LEVERAGING DOWNSAMPLING AND EXPERT SYSTEMS FOR DATA-DRIVEN PROCESS OPTIMIZATION IN THE FORGING INDUSTRY

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The forging industry is increasingly turning to data-driven process optimization and artificial intelligence systems to enhance efficiency, product quality and sustainability. These technologies rely heavily on robust, high-quality databases that provide consistent and reliable data for analysis and decision making. However, in many forging shopfloors, data is often dispersed across multiple separate IT systems, creating significant challenges for integration and utilization of the data. Downsampling methods and expert systems are used to address these challenges and enable the consolidation of scattered data into valuable insights. Downsampling reduces the size of the data sets while preserving the critical information in the data, thus minimising the amount of storage and computing power required and allowing for faster visualisation and analysis of the data. Expert systems complement these efforts by incorporating domain knowledge into algorithms and translating raw data into key metrics that can be interpreted by human process experts. This paper not only describes how these techniques have been used to build a quality data set that contains all the relevant technical data for the forge shop, but also how this dataset was used to build a data visualization dashboard that delivers immediate business value.

KEYWORDS: DATA-DRIVEN PROCESS OPTIMIZATION – DOWNSAMPLING – EXPERT SYSTEMS – PROCESS ANALYSIS

INTRODUCTION

This work was initiated to address one critical challenge faced by voestalpine Böhler Edelstahl GmbH & Co KG: how to leverage existing data for process optimization and technical insights. In modern forging operations, significant amounts of data are collected through sensors, machine logs and maintenance records. While this data is invaluable for ensuring operational reliability and reducing downtime, it also holds unused potential for understanding and improving manufacturing processes. The aim of this work was to unlock this potential, transforming existing data into valuable process optimisation insights.
However, there were several challenges to achieve this goal. The technologically important data was scattered across three major, separate database systems, each serving a different purpose and operating independently. The first database contained furnace data such as temperature profiles and heating durations. The second database held process-related metadata, capturing information like start times, material grades and batch identifiers. These were needed to enable the process data to be clearly assigned to the forged parts. The third and last one stored the high frequency raw data from the two forging machines. This distribution of data across multiple systems made it difficult to integrate and analyse all the relevant information.
Another challenge was the complex nature of the raw data from the forging machines, consisting of high-frequency sensor data, that was difficult for human process engineers to interpret. Analyzing this data manually was time-consuming and required significant effort, limiting the ability to make timely, informed decisions.
These challenges motivated the development of a structured approach to efficiently manage and analyze this data, employing downsampling techniques to make the datasets manageable and expert systems to extract meaningful insights. By addressing these problems, this paper aims to demonstrate how scattered and hard to interpret data can be used for data-driven process optimization, providing an approach to fully exploit data resources.

DOWNSAMPLING OF THE FURNACE DATA

The homogenization, heating and reheating processes in the forging shop take between one and 60 hours. In contrast, the door openings of the chamber and block furnaces take between 30 and 60 seconds. A data recording rate of one second is required to accurately display the processes during these openings, which results in large amounts of data for the heating processes and makes data reduction necessary. Data reduction techniques are used to enhance data management and quality, facilitating the storage, analysis, and visualization of large amounts of data [1]. One such technique is the use of downsampling algorithms that return a subset of the data points present in the original data, retaining only the data points that provide the most information [2].

Steinarsson [2] designed and examined deterministic downsampling algorithms. The results showed that such algorithms yield good results for most data.

Investigations of such generalizing downsampling algorithms have shown that they do not provide satisfactory results for the furnace data. Due to the highly variable temporal resolution no acceptable compromise between data reduction and preservation of important information could be found with these algorithms. For this reason, a different approach was taken to downsample the furnace data. Process knowledge was integrated into the algorithm and a process-related downsampling algorithm was developed. This way, only a few points are stored during the heating periods, yet enough points are stored when the door is open to display the processes accurately.

Fig. 1 shows the downsampling of a prewarming process. The amount of data points is reduced from 26064 points to 46 data points while still maintaining the key characteristics of the process. The in-house developed process-oriented downsampling algorithm therefore minimizes the storage needed by around 99%. This means that significant amounts of storage and processing power can be saved by using downsampling methods.

