

INLINE CONTROL OF A STRIP BENDING PROCESS IN MASS PRODUCTION

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ABSTRACT: The accuracy of a metal forming process is highly influenced by the variation of the process input, such as variation of friction and material properties. Therefore it may be required to decrease the input variation to meet the desired accuracy. However, this may increase the production costs, since stricter requirements generally come with a higher price tag. Other solutions may be to design the process in such a way that it becomes less sensitive to the input variation, or to implement a control scheme in the production line. Adding sensors to measure the state of the production process and actuators to change the process settings during production allows for a drastic increase of the production accuracy.

In this study a numerical comparison is made between different methods to control a thin strip bending process with an over-bending and a back-bending stage. The aim is to implement the method in a mass production line with a production speed of 100 products per minute, which demands for fast measurement, processing and actuation. A discrete control scheme is used, meaning that the process settings can only be adapted in between the process stages. The adaptable control parameter is the amount of back-bending. In the case of the strip bending process, the angle of the measured strip may be used to adapt the angle of the following strip. However, the accuracy of such a control scheme is limited by product-to-product variation. Therefore the force of the over-bending stage is measured and used to construct a predictive model of the process based on measured process data. Hence, the final angle of the flap can be predicted by measuring the force at the first stage of the process. Different factors influence the effectiveness of the control methods: the size and autocorrelation of the input variation, the noise of the measurement system and the predictive ability of the predictive model. A qualitative study on the influence of these factors on different control methods is given in this paper.

KEYWORDS: Thin sheet bending, springback, inline control, manufacturing, proper orthogonal decomposition

1 INTRODUCTION

In the previous century the use of statistical process control (SPC) became common practice in industry. Real-time process monitoring made early detection of process window violations possible. The next step was to use the measurement systems in real-time process control. In the recent years the number of publications on real-time process control for metal forming applications has been increasing. Metal forming processes are difficult to control due to elastic springback after forming and a high dependency on input parameters such as sheet thickness, friction, yield stress and elasticity. Several approaches for control of metal forming processes are found in literature. A large number of publications deal with the air bending process, which is a simple process but strongly influenced by material and thickness variations [1-6]. These authors propose several approaches to predict the final angle of the product after springback. A

common factor in these approaches is the use of the punch force measurement in the control scheme.

Other researchers deal with the control of the blankholder force in deepdrawing processes [7-9]. A reference punch force is defined and a controller is designed to control the blankholder force during the punch stroke. This allows to control for short term variations such as uneven lubrication. Another approach is to decrease the forming error by adapting the reference punch force based on the error of the previous product [10]. This type of control can decrease the errors caused by long term variability of the process.

Another area of research regarding the control of metal forming processes is the design of fast measurement devices for the input parameters of the material. Sheet thickness can be measured and even methods for material characterization during production are developed [11]. More knowledge on the incoming material may help to drastically increase the production accuracy.

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In the present paper the control of a thin sheet strip bending process is investigated. The bending process has three stages: an over-bending stage, a back-bending stage and an angle measurement stage. During over-bending the punch force is measured and during back-bending the punch displacement can be controlled. A numerical model is built to create a ‘virtual process’ which can be used to investigate the effectiveness of different control approaches. The angle and force measurement are available for control, raising the question which features of the force curve to use in the control. The influence of sheet thickness autocorrelation and uncertainty of the noise and angle measurement on the control effectiveness is assessed.

2 VIRTUAL PROCESS

A micro sheet bending process is under investigation. A sheet of steel grade AISI 420 is bent to a target angle of 41.5° . The sheet has a thickness of 0.3 mm, a width of 5 mm and a length of 10 mm. In the first bending stage the sheet is bent to approximately 50° . The depth of the back-bending stroke can be controlled. The end of the first and second bending stage are shown in Figures 1 and 2.

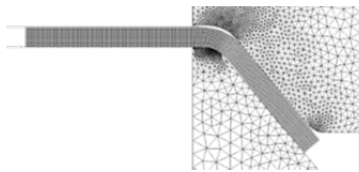


Fig. 1 Strip at the end of overbending stage.

