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# Machine learning-based predictions of form accuracy for curved thin glass by vacuum assisted hot forming process

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*Abstract* – **Thin glass is applied in numerous applications, appearing as three-dimensional smartphone covers, displays, and in thin batteries. Nonisothermal glass molding has been developed as a hot forming technology that enables to fulfil demands of high quality yet low-cost production. However, finding optimal parameters to a new product variant or glass material is highly demanding. Accordingly, manufacturers are striving for efficient and agile solutions that enable quick adaptations to the process. In this work, we demonstrate that machine learning (ML) can be utilized as a robust and reliable approach. ML-models capable of predicting form shapes of thin glass produced by vacuum-assisted glass molding were developed. Three types of input data were considered: set parameters, sensor values as time series, and thermographic in-process images of products. Different ML-algorithms were implemented, evaluated, and compared to reveal random forest and gradient boosting regressors as best performing on the first frame of the thermographic images.**

***Keywords – Machine Learning, Vacuum Assisted Hot Forming, Predictive Quality, Resilient Manufacturing Thin Glass, Nonisothermal Glass Molding.***

## I. INTRODUCTION

Thin glass is finding its way more and more often into numerous applications, particularly appearing in automotive and electronics industries in recent years. Three-dimensional (3D) smartphones, displays, and thin batteries require curved thin glass covers [1]. Concept cars of the future are pursuing thin glass as alternative material solutions to increase fuel efficiency by reducing the weight of automobiles, and for autonomous and connected mobility [2]. Although thin glass products promise lucrative opportunities, glass manufacturers are still struggling to meet the ever-increasing demands of glass processing towards complex 3D curved shapes, ultra precise surface finishes, high form accuracy, yet low-cost production [3]. Over the years, the fulfilment of the technical specifications in the manufacture of glass products was mainly achieved using serial machining steps consisting of grinding and polishing [4]. However, manufacturers fail to fabricate thin glass components with this technique due to the mandatory mechanical clamping that commonly leads to glass breakage. For machining thin glass components, grinding and polishing steps remove a lot of raw material, causing a large amount of material waste, high energy consumption, and long processing times. Therefore, the conventional grinding and polishing processes are not feasible for mass producing thin glass.

In recent years, the so-called Nonisothermal Glass Molding (NGM) process has been developed, allowing the fulfilment of technical specifications in terms of complex shapes (e.g., freeform) and precision requirements while enabling low-cost products. NGM is a replicative manufacturing process based on the nonisothermal concept, i.e., the temperatures of glass and molding tools are different. The NGM process has demonstrated itself a viable technology for the cost-efficient production, where time required for producing a molded glass lens takes only up to a few seconds [5]. In order to enable thin glass molding, further technological enhancement has been achieved by incorporating vacuum during the hot forming process [6]. The so-called vacuum-assisted thin glass molding process further promises an innovative method for producing thin glass components with increasing shape complexity and form accuracy in a cost-efficient manner.

One of the key challenges for the glass optic manufacturers is the prerequisite of parameters that enable the NGM process to satisfy the high form accuracy of glass products (typically below two-digit micrometers) and to minimize the cycle time. In fact, the NGM process consists of three general stages, which are heating, molding, and cooling, each characterized by multiple process parameters. The parameters are highly interdependent making the optimization of the NGM process extremely challenging. Traditional trial-and-error approaches to determine optimal parameters require many iterative experiments. To reduce the number of experiments and its associated costs, process optimization is conducted using numerical simulations. Nevertheless, simulation accuracy greatly depends on the modeling of glass material behaviors, which proves to be complex at the molding temperature due to its thermo-viscoelastic response [7]. The calibration of unknown parameters for process modeling such as heat transfer coefficients during heating and molding, or structural shrinkage behaviors of glass during cooling are additional challenges [8]. Furthermore, these factors are not universal, meaning that the calibration process needs to be repeated with respect to any change of molding conditions or glass materials.

Accordingly, glass optic manufacturers are striving for a more efficient and agile solution that can be used to quickly adapt the molding process to a new product variant, such as a new shape design, or a change in glass material for the same product design. In this paper, we demonstrate that machine learning (ML) can be utilized as a robust and reliable approach for accelerating the process development and production ramp-up phases in glass optic manufacturing. It has been shown that ML for optimizing processes with the help of predictive quality models achieves good results for a wide range of production processes [9,10]. However, apart from [3,11,12], no ML models for predicting quality have been presented in the literature for the NGM process. We demonstrate the prediction quality of ML-Models capable of predicting form shapes of thin glass produced by vacuum-assisted glass molding by using different types of input data. Image data from a thermographic camera, time series data from machine sensors, and machine control parameters are used individually.

