On the use of fixed point translations as input variable for digital twins in deep drawing compared to current methods

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Abstract. Recent work aims at the inverse parameter estimation in deep drawing using pretrained surrogate models for the detection of the current process, material or tool parameters. The use of the methodology requires the definition of state variables to describe the current process state. Whereas our recent work makes use of draw-ins and local blankholder forces, other approaches from the literature also use skid-lines measured after the deep drawing process. For the future, the solution with even higher information content would be to detect the global strain distribution on the final part and use it as a state variable for process detection, which has not been documented in the literature to the best knowledge of the authors.

In this work, we present a first step into this direction by comparing the surrogate model based parameter estimation by using draw-ins and by using the movement of material fixed points on the blank over the deep drawing process. The result shows that the mathematical methods used for parameter prediction based on draw-ins can directly be used for the prediction with fixed point translations as reference. For the investigations, a cup drawing process is used.

1. Introduction
In the 21st century, data-driven methods have increasingly found their way into forming technology. Whereas these methods were mostly introduced for the use in the process engineering phase in the 20th century in the form of special purpose finite element software, they are also increasingly being used during the manufacturing process itself. Worth mentioning is the first closed-loop control system for deep drawing described in [1] and [2].

The most important parts of control systems are the sensors to observe the current state, the controller to determine an action to shift the current process state towards its target and the actuator which executes the modification. Our most recent work deals with the first element (submitted). More precisely, our work aims at developing methods that are applied on sensor data as process output to reconstruct the process input as well as hidden states, see also figure 1. The reconstructed states can then be used for process observation, process or quality control or similar tasks. One of the key problems for this task lies in the choice of observable variable to detect the current process state. Although they could also be viewed as process outputs, we refer to hidden states, as shown in figure 1, as quantities that are not directly measurable on the final part, for example quantities occurring during the process or stresses caused by the forming process.
2. Concept of a digital twin in manufacturing

The literature provides many different definitions as well as use cases for the term digital twin. An extensive and recently published summary is provided by Lim, Zheng and Chen in the form of a literature review. For our purpose, we define a digital twin as a surrogate model generated by digital information that simulates the behavior of a real world system. The goal of our work described in the introduction can therefore be viewed as a classical use case for a digital twin according to this definition. More specifically, if we consider a deep drawing process with inputs and outputs as shown in figure 1, our purpose is to find a digital twin like model that is able to use measurement data from a deep drawing process as input and estimates input parameters or hidden states of the manufacturing process.

Due to our definition given above, the task is to find the observational models only by using virtually generated data which is provided by a stochastic finite element simulation. We will provide a detailed description of the workflow used to train the models mapping from the process output to its input in (submitted). Overall, the workflow consists of these four steps:

1. Modelling of each sensor signal (for example each draw-in sensor) independently as a function of the process parameters.
2. Determination of the sensitivity of each process parameter on each sensor signal using the previously trained models, resulting in a $n \times m$ matrix $S$, where $n$ is the number of parameters and $m$ is the number of sensor signals.
3. Identification of the most independent columns in $S$ by using Algorithm 4 in (5), yielding the most independent sensor positions based on their sensitivities. The number of sensors can be chosen manually or based on a principal component analysis as proposed in (3).
4. Modelling of each process parameter or hidden state independently as a function of the determined sensor positions, which results in the final models.

In the following, the methodology is applied on a cup drawing process given in figure 2 to estimate the original blank position in X- and Y-direction, friction coefficient as well as binder force. The workflow is applied on two stochastic finite element simulations in which friction coefficient and binder force are varied first correlated and then independently resulting in 3 and 4 independent parameters, respectively. All other parameters of the simulations are kept identical. Both simulations are first used to estimate the input parameters by using draw-ins. This result is used later on as reference for the case in which the movement of fixed points on the sheet are used instead of draw-ins.

