QUANTIFICATION OF MICRO-PULLWINDING PROCESS AS BASIS OF DATA MINING ALGORITHMS FOR PREDICTIVE PROCESS MODEL

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ABSTRACT

Cost efficient customization of goods is a very important field of interest in many areas of the manufacturing sector today. New research tries to extend the concept of customized products to the field of medical devices. In particular, the focus is set on the production of minimally invasive disposables. In this context, fiber reinforced plastics (FRP) do not only provide compatibility with all relevant medical imaging technologies but can also be used to realize mechanical customization.

Currently, the physician has to choose from the available product range predefined by the manufacturers. However, to maximize the ease of use of the medical devices and, thus, to optimize the outcome of the intervention a customized product would be the perfect solution. The involved devices are disposable items and today’s production technology is optimized to produce high amounts of these devices with low variability at low costs.

Also an individualized version of these devices would be a disposable. Therefore a still cost efficient and at the same time adaptive production system would be needed to manufacture such individualized disposables. One solution to overcome this challenge would be to link the necessary adaptive production systems in a continuous production line. On the one hand, the product can be produced cost efficiently in an endless process with minimum handling operations, on the other hand the adaptiveness of the involved production systems allows for customized manufacturing. However, the complexity of such combined continuous production system calls for new ways to control and optimize the process using data mining technologies.

In this context, this work presents the initial steps to create a model of a micro-pullwinding process. The micro-pullwinding process as part of the linked production system will be used to produce FRP wires with customized mechanical properties. A process analysis reveals the crucial process parameters and their relationships, which are investigated in more detail afterwards. The results of this quantifying investigation can be used to train a process model based on self-learning algorithms.

1 INTRODUCTION

One of the most powerful imaging technologies in modern medicine is Magnetic Resonance Imaging (MRI). The technology makes use of the different magnetic properties in human tissue mainly based on their water content. This makes MRI ideally suited to visualize soft tissue. In addition, the MRI technology does not transmit hazardous radiation. Both properties make MRI advantageous for numerous diagnostic applications compared to X-Ray based imaging technologies. However, the MRI technology involves strong magnetic fields, that make the use of conventional metallic medical devices unsafe. This inhibits the use of MRI for diagnostic applications. Therefore, alternative materials for the
production of MRI-safe medical devices have to be found. Due to their unmagnetic and nonconductive properties, many types of FRP can be used to produce medical devices that are inherently compatible with Magnetic Resonance Imaging (MRI). In this context, a miniaturized pultrusion process has been developed at Fraunhofer IPT to manufacture puncture needles made of carbon fiber reinforced plastic [1]. In subsequent research, the micro-pultrusion process has been advanced to the micro-pullwinding process by adding winding units to the machine setup. The winding units are used to change the fiber orientation in the winding layers in the continuously running process and thus to modify the mechanical properties of the produced micro-profile. Finally, the micro-pullwinding process was qualified as suitable method to manufacture a minimally invasive guidewire with adapted mechanical properties in a continuous process [2]. An illustration of the micro-pullwinding system is shown in Fig. 1.

In a future application the micro-pullwinding process shall be used with other manufacturing systems in a connected process to produce individualized medical devices in small lot sizes. In order to reduce the process development efforts and to allow for process optimization, the process parameters of the connected machine setup shall be determined with the assistance of data analytics. For this reason, a process model for the most relevant parameters of each involved process is needed. The process models shall provide an in-depth understanding of all relevant inputs, outputs and other factors that are influencing the process and the product quality. The next section present the methods and current results for the modelling of the micro-pullwinding process.

![Figure 1: Analysis of parameters in micro-pullwinding process.](image)

2 MATERIALS AND METHODS

Based on the layout of the machine an analysis of all influencing parameters of the system has been carried out. The parameters are categorized in inputs (blue), outputs (green), disturbance parameters (orange) and intermediate parameters (grey). The result of this analysis is also shown in Fig. 1.

A detailed assessment of all parameters reveals the relationships between these different categories of parameters. Furthermore, the set of parameters is reduced to a subset of most important parameters. These parameters are characterized on the one hand by being essential for the outcome of the process and on the other hand by being fully controllable in the running process.

Especially in micro-pullwinding processes the dimensions of even small rovings (thickness ~100-200 µm) is large compared to the dimensions of the final micro-profile (diam. < 1000 µm). This makes the process sensitive to variations in the roving dimensions and fibre orientation. Therefore, the most relevant parameters can be identified as winding angle, die temperatures and friction force in the die.
The relationships between these parameters are shown in Fig. 2, where an upward arrow on a link indicates, that an increase of the parameter at the origin of the link leads to an expected increase of the parameter at the endpoint of the link, whereas a downward arrow on a link indicates that an increase of the parameter at the origin of the link leads to an expected decrease of the parameter at the endpoint of the link.

