THERMOFORMING OF LOAD-PATH-OPTIMISED, RECYCLED THERMOPLASTIC COMPOSITES: DEVELOPMENT OF AN AI-SUPPORTED EMITTER TECHNOLOGY AND PROCESS EVALUATION

Matthias Froning[1], Maximilian Backenstos[2], Lisa Richter[2], Mesut Cetin[1,3], Thomas Gries[4]

[1]Institut für Textiltechnik Augsburg gGmbH,
Am Technologiezentrum 5, DEU-86159 Augsburg, Germany
Email: mf@ita-augsburg.de, mc@ita-augsburg.de, web page: www.ita-augsburg.com

[2]DatenBerg GmbH, Haid-und-Neu-Straße 7, DEU-76131 Karlsruhe, Germany
Email: maximilian.backenstos@datenberg.eu, lisa.richter@datenberg.eu,
web page: www. Datenberg.eu

[3]Technische Hochschule Augsburg, An der Hochschule 1, DEU-86161 Augsburg, Germany
Email: mesut.cetin@tha.de, web page: www.tha.de

[4]Institut für Textiltechnik of RWTH Aachen University,
Otto-Blumenthal-Straße 1, DEU-52074 Aachen, Germany
Email: thomas.gries@ita.rwth-aachen.de, web page: www.ita.rwth-aachen.de

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ABSTRACT

The hybrid moulding process is a combination of thermoforming and injection moulding. It enables the fully automated production of highly integrated, ready-to-install lightweight structural components based on organo-sheet semi-finished products and therefore fulfils the prerequisites for a high-volume, economical production process for lightweight components.

The paper describes the development of an emitter technology that processes modern, load-path-compatible tailored organo-sheets in which the mass utilisation in the component has been optimised. Tailored organo-sheets in particular offer the possibility of CO_2 savings through resource efficiency and substitution. By developing a high-resolution radiator field, the tailored organo-sheets can be heated homogeneously with a discontinuous wall thickness. The high-resolution radiator field is controlled via an AI-supported control system. This simplifies product changeovers and assembly work can be reduced thanks to the universal emitter field. The explanatory AI also helps to build up an understanding of the process. This increases the efficiency and flexibility of the process.

As part of a process evaluation, the influence of the developed emitter technology on the quality of the heating process, cycle times and energy efficiency will be analysed in detail. Specific key figures such as the temperature homogeneity within the organo-sheets, the heating rate and the thermal efficiency are recorded and analysed. The evaluation shows how the combination of optimised emitter technology and AI control contributes to the development of a robust, energy-efficient and high-quality thermoforming process.

1 INTRODUCTION

In the following paper, the CRISP-DM method is used as a structured framework to systematically accompany the development and evaluation of an AI-supported control system for the thermoforming process. The method is divided into six successive phases (figure 1). It begins with business understanding, in which the overarching objectives are analyzed from an application-related perspective and translated into a data-based problem definition. This is followed by Data Understanding, in which available data is collected and examined in terms of quality, structure and information content. In the Data Preparation phase, the raw data is converted into a format suitable for modeling through selection, transformation and cleansing. This is followed by the Modeling phase, in which suitable algorithms are selected, parameterized and applied to the prepared data. This is followed by the Evaluation phase, in which the quality of the model is checked with regard to the original objectives and the procedure is critically reflected upon. Finally, the Deployment phase involves transferring the developed solution to the practical application context, for example by integrating it into existing systems or by creating usable results for the end user. [1]

