Using AI for Dynamic Reduction of Rheological Measurement Frequency

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Abstract

Variations in input raw materials or deviations in the mixing processes can strongly influence the quality of a rubber compound. Today, this can only be determined after it has passed through the production cycle for example by carrying out a rheometer test. Together with HEXPOL Compounding, the software provider DatenBerg has developed an approach that can be used to predict the quality of the compound based on process parameters. As a recommendation for action, an information about whether to measure the batch or not is derived. This reduces the in-line measurement efforts in average by 70% while maintaining a probability of failure detection of over 99.5%. The result of this work supports employees on the shopfloor in controlling the process and avoiding scrap. The solution implemented at the HEXPOL's mixing plant in Hückelhoven, Germany is used as an example to explain the function and result.

Introduction

The mixing process of rubber compound is very dynamic. As a result, the mill operator has to always remain alert. In addition to this, the operator is usually responsible for many production steps across the chain, this includes taking periodic sample for quality inspection.

The inspection during series production, which is often carried out with a sample size of 100%, is time consuming and represents an additional, non-value-adding effort. Accordingly, there is a great potential for savings. Traditional inspection reduction methods, e.g. in the context of statistical process control, are based on a certain number of the last quality measurements, therefore are thus always subject to uncertainties and can only result in a biased estimate.

Since the manufacturing process generates real-time data, there exists a tremendous advantage of using advanced data analytics and artificial intelligence (AI). Taking advantage of the data acquired during manufacturing can not only make the process more transparent but also facilitate monitoring the complex process. By using AI to predict the quality, the in-line measurements can be reduced, and an inspection only carried out in the case of unclear quality characteristics. The approach can be compared to a non-destructive testing method but is only based on data and does not compensate the destructive inspection with other sensor technique.

In this paper the implementation of such an approach in rubber compounding to reduce the measurement frequency is discussed. The work performed is based on the data analytics platform smartPLAZA offered by DatenBerg, which is currently running in various production lines of HEXPOL in Europe.

Experimental

The recommended action for the employee consists of a simple statement as to whether a measurement is required or not. This should be done as soon as possible, after the so-called "batch drop" (i.e., as soon as the mixture has dropped onto the mill). To ensure the success of the experiment two factors have been considered as important. The reduction factor RF itself, which describes the amount of saved measurements in comparison to the status quo in percent. Furthermore, the probability of detection POD will be considered. The POD is used to verify the capability of an inspection to detect bad quality and is commonly used in non-destructive testing (1).

To model the manufacturing process, various information is required, such as weighing, environmental and mixer data. These are assigned to each batch, with further describing information like recipe version. Based on that holistic view on the process a model can be trained to predict the batch quality. The three described data sources are taken as an input for the prediction model. The model learns based on historical data the relationship between the input and the rheological measurements as an output. As the compounding process is highly not linear and complex, the prediction model XGBoost has been chosen as a prediction model (2).

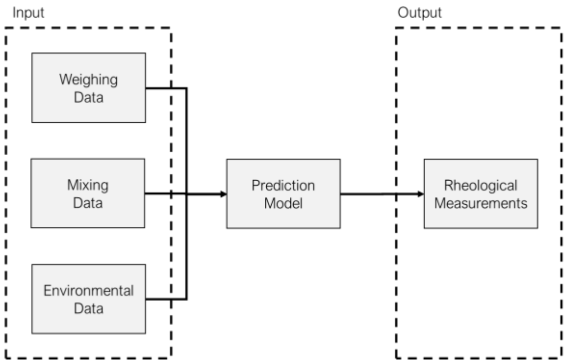

Figure 1 Modelling of rubber compounding with artificial intelligence

The prediction algorithm outputs a prediction for a new set of input data. Furthermore, a statement can be drawn about the accuracy of the predicted values. In case of uncertainty, like due to a newly used material component, a measurement is recommended, to generate new training data. This is required until the accuracy falls below the defined acceptance level for the model accuracy again. As the model learns from all newly added data, it adapts to the new circumstances until the accuracy reaches an acceptable level again.

