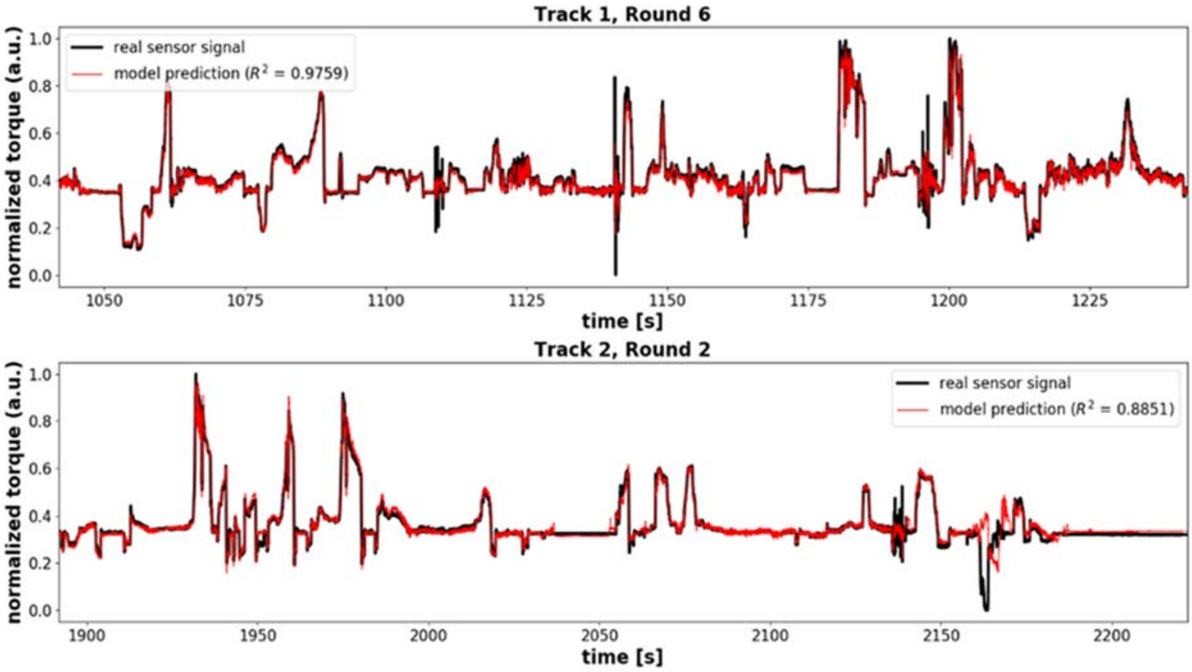

Figure 10: Two exemplary prediction results on two different test tracks.

5 Summary and Conclusion

The advanced state of the digitization in the automotive industry poses great potential for data driven approaches utilizing AI and ML methods to tackle typical problems of modern production scenarios. We presented three exemplary use cases from different domains demonstrating the transferability of such methods.

In the first use case, we forecasted sensory time series signals acquired during the deep drawing of car body parts for process failure prediction. The timely prediction of such a failure, a cracked meta sheet, allows to preemptively react and stop the process to protect the deep drawing tool from potentially critical damage. The intention to forecast time series data to predict the further course of production processes is highly desirable many other scenarios. The utilized architecture of LSTM networks is easily transferable to such scenarios after the adaptation of the preprocessing steps and the model's hyperparameters according to the scenario specific data.

In the second use case, we predicted the quality of automotive windshields by means of machine learning models based on data gathered in previous process steps. We found that the collection and aggregation of relevant process data such as the glass temperature is critical for the success and the predictive performance of the models. The work represents a successful data driven predictive quality approach that complements the manual quality control at the end of the production line. It serves as a basis for an autonomous AI-based predictive regulation of this multi-step production process.

In the third use case, we reconstructed sensory time series signals from internal control units in prototype vehicles to replace these hardware sensors by soft sensors in the series production vehicles. We found that the best reconstruction performance for different sensors was dependent on the choice of control unit signals as input for the regression model. The intention of harnessing the potential of sensory data exploiting complex patterns of correlations between single sensors to create a soft sensor is highly desirable in scenarios in which a hardware sensor cannot be installed due to environmental reasons such as extreme temperatures in furnaces or very high/low pH-values in liquids, due to economic considerations or simply is not desirable to be installed to avoid increased maintenance efforts.

Although the benefits of artificial intelligence are evident in the use cases and beyond, the introduction and eventual sustainable use of such systems is still rare rather than standard. The reasons for this are manifold and are not only of a technical nature. For instance, despite the advanced state of digitization, the automotive industry suffers from a continuous struggle to overcome traditional habits of past developments in the industry that made it as successful as it is nowadays. The sustainable implementation of new technologies such as AI and ML requires the adaptation of traditional roles and established structures as well as the acceptance of such new technologies on a technical and organizational level. At the same time, the high standards in terms of quality and efficiency that were a major factor for the past developments of the industry need to be maintained. Besides technical and organizational aspects, acceptance of new technologies and trust in their benefits rather than fear of the consequences of their adoption needs to be gained on a human level especially when the debate in science and the media are so diverse as is the case for artificial intelligence.

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