## II. EXPERIMENTAL DETAILS

For this study, we selected a simple glass mirror as the demonstration product. The glass thickness was chosen as 0.7 mm and 2.0 mm, which are common standard thicknesses. We conducted 128 experiments in total based on combining all possible changes of input process parameters. The resulting ML-Models were built for predicting the form shape of the second demonstrator – a head-up-display – which is a common interior component of today's automobiles. The experimental procedure and setup of the used forming machine, mold holder unit and mold are presented in the following.

### *A. Experimental Procedure*

The glass molding process requires the heating of the glass preform until it reaches a sufficiently low viscosity. Once this condition is met, glass can be formed into the molding tool by help of mechanical forces. In the context of vacuum-assisted slumping the used mechanical force is a negative pressure between glass specimen and mold cavity. The process chain of the experimental procedure is shown in the top half of Figure 1. The process starts with the loading of a glass preform onto the molding tool. Subsequently, the molding tool and glass preform are moved into the furnace by X-axis and Z-axis movement, where they are exposed to radiant heat. During the homogenizing phase a stable temperature distribution within mold tool and glass is reached. Afterwards the molding tool and glass are moved out of the heating furnace and forming is conducted. During the forming step a proportional valve is opened to alter the intensity of the vacuum pressure. This process is controlled and monitored by flow meters and pressure sensors. Subsequently, the glass is cooled rapidly on the mold tool below the glass transformation temperature and then unloaded. The final process step is annealing, performed in an external furnace in order to release the internal stress developed within the molded glass during the forming step.

The process can be regarded as a black box with limited visual observability - especially during heating,

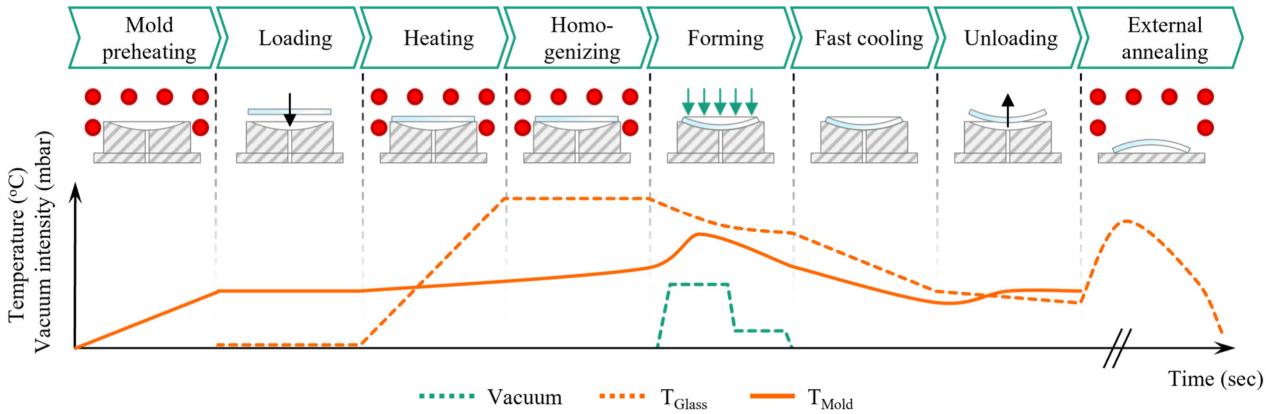


*Fig. 1. Vacuum-assisted thin glass molding process chain variant of the (NGM) process*

homogenizing, and forming within the furnace. For this reason, both mold and glass temperatures are measured with the help of a thermo-camera and pyrometer after the loading and before annealing. Additionally, thermocouples, flow meter and pressure sensors were fitted to the machine. The furnace set temperature and the heating time are assumed to be highly significant due to the extensive experience gained from pressing processes conducted in the past [5]. Based on temperature calibration measurements inside the furnace, a non-systematic error of the furnace's actual temperature in the range of +/-20 °C has been investigated. For this reason, the range of temperature was set rather high at 100 °C to reduce the impact of noise in respect to the range. The mean temperature of 900 °C was defined based on previously conducted pretest and simulative studies. The mean heating time was set to 130 s, as it is believed that the temperature profile within glass and mold would have reached a quasistatic state. This was later confirmed by simulative investigations.

Furthermore, the vacuum duration and the opening degree of the proportional valve are assumed to be significant, since the stresses and their time courses are part of the Maxwell equation, which is used to describe the viscoelastic material behavior of glass [13]. With the defined studying range of the opening angle of the proportional valve, a negative pressure ranging from 0 up to 300 mbar was investigated.