**Figure 2: Relational model of most important parameters for micro-pullwinding process.**

Based on the outcome of the parameter assessment, the following relationships from Fig. 2 were investigated in quantitative tests:

(A) winding angle $\rightarrow$ friction force
(B) winding angle $\rightarrow$ outer diameter
(C) die temperature $\rightarrow$ friction force

The following paragraphs in this section explain some basic geometric considerations, that are relevant for the tests, present the parameters of the evaluated processes, that are fixed during the production run, as well as important pieces of equipment.

**CRITICAL WINDING ANGLE**

For a given configuration of the machine (tool diameters, number of rovings) the increase in winding angle results in two effects (Fig. 3):

**Figure 3: Development of gaps in winding process.**

In the first stage the higher winding angle reduces the gaps between the helically wound rovings. The gradient of the helix increases and the distance between the consecutive turns of the fibre material decreases until the turns of the roving are adjacent and the gaps are closed.

In the second stage the further increase in winding angle results in an overlapping of the fibres which causes an increase in diameter of the uncured profile. The fixed size of the cavity of the forming die
limits this effect by compacting the wound fibres around the core profile. In combination with an elastic deformation of the whole cross section and the very rigid structure of the metal forming die, a certain amount of friction is generated.

Based on the geometric properties of the involved fibres and the size of the winding core, the following equation (1) can be used to estimate a value for the winding angle, where the gaps between adjacent rovings are closed. This is true when

\[ l = nw' \]

where \( l \) is the pitch of the winding and \( w' \) is the width of a single roving along the axis of the winding core and \( n \) is the number of rovings in the winding layer. The estimated value for the winding angle with closed gaps is then (cf. Fig. 4):

\[ \alpha = \cos^{-1}\left(\frac{nw}{\pi d}\right) \]

The friction in the forming die is also affected by two other effects. Directly after the inlet of the die the resin is still liquid and liquid friction is caused. After curing of the profile the friction force is also caused by dry friction and debris in the tool. The ratio between liquid and dry friction in the tool can be regulated by the applied heat (temperature), which is characteristic for each combination of tool diameter, fiber type and resin. [3]

FIXED PROCESS PARAMETERS DURING PRODUCTION

For the quantification of these relationships, tests with two setups were conducted at Fraunhofer IPT using the existing micro-pullwinding machine. The setups differ in the number of rovings that were used for the winding process (cf. Tab. 1). The machine is equipped with two winding units that wind the fibers in opposite directions around the pultruded core profile. The “roving count winding” given in the table is the sum of both winding units, both carrying the same number of rovings.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Setup</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roving count core</td>
<td>4</td>
<td>1/2</td>
</tr>
<tr>
<td>Roving count winding</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>Roving count winding</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>Tool 1 diam. [µm]</td>
<td>470</td>
<td>1/2</td>
</tr>
<tr>
<td>Tool 2 diam. [µm]</td>
<td>750</td>
<td>1/2</td>
</tr>
<tr>
<td>Roving material core</td>
<td>Saint-Gobain EC9, 68 tex</td>
<td>1/2</td>
</tr>
<tr>
<td>Roving material winding</td>
<td>Teijin, T240, 22 tex</td>
<td>1/2</td>
</tr>
<tr>
<td>Resin core/winding</td>
<td>Hexion MGS L-235/H-235</td>
<td>1/2</td>
</tr>
</tbody>
</table>

Table 1: Process parameters for both setups.

In the test series the winding angle was varied for both setups and the corresponding friction force in the forming die was measured. The friction force is measured for at least 200 seconds to have a sufficient amount of data. The critical winding angle was determined for setup 1 upfront. The diameter of the wound profile was evaluated for setup 1 only. The relation between temperature and friction force was
evaluated in the forming die for the core to rule out any effects coming from the winding process.

The friction force is evaluated with a load cell U9B-2KN from HBM, Germany. The force cell is mounted between the carriage of the forming die and the machine frame (Fig. 5). Due to the orientation of the load cell, all force readings caused by friction in the die have negative values. The diameter is evaluated with a digital optical microscope VHX-700FD equipped with a lens VH-Z00 both from Keyence, Japan.