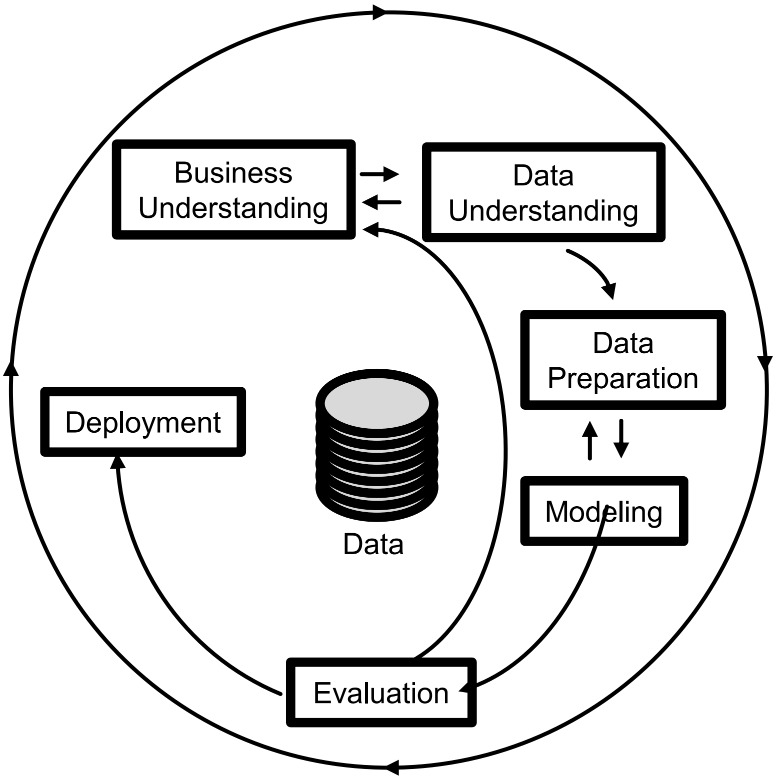

Figure 1: The six phases of the CRISP-DM method [1]

2 BUSINESS UNDERSTANDING

For ecological and economic reasons, the reduction of CO_2 emissions is a key objective in industrial production. In the context of the hybrid molding process (Figure 2), tailored organo sheets offer a promising approach to support this goal through resource-efficient lightweight construction. These are fiber-reinforced thermoplastics with specifically varied wall thicknesses or locally differentiated fiber reinforcement. This material optimization enables needs-based reinforcement along the load paths while reducing the amount of material used and thus the carbon footprint. These tailor-made semi-finished products are processed using the hybrid molding process, which combines thermoforming and injection molding and enables the highly automated production of functionally integrated lightweight components.

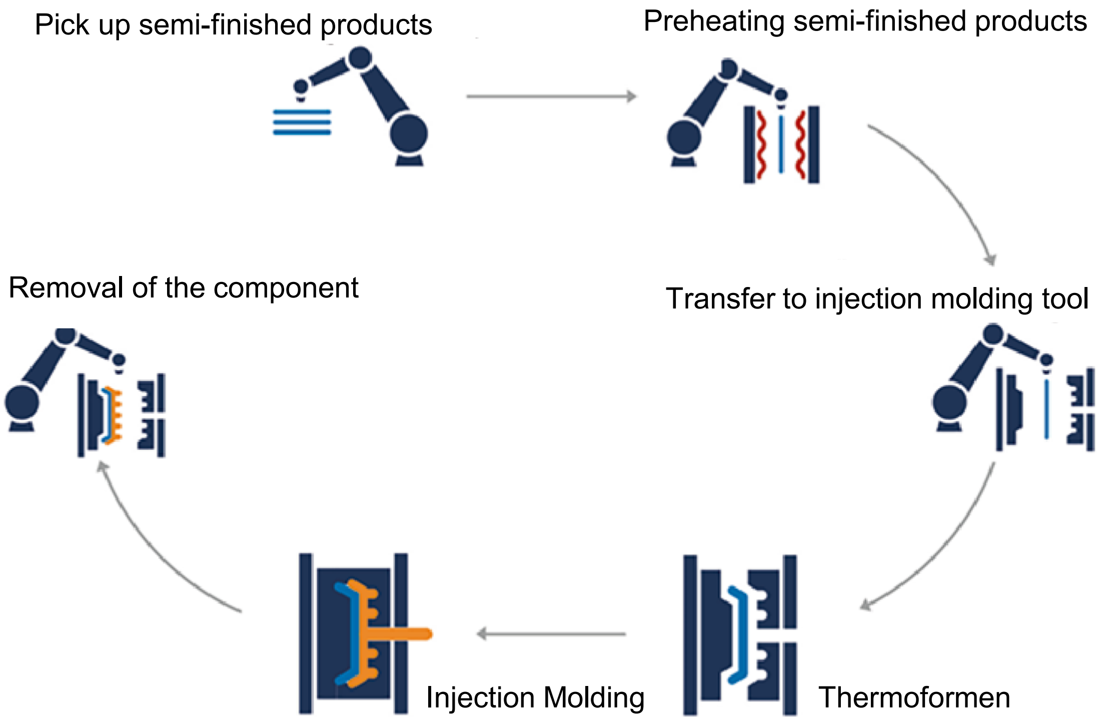

Figure 2: Process steps of the hybrid molding process [2]