All parameters were systematically varied and investigated in a centrally composed experimental design using RSM (Response Surface Methodology). During the experiments the parameters were systematically changed with two repitions each, as shown in Table 1.

*Table 1. Set Parameters*

| Parameter | Range | Increment |
|---|---|---|
| Furnace temperature | 900 °C +/- 50 °C | 25 °C |
| Heating time | 130 s +/- 20 s | 10 s |
| Vacuum duration | 7.5 s +/- 2.5 s | 1.25 s |
| Opening angle of proportional valve | 10% +/- 10% | 5 % |
| Glass thickness | 0.7 mm / 2.0 mm | - |

### *B. Forming Machine*

A glass press is used for the tests. The basic structure of the machine is made up of three pillars which, together with a traverse, form the press frame. This machine is characterized by a high degree of flexibility since all axes of motion and heating devices can be programmed independently. The lower linear axis X1 and the lower vertical axis Z1 are used to generate the motion sequences required for the tests. The Fraunhofer IPT made extensive modifications to the machine, one of which was the addition of a fully automated solution for recording all sensor and actuator signals [12]. Furthermore, extensions were made to the machine with regard to vacuum technology, as well as enabling bending and deep-drawing processes.

### *C. Forming Tool*

The mold, together with the heating equipment, is essential for carrying out the tests. It is mounted on a mold holder. The mold consists of a rotationally symmetrical base body. Due to the high operating temperatures, stainless steel resistant up to 700 °C was used for the mold material. The optical functional surface forms a spherical section with a radius of 150 mm and an opening diameter of 68.8 mm. The choice of this geometry ensures that the specimens can be evaluated after forming using a wide range of measuring equipment. In the center of the cavity there is a micro-eroded hole through which a vacuum can be established under the glass. Furthermore, it is believed that by using a single vacuum bore as opposed to a plurality of vacuum bores, the first-order shape error is larger and therefore can be more easily detected by measurements.

Type K thermocouples are used for thermal measurement of the mold and are placed closely to the optical surface of the mold tool. The vacuum in the mold is created by means of an ejector and can be systematically changed with the help of a proportional valve. The quality of the vacuum is monitored by a pressure sensor and two flow meters with different measuring ranges.

### *D. Heating Devices*

The main heating device is a so-called furnace room. This is a body closed from five sides, heating the inner compartment. The temperature distribution of the heating chamber is of great importance for process development and for defining the limits of the test parameters.

## III. DESCRIPTION OF THE METHOD

The methodological approach is strongly oriented towards [14] and is further inspired by the process steps defined in the CRISP-DM [15]. First, the input data - set parameters, sensor data, image data - are collected from the various sources and integrated. In addition, the target data - form shape measurements - are recorded and processed. These are then pre-processed so that a high-quality database can be optimally used for the subsequent training, validation and testing of the models. For the models, the selection of ML algorithms focusses on regression learning algorithms to predict the form shape. Finally, the models are evaluated and compared with each other. In the following, the detailed steps of model building for the three different inputs are listed.

### A. Data Acquisition and Integration

During the forming experiments, three types of production data were collected and used as inputs to the machine learning model. The first data type comprised of set parameters, which were the values predefined before each experiment and controlled by the machine settings during the forming process. A total of five different constant or scalar parameters were recorded (see Table 1). In contrast, the second type was the real-time measuring data recorded by 114 sensors equipped within the molding machine. Such types of time-series inputs were expected to provide more details of the machine- and process behaviors throughout the entire experiment so that impacts on the form accuracy of the molded glass can be observed clearly. The sensor data was extracted from the machine with an individual sampling frequency between 1 Hz to 25 Hz and stored within a database. The third type is the image data collected in process from a thermographic camera. A video sequence of 300 frames corresponding to 10 seconds of recording time was carried out to gain the surface temperature of glass and mold components for each experiment. Figure 2 shows an example of an image frame recorded at the start of the video sequence.