The setup of the simulations used in this work is as follows. The blank has a circular shape with a diameter of $d = 190mm$ and consists of aluminum AA6014 with thickness $t = 1.15mm$. The drawing depth of the final part equals $h = 50mm$ as can be seen in figure 2a. The draw-in around the part lies in the range between approximately $d_{\text{min}} = 21mm$ and $d_{\text{max}} = 27mm$ with the used simulation settings. For modelling of friction, coulombs friction law with a nominal value of $\mu = 0.15$ as friction coefficient is used. The stochastic finite element simulations are performed with $n = 129$ simulations in total using AutoForm R8.
The parameters varied in the simulations and their ranges are:

- Friction coefficient $\mu$ [0.05, 0.15]
- Binder force [16$kN$, 54$kN$]
- Blank position X-direction $[-2mm, +2mm]$
- Blank position Y-direction $[-2mm, +2mm]$

3. Choice of variable for observation

The machine based observation of deep drawing processes requires the definition of variables to be observed. Observables used in the literature in deep drawing can be divided into distance and force measurements. The classical (distance based) observable used in deep drawing is the draw-in measured on the sheet flange. Maier et al. describe in [6] and [7] (cited in [6]) the use of skid lines instead of draw-in measurements. The authors reasoning is mainly that the observable should be located as near as possible to the area on the sheet that is formed, since this area is of main interest. As force measurements, either the use of punch force signals or local blankholder force signals has been reported in the literature [8], [9]. For an observable to be suitable as input for the methodology proposed in section 2, the following four requirements must be met:

1. The observable has to be determinable using virtual simulations
2. The observable has to be measurable with sufficient accuracy in reality
3. The observable must react sensitively towards the quantities to infer
4. The observable must have sufficient independent sensitivities towards the quantities to infer

Although the third and fourth criteria seem to be very similar, the distinction is important. If multiple independent parameters have to be observed, at least as much independent observables are required since otherwise the parameters cannot be estimated uniquely. If multiple observables are used in this case, for example the draw-in is measured at different locations, an additional observable only adds new information if its measurement signal contains a decorrelated part in comparison to the other observables, since otherwise its signal would be fully redundant. This decorrelated part comes from the fact that the sensor signal behaves with different sensitivities towards the parameters that have to be determined. The independency of sensitivities of the observables towards the different parameters is therefore viewed as an important requirement additionally to the absolute values of the sensitivities itself and important if multiple observables are used, which is usually the case.
4. Draw-ins as observables
The methodology described in section 2 is first applied on the simulation with three independent variables (binder force and friction correlated) using draw-ins as observables. The number of draw-in sensors is set to four and the test set for model validation consists of 30% of the simulations, which is consistently used for all models to ensure comparability of the results. Not surprisingly, all three independent parameters are estimated with very high accuracy, as can be seen on all $R^2$-values being almost equal to one. The $R^2$-values achieved and an overview over all $R^2$-values throughout this paper is given in the end with table 1.

Second, the modelling is repeated using draw-ins as observables with the same settings but using the simulation with four independent parameters. The locations for the draw-in sensors selected by the algorithm is visualized in figure 3. On one hand, the two sensor positions on the top and on the left correspond to the most sensitive locations with respect to the blank positions in Y- and X-direction, respectively, which makes intuitively sense. On the other hand, the sensitivity of the draw-in all around the part with respect to binder force and friction coefficient is very similar. Therefore the two remaining sensors are placed somewhere around the part, mainly influenced by numerical reasons. The resulting parameter estimation of all four parameters on the test set is visualized in figure 4. The result shows that the blank position is still predicted with high accuracy, whereas the model struggles with correctly predicting binder force and friction coefficient with an $R^2$-value of 0.50 and 0.45. The reason for this result lies in the fact that binder force and friction coefficient influence the draw-in in a very similar way, which prevents the model from predicting both parameters independently and precisely based on draw-ins. As can be seen in figure 4a and 4b, the modelling result is still not fully random.

5. Fixed point translations as observables
Based on the four requirements for observables mentioned in section 3, the question arises which type of observable contains the most information about the process parameters in the given example. Since the dynamics of the process itself is defined through the movement field of all material points (or nodes in the simulation), we propose the use of movements of fixed material points on the blank as observable. Worth mentioning is the fact that the draw-in around the part can be considered as a special case of movement of fixed material points, namely on the blank boundary. The same applies to the use of skid lines proposed by 6 and 7. Furthermore, choosing fixed material points enables to chose the observables not only near but directly inside the forming area. The concept of fixed material points can therefore be viewed as a generalization of the existing approaches.