However, the processing of such complex semi-finished products requires precise and locally adapted heating. The current state of the art uses large-area infrared emitters, which cannot ensure homogeneous temperature distribution in tailored organo sheets due to their low spatial resolution. This leads to local overheating or underheating and thus to quality losses in the subsequent thermoforming process. In order to make the quality of the heating process visible, a thermal imaging camera is used to analyze and evaluate the temperature distribution on the surface of the semi-finished products.

The solution presented here is based on a high-resolution infrared radiator field consisting of a large number of compact spot heaters. The resulting heating field resolution exceeds conventional systems by a factor of 25 (Figure 3). Due to the large number of individual emitters, manual parameterization is not practicable. Therefore, an automated, AI-supported power distribution is being developed with the aim of ensuring uniform temperature distribution in the semi-finished product. This uniform heating is the prerequisite for a reproducible and tool-friendly thermoforming process.

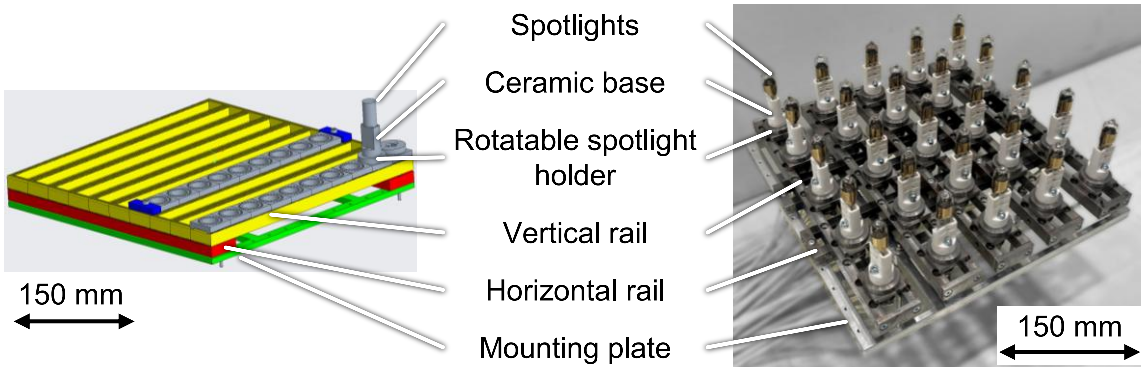

Figure 3: The high-resolution radiator field as a CAD model (left) and real image (right)

The main users of the technology are machine operators who monitor the process. As this is a further development of existing system concepts, existing interfaces must be taken into account and simple integration into established control systems must be made possible.

3 DATA UNDERSTANDING

Various data sources, including both process and sensor data, were used to develop and validate the AI-supported heating concept. The central data basis is an infrared camera that provides thermal images of the tailored organo sheet in the form of CSV files (Figure 4). These images are taken immediately after passing through the radiator field, but before insertion into the forming tool. This positioning allows potential disturbance variables that occur during transportation from the furnace to the tool (e.g. convection influences or temperature fluctuations due to radiation) to be recorded and taken into account in the analysis.

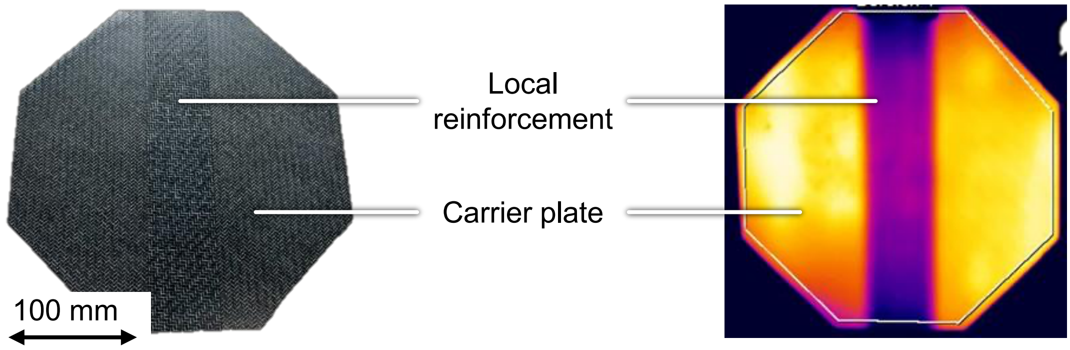

Figure 4: Tailored Organo Sheet as real image (left) and in IR image (right)