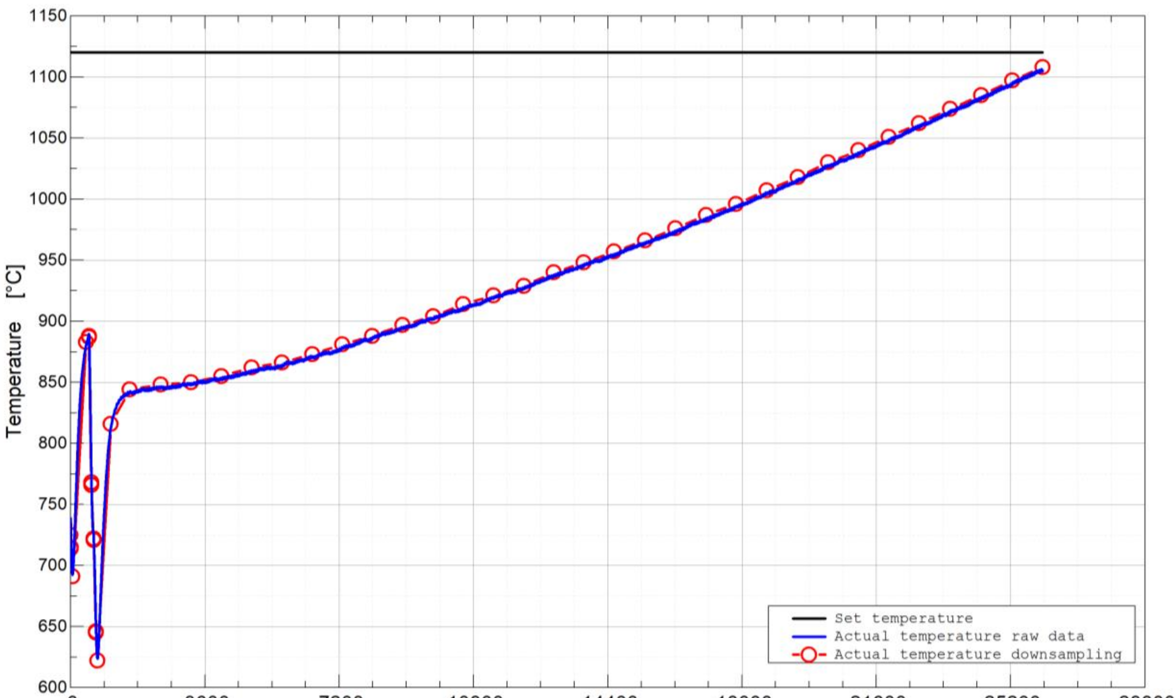


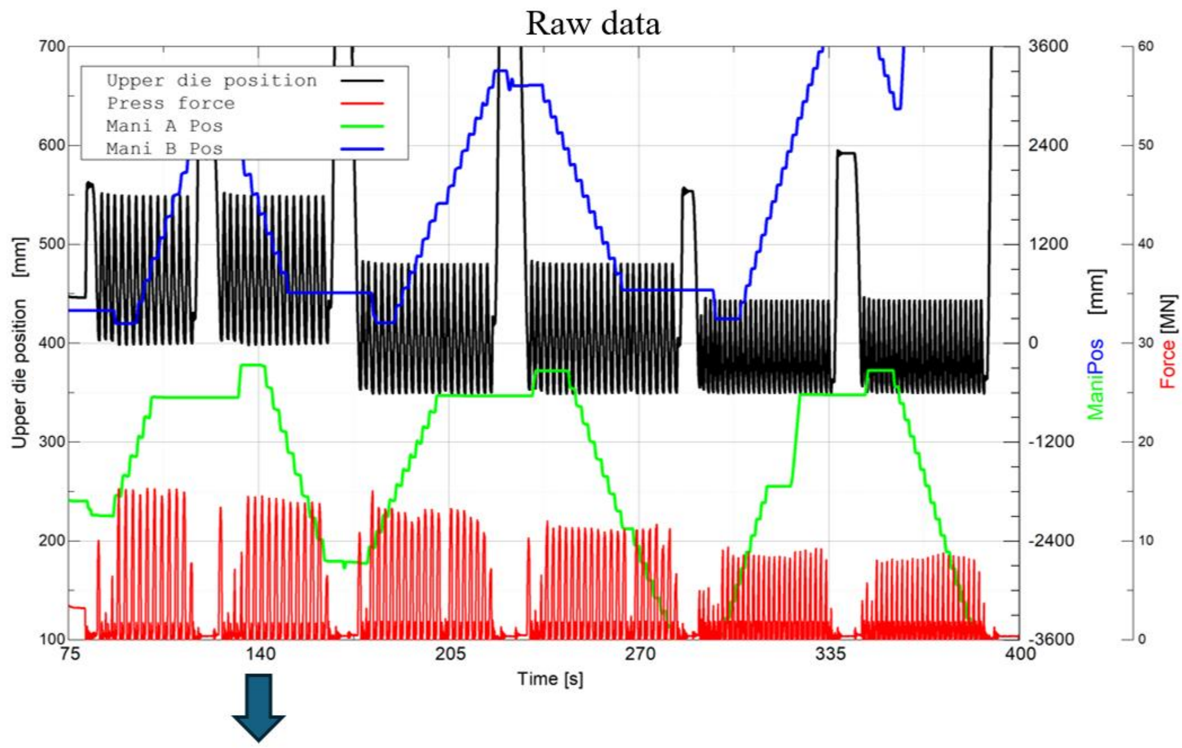
Fig. 1 - Downsampling of a prewarming process

FORGING FINGERPRINT GENERATION WITH THE USE OF EXPERT SYSTEMS

Process data is collected during the forming processes on the hydraulic forging press and radial forging machine. Due to the amount of data (time, pressing force, saddle position, manipulator position, rotation and clamping force, temperature) and the high sampling rate (between 2 and 10 ms depending on the machine), large amounts of data are generated for the forming operations. In addition, this data is very difficult and time-consuming to analyze for process experts due to the complexity of the processes.

