Parameter Forecasting for Vehicle Paint Quality Optimisation

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Abstract

Painting a modern car involves applying many coats during a highly complex and automated process. The individual coats not only serve a decoration purpose but are also curial for protection from damage due to environmental influences, such as rust. For an optimal paint job, many parameters have to be optimised simultaneously. A forecasting model was created, which predicts the paint flaw probability for a given set of process parameters, to help the production managers modify the process parameters to achieve an optimal result. The mathematical model was based on historical process and quality observations. Production managers who are not familiar with the mathematical concept of the model can use it via an intuitive Web-based Graphical User Interface (Web-GUI). The Web-GUI offers production managers the ability to test process parameters and forecast the expected quality. The model can be used for optimising the process parameters in terms of quality and costs.

1 Introduction

Magna is one of the leading suppliers and contract manufacturers in the automotive industry. Apart from supplying vehicle parts and modules, Magna produces complete vehicles for global car brands. Paint coating of the car body in white (BIW) is essential role for the visual appearance and durability of a vehicle. Multiple coatings of paint, each having a special purpose, are applied to modern cars. While the top layer is mainly designed to appeal to the human eye, the layers underneath serve as corrosion protection and level out different textures of the BIW. Hence, flaws in the individual paint layers affects not only the looks, but also the durability of a vehicle. (Geffen & Rothenberg 2000)

At the Magna production plant in Graz, hundreds of vehicles are produced every day. To transform the BIW to a fully-painted body shell, 10 to 15 process steps are required, with about 300 parameters that control these process steps. The process begins with chemical and mechanical cleaning, followed by applying various layers of paint, and ends with ensuring the visual appeal with the base and clear coat. Since customers expect high quality of all surfaces

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of the bodywork, spot repairs have to be performed to correct defects in any of its paint coats. (Guerrero et al. 2011) This takes time, and only a limited number of repairs can be accomplished in-line without disrupting the manufacturing cycle. If a car shell requires extensive repairs, it has to be removed from the production line to undertake them separately. Moreover, each spot repair results in additional costs, which are even higher if a vehicle is taken out of the production line. (Ju et al. 2013)

Production managers, who monitor and control the entire painting process, are required to handle all process parameter in order to minimise spot repairs per produced vehicle body. For process optimisation and worker support, data analytics can be applied for data originating the manufacturing domain (Gröger et al. 2012, Lee et al. 2013). The project described in this paper used data analytics for the accumulated paint shop process data, which were partly collected telemetrically and partly manually recorded. The project goal was to create a forecasting model to estimate the expected paint job quality of BIWs entering the painting process. The forecasting model was later embedded into a visual tool, enabling production managers to optimise the painting process parameters in terms of quality and costs. The final result was a pilot system customised and tested for the electrophoretic painting step.

2 Method and Implementation

Figures from the quality management system evaluating the paint shop were used as target quantities. To achieve a better understanding on the production processes, recordings from spreadsheet calculations specially tailored to monitoring individual stages of the painting process were used. In total, more than 250 relevant parameters were identified. To interpret the data and to gain insights into the painting process, extensive discussions with production management and personnel in the paint shop were conducted.

As a pre-processing step, the collected data had to be cleaned and transformed into a unified, multivariate time series to form a data base for all further investigations. Depending on the quality and format of the input data, various measures had to be taken:

- *Quantification*: Non-numeric values were quantified since the mathematical models can only function with numeric values.
- *Outlier detection and removal*: Outliers may originate from sensor failures or drift and typos in the manually-entered data.
- *Interpolation*: Since the measurements have to be recorded with equal frequency, less frequently recorded values must be interpolated to align all recordings.

The Key Performance Indicators (KPIs) in the quality management system are not detailed enough to track individual stages of the paint shop since there are designed to capture the complete production cycle. Hence, more fine-grained KPIs had to be defined in close coordination with the domain experts. The new KPIs were used as the target values of the model.

The model development began with an analysis phase that evolved conducting a cross-correlation analysis, which indicated many inter-correlated predictor groups. Figure 1 shows an example of a generated correlation plot. With the help of these correlation plots, the discussion about true and deceptive correlations could be conducted with the domain experts. The outcome of the discussions, combined with considerations of the data's marginal distributions, prompted towards the selection of a Least Absolute Shrinkage and Selection Operator (LASSO) model (Harrell 2015) as the most promising approach. The LASSO model, as applied here, derives forecasts from past production data and three additional input parameters:

- *Underlying historical data*: The LASSO model contains a large amount of historical data, and the temporal range used for a particular simulation can be selected arbitrarily. This is required since some characteristics of the paint shop environment change over time.
- *Number of input variables*: The model parameter α determines indirectly how many of the most influential variables are accounted for. The variables are sorted depending on their effect on the output result.
- *Variables*: For those variables that contribute to the model at a given value of α, the value can be specified.

A LASSO-based modelling system was implemented in the Python programming language. A Web-based graphical user interface (Web-GUI) was provided to the users to allow non-experts to interact with the system. Figure 2 depicts a screenshot of the Web-GUI, which is a dynamic web page accessing the computational Python kernel. Production mangers can interactively adjust the model's parameters and input variables to immediately obtain the estimated quality output as the expected defect rate per vehicle. Additionally, markers in the value selector for the input variables indicate which input variable setting yields the lowest defect rate.

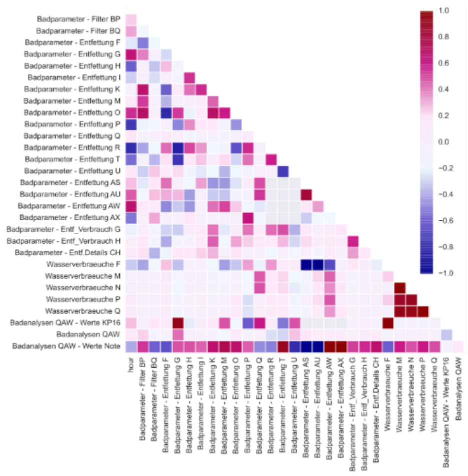

Figure 2: Correlation plot of parameters that have the most influence on the process error rate

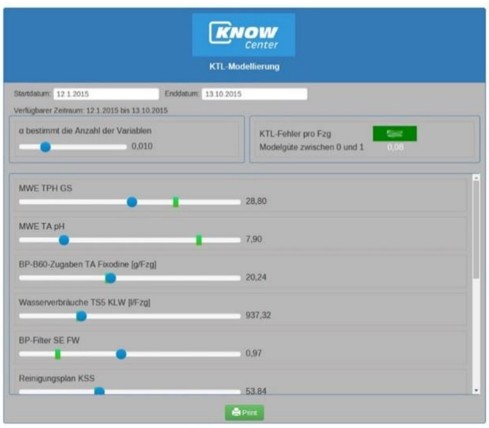

Figure 2: Screenshot of the interactive prediction Web-based Graphical User Interface (Web-GUI)

3 Results and Conclusion

The cleaned and normalised data, combined with the insights gathered during meetings with the production managers, were the basis of the implemented LASSO model. The Web-GUI ensures an easy application of the model, allowing even those users who are not familiar with mathematical modelling or the Python programming language to derive quality forecasts. This fast and user-friendly forecasting approach enables production mangers to identify facility parameters that can be modified to achieve a better car body painting quality. Additionally, the necessary influential directions and alteration magnitudes are suggested.

Close collaboration and discussions between the data analysts and the involved paint shop personnel was an important factor. The combined expertise in vehicle painting and mathematical process modelling ensured the success of the project. This shared understanding of each other's domain is crucial for any data analytics project.

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