![Load cell between forming die and machine frame](image)

**Figure 5: Load cell between forming die and machine frame.**

### 3 RESULTS

In Fig. 6 the roving width w (cf. Fig. 4) of a Teijin Technora, T240 22 tex roving was evaluated to 273 µm in average for a 0° orientation. Using equation (2) the critical winding angle for setup 1 can be calculated ($\alpha = 55.3^\circ$). For the calculation of the critical angle the neutral fiber of the winding layer was used:

$$d_{NF} = (d_{Tool1} + d_{Tool2})/2$$  \hspace{1cm} (3)

![Evaluation of roving width for Teijin Technora T240, 22 tex.](image)

**Figure 6: Evaluation of roving width for Teijin Technora T240, 22 tex.**

(A) WINDING ANGLE → FRICTION FORCE

The following Fig. 7 shows the relation between the winding angle and the resulting friction force in the forming die of the winding section for the two different setups of the micro-pullwinding machine.
The figure shows clearly the transition between the two stages of winding angle change. For small winding angles the change in friction force is reduced due to gaps between adjacent windings. As soon as the critical value for the winding angle is reached, the friction force increases quickly due to overlapping of adjacent windings. The critical winding angle for setup 1 is located between 50° and 55°, the critical winding angle for setup 2 is located between 30° and 35°.

![Figure 7: Relationship between friction force and winding angle.](image)

Both sets of measurements are approximated with both an exponential function $f_e(x) = a + b \cdot e^{cx}$, straight line, and a trigonometric function $f_t(x) = a + b \cdot \tan(c + dx)$, dotted line, where $x$ is the winding angle.

The resulting approximating functions are:

$$f_{e1}(x) = -2 + 0.00041 \cdot e^{0.212x} \quad R^2 = 0.909 \quad (4)$$

$$f_{e2}(x) = -0.75 + 0.00005 \cdot e^{0.4x} \quad R^2 = 0.955 \quad (5)$$

$$f_{t1}(x) = -2.3 \cdot \tan(0.565 + 0.0175x) \quad R^2 = 0.925 \quad (6)$$

$$f_{t2}(x) = 1 - 0.6 \cdot \tan(0.965 + 0.0175x) \quad R^2 = 0.929 \quad (7)$$

The quality of fit is given for each approximating function. For the calculation of $R^2$ the outliers indicated by the markers without filling in Fig. 7 were excluded.

(B) WINDING ANGLE → OUTER DIAMETER

The diameter of the resulting FRP profiles from setup 1 was evaluated for selected angles. The results are shown in Fig. 8. The results are approximated with a linear function (dotted line):

$$f_{l1}(x) = 675.3 + 1.29 \cdot x \quad R^2 = 0.995 \quad (8)$$
(C) DIE TEMPERATURE → FRICTION FORCE

The following Fig. 9 shows the relation between the curing temperature and the resulting friction force for a given tool diameter of 470µm. The tests were done using the forming die for core production in order to rule out any effects coming from the winding process. A start temperature is chosen which ensures a sufficient curing of the profile (cured profile is not tacky at the outlet of the forming die). The results are approximated with a linear function (dotted line):

\[ f_{I2}(x) = 224.8 - 1.70 \cdot x \quad R^2 = 0.845 \]  

Figure 9: Relationship between friction force and die temperature.

4 DISCUSSION

The calculated critical winding angle for setup 1 (\(\alpha=55.3^\circ\)) corresponded well with the findings from the test runs, where the friction force started to increase excessively between 50° and 55°. For higher these winding angles also the variation of the friction force is increased. This is a result of recurrent
peaks in the force measurements caused by small disturbances of the process. For winding angles clearly below the critical value, these disturbances do not have an adverse effect on the process and thus the variation of the force measurement is low. In the future, the estimation of the critical angle should be improved by further investigations. For example, the width of the round roving could be evaluated empirically for more core diameters and different winding angles. With this additional information a more detailed estimation of the critical angle can be realized.

The relationship between winding angle and diameter of the profile corresponded also well with the results from the force measurement. For small winding angles between 15° and 25°, the diameter of the profile was clearly smaller than the diameter of the forming die and the detected friction force was close to 0. With increasing winding angle the diameter of the produced profile increased linearly and reached a value close to the diameter of the forming die (750µm) for α=50°. At this point also the friction force started to increase excessively. Further investigations should link the geometric properties like the winding angle and the resulting profile diameter with the detected friction force in the die. For these investigations further information for the rheological and mechanical characteristics of the production process are to be taken into account.

The test results regarding the relationship between temperature and friction force show more friction in the die for higher temperatures. This trend is in conformity with the results from Schmitz and Schütte [5, 6] for micro-pultrusion and micro-pullwinding processes. However for macroscopic pultrusion, decreasing friction forces for higher temperatures are reported.

5 OUTLOOK FOR DATA MINING

The identified mathematical relationships can be used to train a predictive process model. In the context of a continuous production line for customized production, this process model will support the operator of the machine.

Figure 10: Concept of cyclic data mining.

