Forecast Model for Optimization of the Massive Forming Machine OEE

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Abstract The EMuDig 4.0 project target is to link all relevant systems and sensors inside a massive forming company with influencing systems from outside as basis for a smart factory. Data and information extracted from integrated sensors and systems in connection with new methods for analysis and algorithms shall be used to optimize the OEE of massive forming machines. The primary target is a quick and direct information to indicate machine irregularities as soon as they appear. The available information not only allows efficiency improvement of single process steps. It supports the optimization of the whole value-added chain.

1 Introduction

The massive forming industry is affected by changing market and product requirements. Increasing demands on quality and new challenges, for instance due to lightweight design and electric mobility, will be the major affect for the massive forming industry in the future or already today. The necessity to produce the different products with optimized OEE is essential in order to stay competitive in the worldwide massive forming industry. This requires more effective engineering for parts and processes, greater efficiency, widening of the process limits, global networking of supply chains or increased flexibility through smaller lot sizes. One of the central questions facing the engineering in the massive forming industry (design of the product properties, processes and plants) here will be to what extent the planning and design process, the efficiency and the stability of the whole value-added chain can be further increased through digital transformation and

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broader know-how bases. It is already recognisable today that the customers of the massive forming industry see digital networking as offering great opportunities for meeting their future challenges. They will therefore very soon start demanding the strategic approach in the sense of Industry 4.0 also from their suppliers. Studies show that large companies are already working far more intensively on Industry 4.0 solutions.

2 Overall Project Description

The research project EMuDig 4.0 is to provide the massive forming industry with an improved Overall Equipment Effectiveness (OEE) through the integration of digital networking of the whole value-added chain. Scientific institutions are to be interconnected with industry partners to put creative ideas and research results into practical application. The research project is funded by the Federal Ministry of Economic Affairs and Energy (BMWi). The EMuDig 4.0 project gives an important impulse for further development of Industry 4.0 within the massive forming industry domain.

The activities under the research project are subdivided into the following subprojects to form a consortium of four academic and three industrial partners:

Subproject 1, **Generation of raw material**:
OTTO FUCHS KG (process chain aluminium)
Hirschvogel Umformtechnik GmbH (process chain steel)
Subproject 2, **Forming process**:
University of Stuttgart, Institute of Metal Forming Technology
Subproject 3, **Production plants**:
SMS group GmbH
Subproject 4, **Production tools**:
South Westphalia University of Applied Sciences, Laboratory for Metal Forming (LFM)
Subproject 5, **Logistics process**:
University of Stuttgart, Institute of Industrial Automation and Software Engineering
Subproject 6, **Factory cloud and data analytics**:
TU Dresden University, Centre for Information Services and High Performance Computing (ZIH)

The involvement of the associated partner “Industry Association of Massive Forming” will ensure that the results of this research project are distributed to the companies of the German massive forming industry.

2.1 Problem Definition

The massive forming process already today comprises a challenging value-added chain:

- Raw material production
- Tool making
- Production of the raw part
- Subsequent heat treatment
- Machining and further finishing to create the part ready for installation

With a view to the challenges of tomorrow already described, we have to see that we do not have a sufficient command of the complex interaction of the numerous parameters and their various interrelationships with the current approach. The challenges of massive forming today can be summarised as follows:

With the state-of-the-art in massive forming, the process stability is not described by process parameters. The process stability will measure with a great time lag at the end of the forming and/or heat treatment process using random sample tests of product properties (e.g. cpk value). The product diversification cannot be attributed to individual process stations, so that a clear identification of the causes is achieved only very seldom. Open-loop or closed-loop interventions in the production process are only possible with a significant delay, if at all. The limited process stability reduces the plant efficiency which leads to considerable financial losses with the capital-intensive forming plants with their hourly rates of up to EUR 1,600.

The **lack of correlation** between the process and the product properties prevents a strategic overall optimisation of the process with the goal of attaining a sustainable boost in efficiency.