Analogous to the results mentioned above, the same methodology is applied again to the cup drawing process, but instead of the draw-in as observable, the movement of each node in X-, Y- and Z-direction is used. Due to the almost radial symmetric movement of the material
points during forming, a coordinate transformation from cartesian to cylindrical coordinates is performed. Furthermore, the angular movement of the nodes was neglected since its magnitude is below 0.1° and would therefore most probably not be in a measurable range in a real world application. In order to prevent the generation of new nodes during the simulation, mesh refinement was disabled and a fine mesh with initial element size of 1.5mm was used, leading to a total number of 29084 triangular shell elements and 14944 nodes. To reduce the computational cost, 2000 nodes uniformly distributed over the blank were selected for all following steps. The location of these 2000 nodes is visualized in figure 5a on the blank before forming.

Applying the methodology on the simulation with three independent variables (binder force and friction correlated) leads again to a very high prediction accuracy for all three variables with a $R^2$-value of almost one which can be seen in table 1. As with the draw-in, the number of nodes was set to four and the models were validated on a test set consisting of 30% of the data.

Second, the methodology was applied on the simulation with four independent parameters. The nodes selected by the algorithm out of the 2000 possibilities are visualized in figure 5b. Due to the more complex sensitivities of the parameters on the node position, the resulting choice of nodes is not easily interpretable anymore. However, the selected nodes again are located approximately on the X- and Y-axis, resulting in a high sensitivity on the X- and Y-position of the blank, and are mostly positioned in the forming area. No node in the sheet flange is chosen.

The resulting parameter estimation of all four parameters on the test set is visualized in figure 6. The result shows that although the prediction accuracy for binder force and friction coefficient are lower compared to the simulation with three independent parameters, the accuracy can still be classified as sufficient for all four parameters.
Figure 5: Nodes at which the movement was evaluated during processing of the data.

(a) All possible nodes used on the blank

(b) Nodes selected by the algorithm

Figure 6: Result of prediction on test set using material points ($MAE = \text{Mean absolute error}$)

(a) Binder force: $R^2 = 0.914$, $MAE = 2825N$

(b) Friction coeff.: $R^2 = 0.839$, $MAE = 0.007$

(c) X-position: $R^2 = 0.999$, $MAE = 0.027mm$

(d) Y-position: $R^2 = 0.996$, $MAE = 0.045mm$

A comparison of the results shows that draw-ins and fixed material points are both capable of predicting the blank position as well as overall restraining on the sheet accurately. Whereas the accurate prediction of binder force and friction coefficient independently is not possible with draw-ins as observables, the use of fixed material points increases predictability of these
two parameters. The reason can be found in the fact that a higher binder force increases the thinning on the whole part, but a higher friction coefficient also acts on the contact between blank and punch, leading to a support of the bottom of the cup with less thinning and therefore more concentrated thinning in the area between the bottom and the flange of the cup. The difference of the movement of the nodes in the sidewall of the cup is directly influenced by the thinning of the sidewall, which makes it possible for the model to distinguish between the influence of the friction coefficient and binder force if material points are used.

All modelling results on the test sets are summarized in table 1.

| Observable            | Simulation | Friction coef. | Binder force | Position X | Position Y |
|-----------------------|------------|---------------|-------------|------------|------------|
| Draw-ins 3 parameters | 0.997      | - (correlated)| 0.998       | 0.997      |
| Draw-ins 4 parameters | 0.453      | 0.500         | 0.988       | 0.965      |
| Material points 3 parameters | 0.987 | - (correlated) | 0.999       | 0.999      |
| Material points 4 parameters | 0.839 | 0.914         | 0.999       | 0.996      |

6. Conclusion
In this work, the use of the movement of fixed material points as an alternative to draw-ins as observable for process observation on a cup drawing process was examined. The following conclusions are made:

- Models and methods developed for the determination of predictive models for process observation using well known process quantities in deep drawing can be directly applied to the movement of fixed material points.
- The movement of all material points includes the draw-in. In contrast to the draw-in, choosing the movement of material points as observable enables the possibility to measure material flow directly in the forming area. The information content in the observables can thus be increased.
- In the parameter prediction carried out in this work, using fixed material points instead of the draw-in enables to distinguish between a variation of binder force and friction coefficient, which is not the case if the draw-in is used as observable.
- More research is needed to understand the relationship between the movement of material points and their usage for process control as well as other tasks in deep drawing. The usage of material point movement maps analogous to draw-in maps described by Wang et al. can be a possible usage for the future.
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