Maier [3] developed an expert system for analyzing complex forging processes. It was shown that such logic-based algorithms are suitable for analyzing open-die forging operations and the inline capability of these could also be demonstrated. The use of these systems not only significantly reduces the amount of data, but also extracts key characteristics from the raw data, enabling process engineers to assess the production process more quickly. In addition, similar production processes can be compared using the forging schedules derived from the actual data.

A schematic overview of the process data analysis with an expert system can be seen in **Fig. 2**. Using a complex rule set that integrates process knowledge into the algorithm, a stroke table is created in the first step. To simplify an initial assessment of the processes, a forging schedule is recreated from the real machine data. This means that the compact forging schedule can be used for the first evaluation of the process and the stroke table, which contains the characteristics of each individual stroke, is available for more detailed analysis.



Stroke table

Bite Nr	Pass Nr	RotX °	Bite width mm	Forging Dimension mm
1	1	0	0	403
2			252	399
3			250	399
4			237	399
5			251	399
6			250	400
7	2	-90	0	403
8			-251	398

Forging schedule

Pass Nr	RotX °	Bite width mm	Forging Dimension mm
1	0	251	399
2	-90	-250	399
3	-90	198	350
4	-90	-200	349

Fig. 2 - Schematic overview of process data analysis using an expert system

CONSOLIDATED DATABASE AND ANALYSIS TOOL

A system based on a NoSQL database is used to store the consolidated process data. These databases have the advantage that they are very flexible, easy to scale (especially horizontally) and allow a high data throughput [4]. Such a system was chosen primarily because of its flexibility, as this allows the process chain to be displayed clearly even in the event of process changes or deviations.

Matplus EDA® is a system that combines this database technology with mathematical functions, visualization options and a multi-user environment [5]. In addition to these functionalities, EDA® has a functionality for displaying process chains and inheriting data in these process chains, which is ideal for the holistic display of the entire process data.

Fig. 3 shows the process chain of a forging block in the shopfloor at voestalpine Böhler Edelstahl GmbH & Co KG. In the existing IT-systems it was defined that the first prewarming and warming processes are separate operations while for each following forming and warming process the processes are combined in one operation.

Fig. 3 - Forging process chain

To make it easier to get started with the new system and to avoid creating more differences between the systems, this convention has also been adopted in the new system. Metadata and process data are attached to each operation in the material database. The data is passed down the process chain, so the entire process history of the block up to the current operation is available.

The data representation in Matplus EDA® is shown in **Fig. 4**. Each of the tabs contains metadata and process data for the respective operations. This means that all process-relevant data is available in a database and can be visualized with just a few clicks. Access to this system is web-based and therefore available to every employee on the voestalpine Böhler network. The process engineers therefore have the possibility to access a production process from the point of arrival at the forging plant to the final production process and to evaluate it both qualitatively and quantitatively.

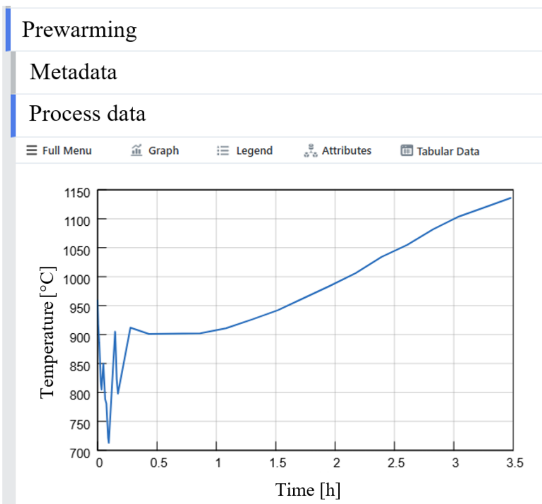


Fig. 4 - Exemplary data consolidation in Matplus EDA®

CONCLUSION

This work demonstrated that the use of downsampling techniques and expert systems significantly reduces the amount of data without compromising its technological relevance. By focusing on essential data points and applying domain knowledge, the vast amount of sensor and process data was condensed into manageable datasets, making it easier to derive actionable insights.
Additionally, the development and implementation of a visualization tool using Matplus EDA® represents a significant achievement in this effort. This tool contains all process-relevant data that was previously distributed across several systems and provides process engineers a single point of access for the entire forging route.
A key strength of the approach lies in the scalability of the Matplus EDA® infrastructure. The flexibility of the system allows for the seamless integration of additional data, such as testing data, in the future. Expanding the amount of available data in this manner will unlock even greater value, offering a more comprehensive view of production processes and improving the understanding of key parameters that influence product quality. By enabling engineers to access, understand and analyze critical information efficiently this approach lays the groundwork for data-driven process optimization.

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