In addition to thermographic detection, non-contact temperature measurement is carried out during the heating process in the oven using a pyrometer, which is integrated into a classic control system on a PLC (Figure 5). The individual emitters are controlled via pulse width modulation, with the relative duty cycle within a network phase serving as the control variable. The control system accesses a material-specific database that contains setpoints, maximum temperatures and upper and lower specification limits for the respective organic sheet material.

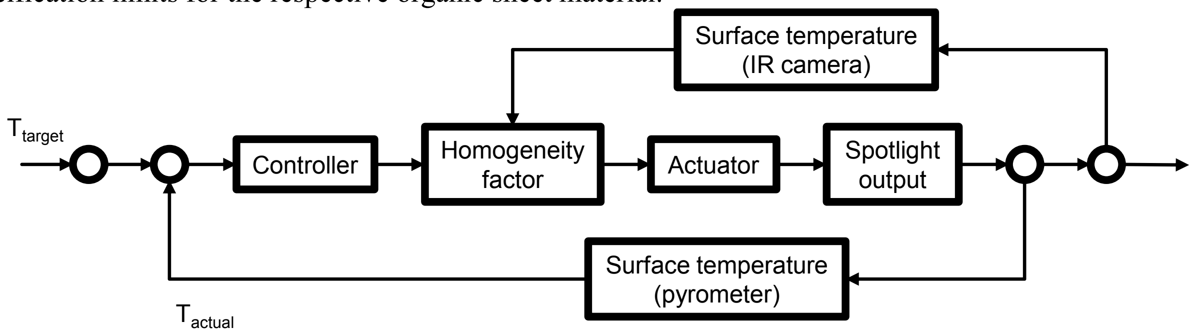

Figure 5: Controller architecture

Based on the evaluation of the thermal image data, a maximum switch-on time for the following heating cycle is specified for each spot heater via an OPC UA interface. This indirect control leads to a system-related latency between temperature detection and power adjustment, which must be taken into account when allocating data over time.

The data is collected using an adapted test setup based on a conventional IR oven, which has been expanded to include the newly developed high-resolution radiation field and thermographic measurement technology. To reduce material consumption and increase reproducibility, the heating process is carried out several times on one and the same tailored organo sheet (PA matrix with glass fiber reinforcement). The target temperature is limited to 100 °C in order to ensure thermal stress below the melting point. A defined cooling time of ten minutes is maintained between the heating cycles to ensure identical initial conditions.

Another technical aspect concerns the power supply: Due to high switch-on currents with cold infrared radiators, there is a risk of overloading the fuses. For this reason, a cascaded switch-on procedure was implemented as part of the project, which staggers the switch-on times of individual emitters and thus enables stable operation.

The analysis of the data obtained shows a high degree of variance in the temperature distribution, particularly in areas with variable wall thickness. This heterogeneity forms the starting point for the subsequent development of a model for targeted radiator power distribution.

4 DATA PREPARATION

The central data source for modeling is the thermal image of the heated organic sheet. This is available in CSV format for each heating cycle and contains the temperature values as a pixel matrix. A threshold value method is used to separate the relevant image areas (organosheet) from the background: All pixels with temperatures above a defined threshold value are assigned to the organosheet, while pixels below this value are classified as background and excluded from further analysis. This procedure makes it possible to dispense with the product-dependent transfer of geometry information (e.g. CAD files or wall thickness curves), which simplifies system integration and increases generalizability.

To quantitatively evaluate the temperature distribution in the heated semi-finished product, the standard deviation of the temperature values within the detected component area is calculated for each image. This key figure serves as a direct measure of the homogeneity of the heating and at the same time forms the target value for the optimization model.