Information on the tools is essentially limited to the production volume achieved that can **vary by up to 100%** without any identifiable reasons.

Machines and plants are repaired in the event of standstill and/or undergo preventive maintenance at fixed intervals. **There is a lack of the necessary data** as well as suitable forecast models for load-oriented maintenance cycles.

The lack of networking between the individual links of the value-added chain and the part properties prevents an overall strategic optimisation of the process with the goal of attaining a sustainable boost in efficiency.

The massive forming process is generally a mass production process in which several hundred up to several thousand parts are produced and logistically tracked/identified in a production lot; single part tracking and identification is employed today only in exceptional cases (e.g. aerospace industry) and then at great expense. It is therefore not possible at the present time to **correlate parameters** of the value-added chain with the property of a part.

2.2 Project Aim and Methodological Approach

This project aims to show that, and in how far, OEE and cost effectiveness of two different value-added chains for massive forming of steel with large batch sizes and aluminium with small batch sizes can be improved through digital technologies and control concepts.

The envisaged solution involves adapting and integrating available digital technologies in the engineering of the whole value-added chain to the needs of massive forming. In order to achieve this, a methodological approach is to be developed, tested and evaluated as part of a joint research project using two demonstrator and one model application. The data from complex production facilities can be recorded, saved, processed and analysed along the value-added chain in order to boost the overall plant efficiency through interdisciplinary cooperation between plant owner, plant manufacturer, cloud operator, software producer and science.

With the aim of achieving fundamental, reliable and transferable results, the following elements of the value-added chain are essential for the efficiency of a process and are taken into consideration in the planned demonstrator/model application:

The raw material production, with the aim to interlink the semi-finished product (starting material) technologically and logistically with the further processing process chain ("predictive material property"). This will be achieved with a unique "digital fingerprint" with respect to semi-finished production and property data.

The production process of forming and heat treatment, with the goal of achieving reliable control of all the product properties ("predictive quality") and reducing the scrap rate. This is attained through close links with the raw material production, the tool and plant condition, the process engineering and involving an active control system for influencing the part properties.

The production plant, with the goal of obtaining a load-dependent prediction of plant conditions and corresponding preventive service and maintenance measures ("predictive maintenance") through close links with the forming process, with maintenance and with spare parts procurement logistics.

The production tools, with the aim of predicting the tool condition/wear in relation to the "tool life history" in order to enable corresponding preventive measures. For example adapting the lubrication/spraying condition to the prevailing situation or initiating the planning of a tool change ("predictive tool management") through close links with tool engineering, logistical control of tool making and the incorporation of 3D technologies for in-process assessment of tool states.

The logistics process, with the goal of logistical control and traceability down to the "smallest possible sub-quantities", ideally single part tracking of a complete production lot ("smart logistics").

The factory cloud and data analytics, with the aim to select and further development of methods to implement a system for analysis of the efficiency of the whole value-chain ("big data").

The aspired result of the presented subproject "Production Plant" in Chap. 3 is a forecast model allowing load depending forecasts of the plant condition and according maintenance measures (predictive maintenance). The following milestones have to be achieved to realize this result:

The identification of relevant reasons for machine downtimes and development of a specific sensor concept. Target is collection and quality control of OEE-relevant machine data.

Investigation of correlations between massive forming machine data and performance failure aiming to develop the specific forecast model.

Identification of predictive maintenance measures to improve OEE of massive forming machines.

Realization of an onsite demonstrator with a massive forming application including development of process relevant interfaces and linked with hard- and software for data analysis.

3 Subproject "Production Plant"

3.1 Introduction

The production plants in the massive forming industry manufacture a wide range of products and materials of steel, aluminium, nickel and titanium. Product geometry and product material represent the main influencing factors on the load collective to which the massive forming machines are exposed. This results in a specific wear situation for the respective machine. In addition, the load on the plants and the quality and quantity of their maintenance are further factors influencing the specific wear situation.