To additionally protect the prediction model against process fluctuations, fixed rules are defined. For instance, that at least three batches are measured after a mixer standstill. These covers known, quality-critical process states, such as the first-batch effect.

Based on the predicted values, the accuracy and the defined set of fixed rules, a decision is made automatically. For the decision-making also the tolerances of the specific batch are taken into consideration. The ratio behind the evaluation is shown in detail in table 1.

Situation	**Decision**
Prediction inside tolerance limits	Quality is assumed as okay, only random measurements are recommended for re-calibration
Prediction is close to tolerance limits **OR** Safety rules are violated **OR** Model is unsure	Quality unknown, measurement recommended
Prediction is outside the tolerance limits	Batch rejected; no measurement required

Figure 2 Reasoning based on predicted values

The operators are informed about test requirements by the analytics platform via an easy to configure dashboard, which can be customized. Ideally, the operator receives the information via a simple dashboard with traffic light function. Figure 1 shows the final implementation in the software. In the upper area the current prediction for the batch number 1366 is shown with three different quality tests.

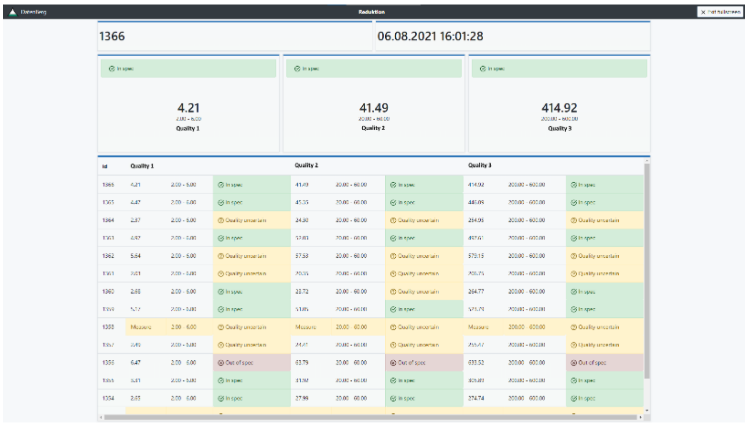

Figure 1 Dashboard

Results and Discussion

To bring the described concept to the plant, an iterative, agile procedure was chosen. In several sprints, the concept was refined, integrated, and finally brought to the shopfloor.

In the first step, HEXPOL and DatenBerg worked out the security concept together to define specific requirements, like the set of fixed rules. More than ten critical scenarios were defined when measurements should be requested in any case. In addition to the first-batch effect, borderline cases such as shift changes or anomalies in the mixing process were also integrated. For an efficient validation, five recipes with high quantities were selected to test the approach in the first place. On the long term, also recipes with smaller quantities should be integrated as well. The moving die rheometer (MDR) on the mixer line was defined as the target test, which should be reduced. Four series-accompanying test parameters ML, MH, TC10 and TC90 were examined, to evaluate how often they can be compensated with a prediction.

During the first iteration, the concept was evaluated and prototyped in the DatenBerg smartPLAZA. It quickly became apparent that the concept already enabled high reduction rates of over 70% for some recipes. However, the average reduction rate has been 50%. Together with the process experts, this has been traced back to the fact, that these recipes contain several feeding steps of the same raw material. This means, that e.g. the carbon black is not added all at once. This information was not yet included in the data, which is why the prediction models could not correctly map the recipes. However, with HEXPOL's own IT, this data could be quickly integrated. As a positive side effect, the quality management in the factory was able to use this data for manual cycle time optimization with the visualization options of the smartPLAZA.

In the second iteration, the reduction rates for the recipes could be further increased due to the expanded data basis. The reliability of the prediction model was also investigated further. In some edge cases, the prediction turned out to be wrong. To better classify these errors, they were categorized further:

- **Non-critical errors:** Batch with good quality classified as "Out of specification / critical".