The linking of formerly separated manufacturing stations to a continuous production line creates a system of very high complexity in terms of parametrisation. The complexity is even increased by the idea of manufacturing many different product configurations in the same production run. The model shall be used to propose suitable process parameters for stable and reliable manufacturing of a certain
product configuration. In order to fulfil this task, the model needs to handle data at three different levels. Before the start of a production run, the model is fed with a set of individual product specifications (product level) and returns a stream of process parameters to run the process (machine level). The translation of specifications into parameters is done based on a set of rules that is created by training the model regularly with historical data. This historical data is generated permanently by in-process metrology units and additional quality control procedures (quality level). A fourth level is located outside of the closed loop of the first three levels where the desired product configuration is defined by the end-user (customer level). The concept of this is shown in Fig. 10.

DESCRIPTION OF MODELLING AND CALIBRATION TECHNIQUES

Initial testing for the modelling of the pullwinding process based on the data described in this work was conducted using two machine learning techniques. In this section, the techniques used to simulate and model the physical process are described briefly and some initial results are given. As machine learning techniques M5Rules and KRLS were used.

KRLS [7] is a non-linear kernel-based version of the Recursive Least Squares (RLS) algorithm. The Kernel-RLS (KRLS) algorithm performs linear regression in the feature space induced by a Mercer kernel, and can therefore be used to recursively construct the minimum mean squared-error regressor. KRLS is highly referenced in the literature, was shown to be competitive with SVR (Support Vector Regression), and adequate for time series processing with numerical data.

M5RULES [8] is a tree induction algorithm which generates a decision list for regression problems using separate-and-conquer. In each iteration, it builds a model tree using M5 and makes the "best" leaf into a rule.

Monte Carlo methods (or Monte Carlo experiments) are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results. Their essential idea is using randomness to solve problems that might be deterministic in principle. One of the first references to applied Monte Carlo method is that of Metropolis et al. [9]. In the present work we use a Monte Carlo method for optimizing the output for a given set of inputs, that is a calibration problem. In order to do this a large number of candidate input sets is generated and those set(s) which give the output which is closest to the desired output are identified. However, instead of generating pure random values as candidate inputs, random values probabilistically following a “Gaussian distribution” were generated [10]. For the modelling of the pullwinding process, a random number generator which follows a Gaussian distribution was used, guided by the mean and standard deviation for each input of the model. This is a standard technique and which has been validated as viable in the following paragraph.

INITIAL RESULTS OF MODELLING AND CALIBRATION

Input configurations are presented in turn to the model, together with the output (outcome) value and the model incrementally learns to predict the output for a given input parameter combination. Once the model is trained, it is then executed in a calibration process to find the optimum input parameter set for a required output. For example, the model can be used to find different parameter combinations in terms of the winding angle, diameter and temperature which give a friction force value which is within the allowed limits (e.g. greater than -20). Another required output parameter could be the Young’s modulus (the stiffness), so the input parameter combination could also be trained to give a required Young’s modulus with an acceptable friction force. The calibration iterates until a combination of inputs is found which produces the required Friction Force and Young’s Modulus value, for example.

In this context, Fig. 11 (a) shows the relative absolute error for initial data modelling of the pull-winding process using the M5Rules rule induction algorithm. In the case of the pull-winding modelling results FF2 refers to the friction force on die 2 and the datasets (6.1 to 6.4) correspond to different empirical test runs.

Figure 11 (b) shows the results for initial calibration testing, using a KRLS trainer with a Gaussian generator which has proven effective in initial trials with the IPT pull-winding dataset in order to model the friction force on die 2. This achieved an acceptable calibration precision ($\pm 1 \times 10^{-3}$) for producing the output (FF2, friction force on die 2) from the inputs (derived from winding angle and temperature).
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Figure 11: (a) Histogram of Relative Absolute Error (M5Rules, modelling) for different datasets; (b) Box with whiskers – Relative Absolute Error (KRLS, calibration).

These simulation techniques enable us to build a software simulator of the physical system, a key theme of the Industry 4.0 initiative. This “doppelgänger” allows for exhaustive parameter testing without having to use expensive time and physical resources in destructive testing. This is also a key aspect in order to make customized mass production possible.

6 CONCLUSION

The relationships between important process parameters in a micro-pullwinding process were investigated. The relationships were winding angle → friction force, winding angle → outer diameter, die temperature → friction force. For these relationships quantitative data was generated and first mathematical descriptions of the data were sought. The identified mathematical relationships for the micro-pullwinding process can be used to determine the maximum winding angle for a given setup. Further investigations will be carried out to refine the mathematical relationships and to cover more process parameter combinations. In the future, based on these results a predictive process model can be trained to predict the process stability. A first implementation of a predictive model based on this work has been presented in [4]. Further research is needed to analyze the influences of the linked production line and the cyclic data mining. An important aspect in the model development will be to link the mechanical properties (Young’s modulus) as key characteristic of the product to the inputs of the process such as winding angle and diameter.

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