Determination of the individual wear situation of a plant in massive forming and the derivation of predictions for the availability-critical wear states are major problems facing the massive forming industry. **Valid statements on the wear allowance** of a machine are consequently difficult to make.

3.2 Current Status/State of the Art Technology

Condition monitoring is currently a widespread concept for describing the wear condition and diagnosing the wear allowance for a wide range of machines and plants as basis for predictive maintenance. These will be accomplished using for instance temperature, vibration and torque sensors (Fig. 1 Predictive maintenance principle [1]).

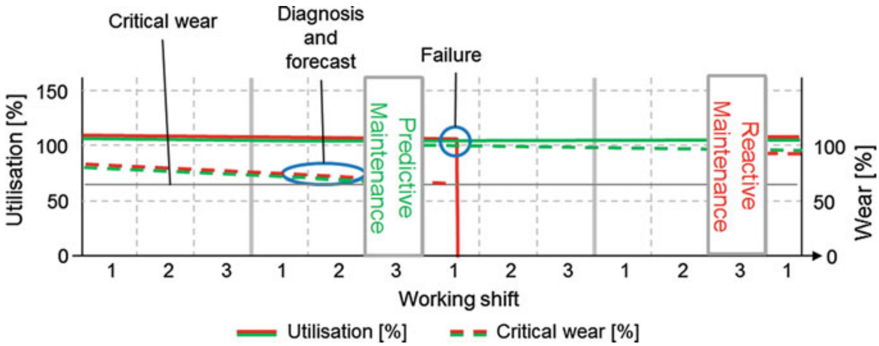

Fig. 1 Predictive maintenance principle [1]

For massive forming machines, these diagnoses are far more difficult to make. Many of the parameters used for conventional condition monitoring can be affected or superimposed by ambient and process influences, e.g.:

Vibrations in and around the machine that are superimposed e.g. by vibrations due to bearing wear during the forming process on mechanical closed-die forging presses.

Particularly during hot forming, temperature measurements can also be influenced by the heated workpiece.

Soiling of the plants caused by separating agents or scale.

These exemplary ambient and process influences result in a significant limitation on the validity of the condition monitoring. As a result, optimum use is not made of the wear allowances of critical components and assemblies, with the following negative impacts on the overall plant efficiency:

Downtimes
Quality issues
Maintenance schedules too short or too long

3.3 Target

The target for this subproject is to improve the overall equipment effectiveness (OEE) by using predictive maintenance for the production plants. For the two demonstrator plants, predictive models are to be developed in cooperation between Engineering and operative experts from plant manufacturers and plant operators that enable predictions of availability-limiting events to be made. These are then to be used to improve the availability of the plants.

Networking of the various sub-projects and the associated exchange of information, e.g. on the tool condition and the part quality, should then help to enhance the validity of the predictive models.

3.4 Innovation

The main innovation of the sub-project does not lie in the area of the measurement data acquisition. This lies in the development of a specific predictive model for the predictive maintenance of massive forming machines that includes the largest possible number of condition parameters.

The results of this sub-project are as follows:

1. **Holistic measurement concept** for early indication of part and assembly damage for massive forming machines in two representative production lines in the plants of the application partners.
2. **Prediction model** derived from the measurement concept for forecasting unscheduled standstills, e.g. on the basis of remaining wear allowances.
3. **Optimised maintenance measures** for massive forming machines to sustain the plant availability (e.g. time, scope, optimum use of wear allowance, etc.).

3.5 Practical Application

During the preliminary work on predictive maintenance outside the field of massive forming, not only innovative measuring methods such as video motion amplification, but also classic measuring methods were used.

Torques
Vibrations
Temperature
Forces
Oil flow, particles and viscosity,

For a closed-die forging press, the set-up for data collection and analysis planned for this project is shown in Fig. 2.