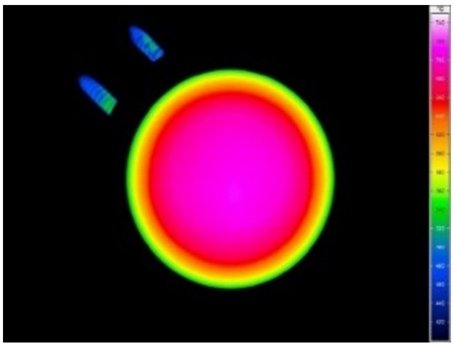

*Fig.2. First frame recorded by the thermographic camera*

The target data refers to the final shape used to quantify the form accuracy of the molded glass components. The molded glass components were measured on the side facing the molding tool at the end of the forming process. A tactile form profilometer from Taylor Hobson was used to measure the glass shape. The acquired data, which was integrated into a single database. In the database the experimental meta data is used to structure the information and to ensure the traceability of the hot formed samples to the production data.

### B. Data Preprocessing

The methodology for a data preprocessing pipeline proposed by [16] was followed. Goal of the data preprocessing was to gain a dataset with high data quality. Hence, time series data as well as image data needed extensive preprocessing and feature extraction.

First, the input data was extracted from the database into .csv files for preprocessing. The set parameters needed the least preprocessing since the scalar values were without error after checking their initial data quality. For integration with a machine learning algorithm's data loading stage, the set parameter table was restructured.

In contrast, the data quality check of the time series data revealed that the sensor data needed more preprocessing. First, data from inactive sensors were removed, leaving the following complications:

The time stamps were recorded independently for the sensors. Synchronization between the sensors was performed. Furthermore, due to complications with the machine controls, the sampling frequency of the sensor values was not constant. However, the amount of recorded data points was correct. Therefore, a rearrangement of the data points according to its respective sampling frequency was performed. Since the sensors had different sampling frequencies, missing values of sensors with lower frequency were filled using interpolation. This might generate noise in the data or interfere with relevant process information. Additionally, data from certain process steps like loading were irrelevant for the analysis. For instance, the pressure and flow sensors recorded useful information only after the glass deformation started, otherwise containing only noise. This data cannot be integrated with data from sensors, which record useful information across a wider range of stages, for example the temperature sensors. Finally, errors in values were individually removed that were caused by defective sensors. The removed values were replaced by interpolation.

Moreover, to utilize the sensor data efficiently and the consequent computational resources, feature extraction was applied in the next step. It is essential to infer which parts of the time-series data may contain significant impacts on the product quality, and to break down the time-series into a set of scalar features.

Finally, to make the image data from the thermographic camera usable for regression algorithms, the data was preprocessed, and features were extracted. First, an edge detection algorithm was applied to find the circular edges of the glass specimen in the image. The temperature profile vectors along the diameter of the glass were then calculated for each experiment and reduced to a length of 100 points by cubic spline interpolation.

The target data was obtained using the profilometer. A needle of the measuring device passes through a calibrated direction of the diameter of the glass. The measurement is then repeated along a perpendicular diameter by rotating the measuring bed by 90 degrees. Hence, for each experiment, two form vectors, each comprising of 69,000 datapoints are available. Preprocessing was performed to trim irrelevant data points from the edges, level the measurement by rotating, and reduce the datapoints to a manageable (regarding processing time) amount of 30. The rotation symmetry was established by computing the absolute Peak-to-Valley (PV) errors between the mold shape and each of the form profiles, as well as within the two profile measurements.

### C. Selection of Suitable Machine Learning Algorithms

The selection of suitable algorithms for predicting the form shape was narrowed down to regression algorithms. A preselection was made based on reviews in the literature [17], the data at hand and similar previously conducted use cases. Linear regression and decision trees were chosen due to their simplicity and interpretability. Random forest and gradient boosting machines due to their performance.

### D. Implementation of Machine Learning Algorithms

First and foremost, the three data types were split into train, validation, and test sets. A split of 80 % for the training and 20 % for testing and validation was used. From the image data, only the first and last camera frame were used and preprocessed into a temperature profile vector. To predict the glass shape, multiple gradient boosting regressors were implemented as single output regressors. The other stated algorithms were implemented as multiple output models. Permutation importance is used to determine the most useful features from the set of the input data. Model Evaluation

The Root Mean Squared Error (RMSE) was considered to compute and quantify the quality of the selected machine learning models. Using a 5-fold forward chaining cross validation, the models for each data type are evaluated and subsequently compared.

## IV. RESULTS AND DISCUSSIONS

Table 2 shows the RMSE values for the implementations of the four ML-algorithms on the test sets of the three different types of input data.