The data was collected as part of a systematically planned experimental setup in which the duty cycles of selected heaters were varied according to a design-of-experiment (DoE). This created a controlled variation of the heating power with the aim of investigating its influence on the resulting temperature distribution. Missing or incorrect data sets, for example due to software crashes of the IR camera, were replaced as far as possible by repeating the affected experiment. These measures made it possible to create a consistent and complete data basis for the subsequent modeling.

5 MODELING

The modeling phase comprises three consecutive steps, each of which maps specific aspects of the heating process and is linked together to enable precise prediction and optimization of the temperature distribution in the organic sheet.

In the first step, a regression-based model is set up that describes the relationship between individual radiators and their local temperature influence on the surface of the component (Figure 6). This model is furnace-specific and was determined on a reference organo sheet without local reinforcement structures. For each emitter, the extent to which its power contributes to the temperature increase in defined areas of the thermographic image is quantified. To ensure sufficient model accuracy, at least one test run is required for each emitter used. By spatially limiting the potential influence zones based on the results of this step, the test effort can be significantly reduced in the second step.

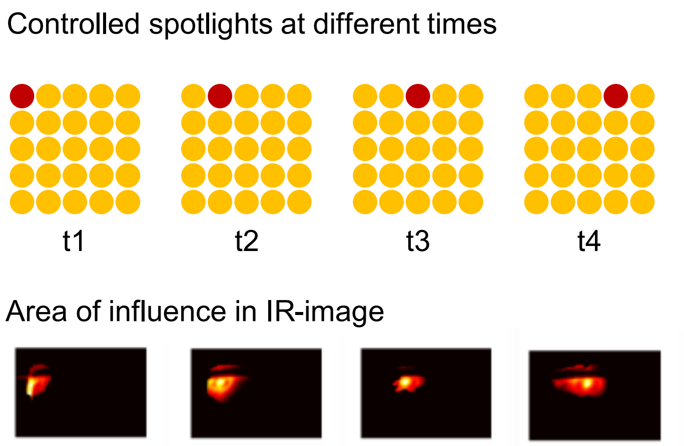

Figure 6: Correlation between emitter and IR image

The second step involves modeling the organic sheet itself. The aim is to map the thermal reaction patterns of the semi-finished product as a function of geometry, wall thickness distribution and material behavior. Based on the radiator influence model learned in the first step, a simulation can be created that predicts a complete thermal image of the component from a given radiator switch-on scenario (Figure 7). This simulated thermography serves as the basis for subsequent optimization.

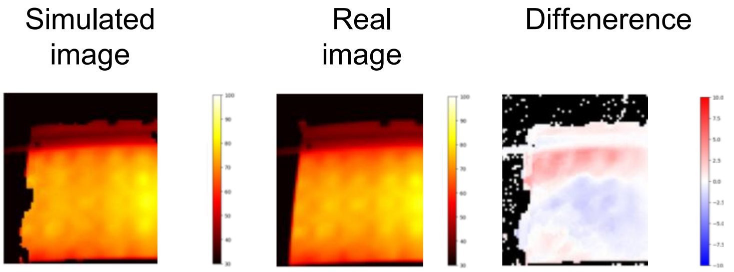

Figure 7: Comparison of simulated IR image and real recorded IR image based on the emitter parameters

In the third step, the radiator power distribution is optimized with the aim of achieving the most homogeneous temperature distribution possible across the component surface. The standard deviation of the temperature distribution within the detected organic sheet serves as the target value. A genetic algorithm is used for optimization, which strives for a global solution in the high-dimensional parameter space by iteratively varying the radiator switch-on times. The use of a simulation-based prediction model makes it possible to carry out this optimization process efficiently and in a material-friendly manner without having to carry out large-scale real test series.

This three-stage model structure allows both the physical properties of the system and data-based correlations to be taken into account. At the same time, it ensures that the final model combines high forecasting quality with realistic feasibility in process control.

6 EVALUATION

A pilot production was carried out to validate the developed model architecture. A cruiser skateboard was used as a demonstrator, which is provided with targeted local reinforcement in the area between the axles. This constructive measure enables a weight-saving design of the component and at the same time places increased demands on temperature homogeneity during the heating process. Different material systems were used to evaluate the generalizability: a laminate consisting of an organic sheet with a unidirectional tape made of hemp and polypropylene as well as another laminate based on glass fibre and polyamide. The geometry remained constant so that the influence of the material properties on the temperature behavior could be analyzed in isolation.