The SMS Genius Condition Monitoring system is integrated into the forging press for this purpose. This receives values out of the PLC system, signals from sensors already installed and additional installed sensors according to the demands are defined for the early indicators for the failure of availability-critical components and assemblies. The Genius CM System can be linked to an MES/ ERP system on site.

Working principle of Genius Condition Monitoring

The Genius CM is based on an independent software solution that has been successfully invented by the SMS group. It all starts with Genius CM recording your plant's process data and sensor signals. This information goes into the analysis of the actual component status. Out of this comes a perfect picture of the process-dependent conditions which the system can clearly display.

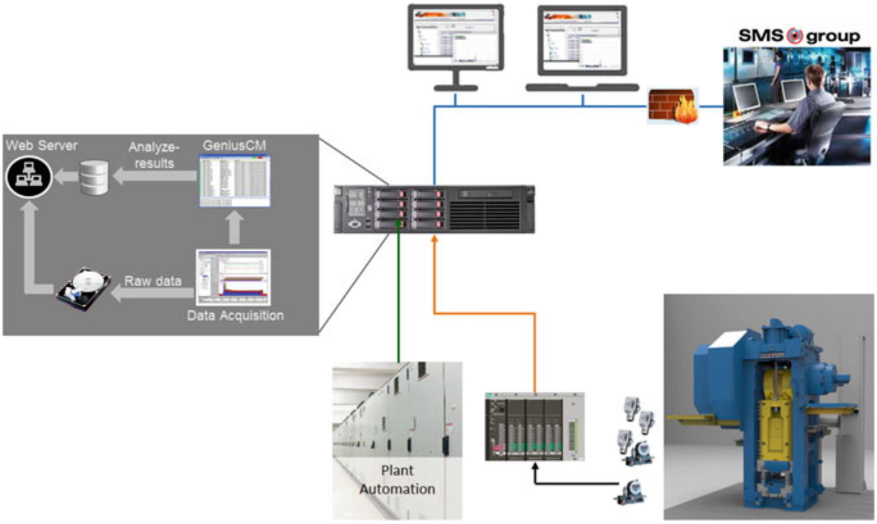

Fig. 2 Example setup for an closed-die forging press [2]

Unique to Genius CM is its modular design so the user can tailor the configuration that he needs. There are field units he can use for online data capture on site. That provides for scalability and problem-free expansion. The system monitors a large number of critical or at-risk components simultaneously.

Condition Evaluation

After collection the data of all different kind of signals the correct conclusions have to be made. For reasons that some damages can occur very quickly, an online evaluation which represents the current status of the components in real time is essential. In addition, the process- oriented evaluation offers the possibility to record dependencies and effects between production parameters and system state (Figs. 3 and 4).

In order to develop a specific predictive model for the predictive maintenance of a massive forming machine, the implementation model shown in Fig. 5 will be applied.

3.6 Conclusion

A forecast model for optimization of the massive forming machine OEE has a beneficial impact for a sustainable asset management and to improve the competitiveness not only in the area of the massive forming industry.

The major challenge of this project is to link all relevant influencing systems inside and outside of a massive forming company as basis for a smart factory. Due