- **Critical errors:** Batch with poor quality classified as "Within specification".

While non-critical errors cause unnecessary measurement costs, these can be seen as negligible compared to a critical error. This is because critical mispredictions could lead to undetected poor quality. This figure can be also named as the Probability of Detection. Therefore, another optimization goal was to minimize critical errors while maximizing the reduction rates. A correlation between the process capability indices (cpk value) of the individual recipes and the measurement reduction rates has been identified. The more stable a recipe is produced, higher reduction rates and fewer prediction errors, both for critical and non-critical failures, can be observed.

In the final iteration, the approach was tested holistically on a production dataset covering half a year. For this purpose, a real production flow was simulated with historical data, as it would have taken place during real-time operation. To avoid building models for each recipe, which would have excluded smaller lot sizes, the recipes have been categorized into hardness classes. Mixtures of one class share a prediction model that abstractly maps the process behavior. With this approach, the reduction rates could also be increased for recipes with smaller lot sizes, as a bigger data base is available for training the model. On average, the action recommendation "Quality ok - Do not measure" could be given in 68% of the production cycles over the half year. Which is directly leading to a saving potentials of 68% of the measurements performed. For very stable mixtures, this reduction rate could even be increased to over 80%, with a critical error rate of less than 0.5% of all batches.

For real-time integration, the individual data saving procedures of the different IT systems involved were analyzed. The aim here was to ensure that the process parameters are written to a database in a timely manner, as soon as the batch falls. The algorithm then must decide in about three seconds which recommended action to take. Figure 2 shows a summary of the individual iteration stages with the main improvements.

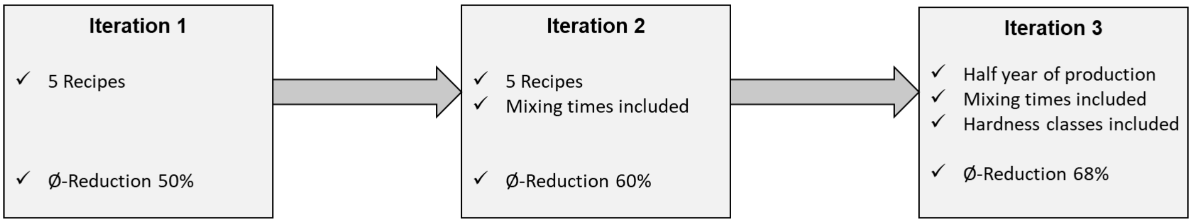

Figure 2 Iterative project approach

Summary and conclusions

During the five-months project, the iterative approach proved to be very effective. The model improved step by step and was ready for real-time deployment, this was possible thanks to the close collaboration between data scientists and process experts. The measurement reduction rates were continuously increased, and, above all, process reliability was ensured. With an average reduction rate of 68% and maximum savings of over 80%, the added value becomes clear. The project shows how Industry 4.0 can be implemented in practice and how artificial intelligence helps to improve efficiency and quality. "In the next step, we would like to bring the optimization possibilities into real-time use in agreement with our customers and, in parallel, we are developing new ideas for further fields of application. We see great potential to sustainably improve our processes through AI," comments Daniel Pankert, Process Intelligence Manager at HEXPOL Compounding.

In recent years HEXPOL has invested heavily in extensive data acquisition and standardization of data structures between the plants. Today, an average of 56 measuring points per production line and second are recorded at the sites in Europe and Asia, which are used for process analysis and improvement. "The close cooperation in the iterations between the business department and our data specialists enabled the successful real-time deployment," explains Maximilian Backenstos, Managing Director at DatenBerg GmbH.

With the help of standardized data management, the described solution can easily be rolled out to other production lines. The described methodology trains itself independently on a new line without further manual customization.

While the approach described is aimed at the tests accompanying series production on the mixer, the procedure can also be transferred to other quality inspections. Today, more complex measurements such as hardness testing are often only carried out for a small sample size. With the help of an accompanying prediction model, the hardness can also be monitored for each batch.

Reference

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