*Table 2. RMSE values of tests results for algorithms trained on input data*

| Algorithm | Set para-meter | Sensor data | First frame | Last frame |
|---|---|---|---|---|
| Linear regression | 1.12 | 1.13 | 1.80 | 2.06 |
| Decision tree | 1.17 | 1.06 | 1.11 | 1.10 |
| Random forest | 1.12 | 1.01 | **0.95** | 1.07 |
| Gradient boosting regressor | 1.09 | 1.01 | **0.95** | 0.96 |

The findings show that the image data from the first frame holds most relevance when predicting the molded glass shape. This can be explained by the lowest values of 0.95 RMSE obtained from the random forest and gradient boosting regressor algorithms. Secondly, it can be observed that simple algorithms like linear regression and decision trees better capture information from simpler data (set parameters, sensor data) compared to complex input data (temperature profile vectors). On the other hand, for ensemble algorithms, the image data from the first camera frame helps derive better information on relationships between input and output compared to the use of set parameter features. The temperature profile captured in the last camera frame, has lost some information about the process since the mold part and the deformed glass parts have undergone a period of cooling. Hence, while it still makes decent predictions, the accuracy seldom matches those made using the first camera frame. Overall, the best average RMSE across algorithms was achieved with the time series data of the sensors.

An important observation is the range in which the RMSE varies. It is observed that most error converges around a value of 1.0. An RMSE of 1.0 corresponds to a form shape predicted over the normalized range from 0 to 50 (equivalent to 5 mm of the actual measure part), each point on the form is deviated from the actual form profile by an average of 1 unit, or 0.1mm. Process experts determined that a threshold of 1.0 RMSE or less constitutes a useful prediction for optimizing process parameters and thus comply as good predictions.

Analyzing differences between the input data types, it is evident that the information contained in the set parameter data is insufficient to predict the shape according to the requirements. The training and validation curves do not fully converge, indicating a requirement of additional data for the algorithms to converge to an optimized bias and variance level. The sensor data recorded as time series data throughout the experiments shows good convergence and results. This is in part due to the additional information of the sensor data from the conditions of the environment of the experiment, e.g., influences on the temperatures from small wind surges in the production facility. Hence, using time-series data compared to set parameter data leads to predictions with higher accuracy.

A closer look at the learning curve for the best performing overall model in Figure 2 reveals the least overfitting tendencies as seen by a lower gap between the curves compared toother algorithms.

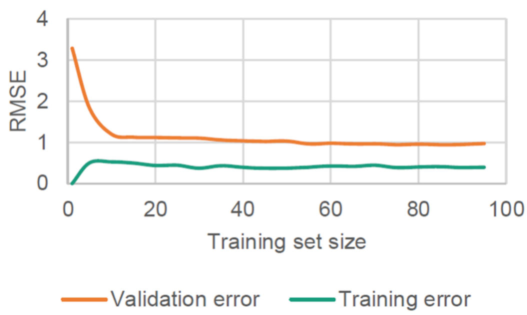


*Fig. 2. Learning curve of random forest on first camera frame data*

It is also noteworthy that no more than 40 images are necessary for RF to capture the information relating image data to the shape. After this saturation, the model shows a low bias error and the prediction accuracy, as seen by the end value of the validation error, is well within the defined threshold. Hence, RF is a reliable predictor when using image data from the first frame.

## V. CONCLUSIONS AND OUTLOOK

Over the years, a large amount of process data was collected by glass manufacturers. In this context, the use of ML to solve existing challenges in the process development is of interest, as good results have been achieved in other production domains.

In this paper we demonstrated the prediction quality of ML-models predicting final shapes of thin glass produced by vacuum-assisted glass molding, using three types of input data. The image data from a thermographic camera, time series data from machine sensors, and machine control parameters were considered in this study. After data preprocessing and feature extraction, four algorithms – linear regression, decision tree, random forest, and gradient boosting regressor – were trained, validated, and tested. The best results were achieved by the random forest and gradient boosting regressors on the first frame of the thermographic images with an RMSE of 0.95. Overall, the sensor data enabled the best average RMSE values across all algorithms implemented.

Excellent prediction accuracy observed for both glass demonstrators by this study highlights the successful implementation of ML allowing industrial manufacturers to accelerate the process development. Using the predictions of the ML-models enables adjustments of process parameters manually or in an automated manner. In addition, the procedure and methods shown here can be transferred to other glass forming processes. Examples are primary forming in e.g., container glass and optics production, as well as secondary forming in e.g., modling of bulk glass for lens production.

In the future, improvements to the study can be made by implementing algorithms for multi target regression since correlation between targets in the implementations presented here, is not learned. Image analysis may also be further investigated by using deep learning algorithms on the raw image. Multimodal models may make use of all the data shown here in one single model to investigate dependencies between data types. Finally, the developed models may be used in conjunction with process parameter optimization techniques.

## VI. ACKNOWLEDGMENTS

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