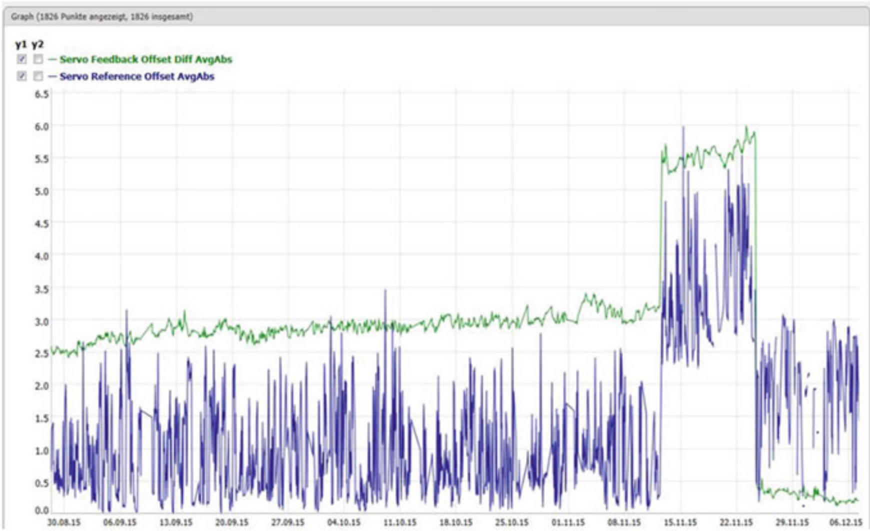

Fig. 3 Online evaluation [2]

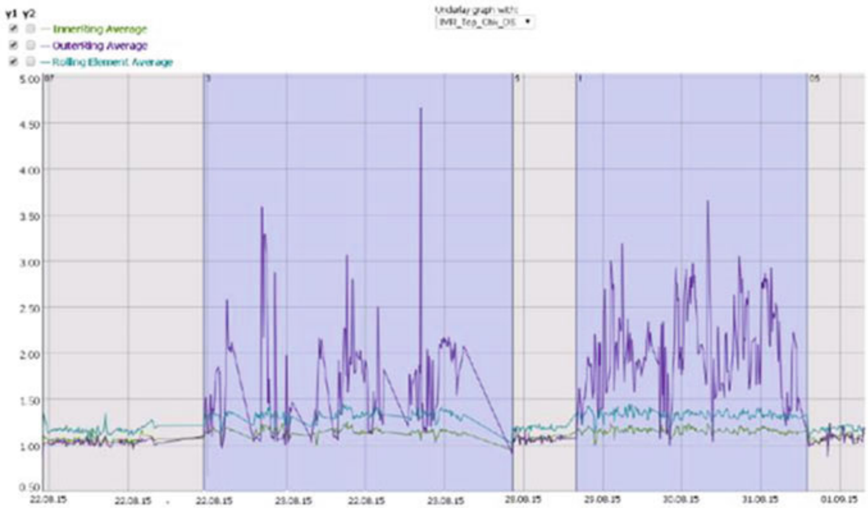

Fig. 4 Process oriented evaluation [2]

to the integration of digital networking of the whole value-added chain a big amount of data will be collected and analysed. The data from complex production facilities can be recorded, saved, processed and analysed in order to boost the

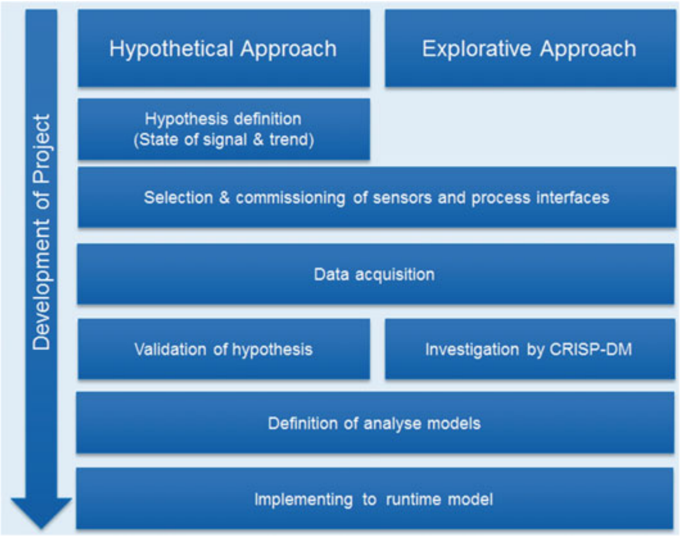

Fig. 5 Implementation model [2]

overall plant efficiency through interdisciplinary cooperation between plant owner, plant manufacturer, cloud operator, software producer and science.

During the early project phase it became obvious that the bilateral interaction of the involved scientific institutions and industry partners as well as a clearly structured appliance is of paramount importance for a successful project.

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