To validate the model, the simulated temperature image generated by the genetic algorithm was compared with real thermal images. Table 1 shows examples of the deviations between simulated and measured data based on the parameters mean value, standard deviation, minimum and maximum temperature. The differences are less than 1 K in all cases, with the mean temperature deviation being only 0.39 K. The standard deviation is particularly relevant as a target value for optimization: with a difference of only 0.83 K, there is a good match between simulation and real behavior.

Table 1: Comparison of characteristic values based on simulated and real IR images

	Average [°C]	Standard deviation [K]	Minimum [°C]	Maximum [°C]
Simulated image	70,42	4,95	50,64	78,13
Real image	70,03	5,78	50,10	79,00
Difference	0,39	0,83	0,54	0,87

An interactive dashboard was used in the pilot environment to make the model decisions comprehensible for the operating personnel and to increase practical suitability (Figure 8). This visualizes the resulting spotlight settings and enables the machine operator to understand and manually adjust the suggestions. As a result, the human operator retains the decision-making authority and a human-in-the-loop approach is implemented, which both creates trust in the AI application and increases process reliability.

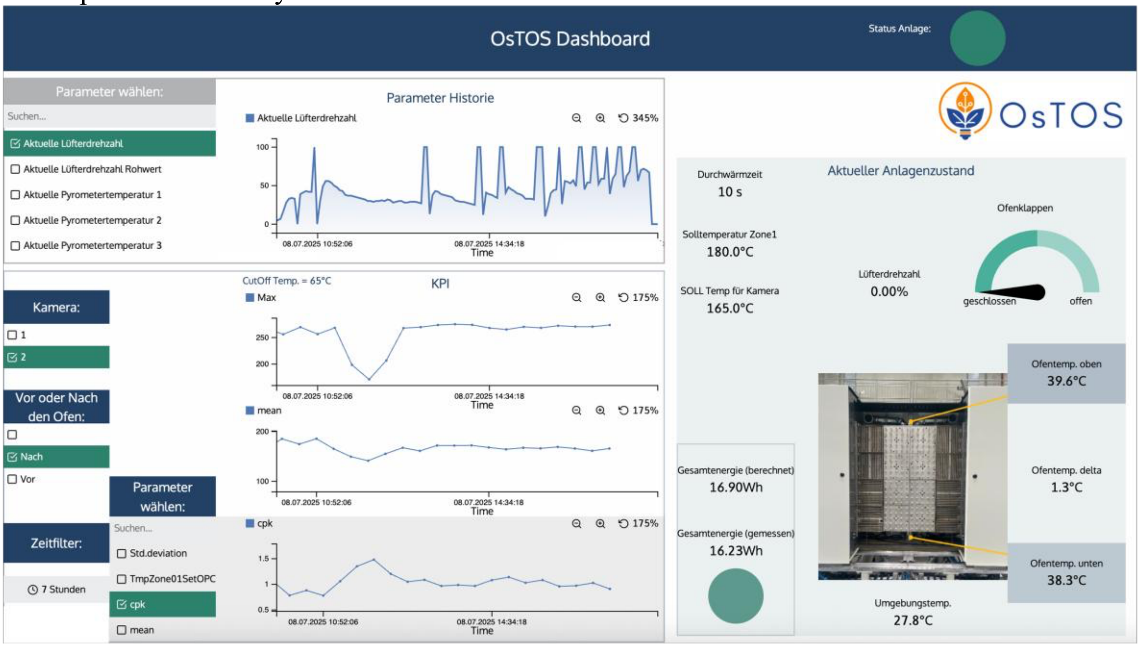

Figure 8: Dashboard for process visualization

The evaluation confirms that the model is able to predict the desired temperature distribution with high accuracy and thus fulfills the objective of developing a robust, AI-supported control concept for homogeneous heating of tailored organo sheets. In addition, the tested solution enables material-specific adaptation without the need for changes to the model structure. This ensures practical applicability in varying industrial scenarios.

7 DEPLOYMENT

The thermographic images are evaluated on an external industrial PC, which communicates with the machine control system via a standardized OPC UA interface. The AI model is executed cyclically in the production process: For each heating cycle, the relevant process data, in particular the individual duty cycles of the spot heaters, are buffered in the PLC and used for control in the following cycle. This buffered procedure allows the system to react continuously without jeopardizing the real-time capability of the control system.

The system architecture is designed in such a way that the operator can actively intervene in the process at any time. The dashboard already used in the evaluation context will continue to be used during operation. It is used to visually display the control suggestions generated by the model, to make them comprehensible and to modify them manually if necessary. In this way, humans remain an integral part of the control loop, in the sense of a human-in-the-loop approach that combines automation with operational responsibility and strengthens trust in AI-supported processes.

The deployment is currently in the final implementation phase. Initial integration tests have demonstrated the functionality of the communication and control chain as well as the practicality of the model-based control system. Specially designed demonstrator tailored organo sheets were manufactured in order to further test the generalizability and resilience of the system under realistic conditions. These consist of high-temperature resistant PAEK with carbon fiber reinforcement. (Figure

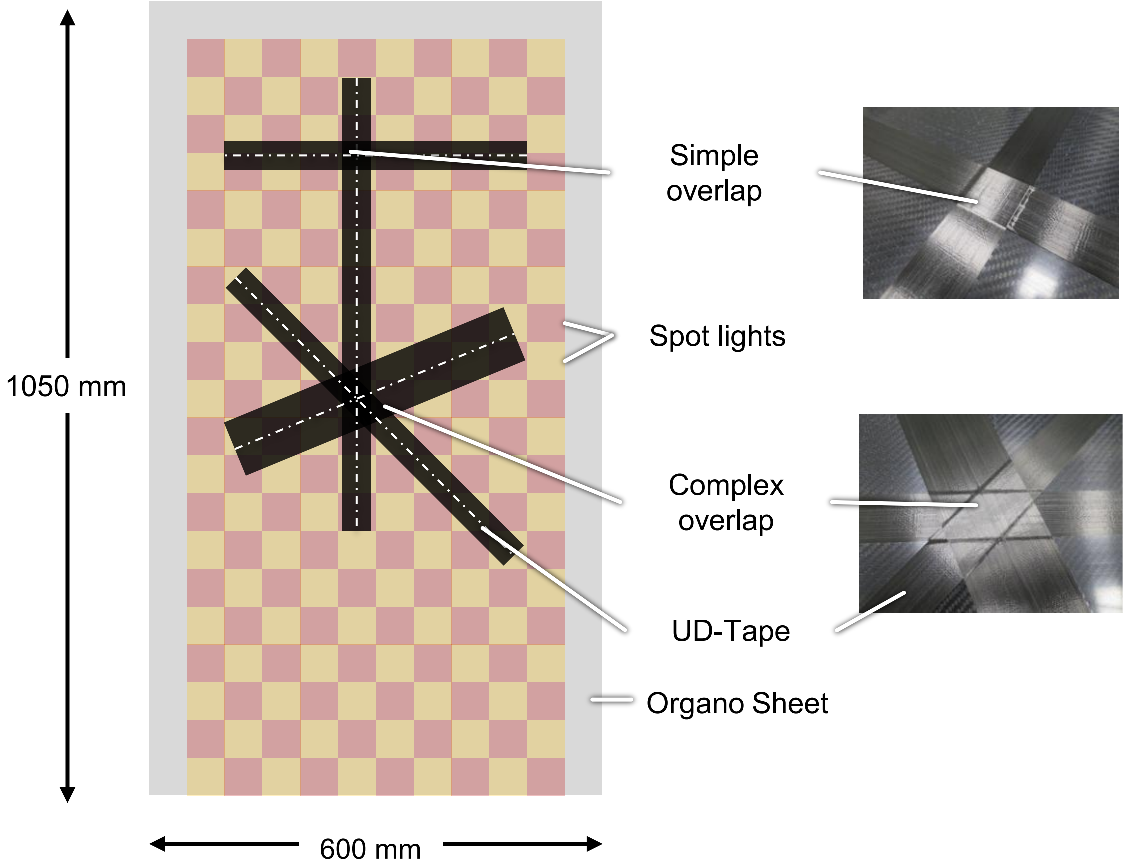

Figure 9: Tailored Organo Sheet Demonstrator with different UD-Tape reinforcements

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PtJ Projektträger Jülich Forschungszentrum Jülich

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