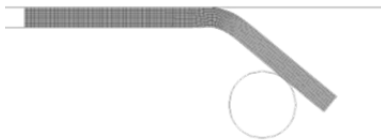


Fig. 2 Strip at the end of back-bending stage.

The assessment of the control strategies can be performed using a ‘virtual process’. This means that the real process is mimicked through a numerical model. It is aimed to include a large amount of complexity to the ‘virtual process’ to have a valid representation of the real process. To construct a ‘virtual process’, a Finite Element (FE) model is built (Section 2.1). A large number of simulations with varying input parameters are performed and this is used to build metamodels of the process final angle and of the process forces (Section 2.3). To build the metamodels of the process forces, the results of the simulations are decomposed using the Proper Orthogonal Decomposition (POD) method (Section 2.2). Finally, an educated guess on the input variations within the process has to be made (Section 2.4). With these components, the ‘virtual process’ can be run and the effectiveness of different control approaches can be assessed.

2.1 FINITE ELEMENT MODEL

A 2D FE model of the process has been constructed using MSC.Marc. The elastic behaviour of the tooling is modelled for the first bending stage. Rigid tooling is modelled in the second bending stage, since tooling deformations are lower due to the lower contact forces. Two dimensional plane strain elements are used to model the sheet and the tooling. The number of elements used for the sheet is 3600 and for the tooling 5376 elements are used. An impression of the mesh is given in Figure 1. The hardening behaviour is modelled with the Hockett-Sherby law. The average time for one simulation is ten minutes.

Both process and material variations are included in the model (Table 1). Modelled material parameter variations are yield stress, elasticity and thickness of the sheet. As process variation, the friction coefficient and the depth of the stroke at the first bending stage are varied. The control variable is the depth of the stroke for the second bending stage.

A total of 1677 simulations in the full parameter space have been run to build the process models.

Table 1: Ranges of parameter variation.

| | Min | Max |
|---------------------------|-------|-------|
| Yield stress [MPa] | 266 | 326 |
| Elasticity modulus [GPa] | 190 | 230 |
| Sheet thickness [mm] | 0.29 | 0.31 |
| Friction coefficient [-] | 0.06 | 0.18 |
| Punch 1 end distance [mm] | 0.315 | 0.325 |
| Punch 2 end distance [mm] | 1.13 | 1.17 |

2.2 PROPER ORTHOGONAL DECOMPOSITION OF FORCE CURVES

One single FE simulation can have a large set of output parameters, such as nodal displacements, strains and stresses, force-displacement curves of the tooling and several other outputs. When trying to identify trends of these outputs, it is useful to reduce the size of the output space. Recently this has been done by several researchers in metal forming through use of the POD method [12-13].

With the POD method a set of basis vectors of the result space that include most of the output variation are identified. Therefore, all N results of all M simulations have to be gathered in a so-called snapshot matrix \mathbf{U} with size N by M . After computing the eigenvalues (λ_i) and eigenvectors (\mathbf{v}^i) of the matrix $\mathbf{D} = \mathbf{U}^T \cdot \mathbf{U}$, the i -th POD basis vector can be found with [12]:

$$\boldsymbol{\varphi}^i = \mathbf{U} \cdot \mathbf{v}^i \cdot \lambda_i^{-\frac{1}{2}} \quad i = 1..M \quad (1)$$

These vectors can be gathered in a POD basis matrix $\boldsymbol{\Phi}$ with size N by M . Now the snapshot matrix

\mathbf{U} with all simulation results can be expressed in the POD basis with $\mathbf{U} = \Phi \cdot \mathbf{A}$. The matrix \mathbf{A} with size M by M is the set of M coefficients for each of the M result sets, and can be found with $\mathbf{A} = \Phi^T \cdot \mathbf{U}$. Finally, a reduced result set can be defined by truncating the coefficient matrix \mathbf{A} to a size $N_{reduced}$ by M , and by truncating the POD basis matrix Φ to a size N by $N_{reduced}$: $\mathbf{U} \approx \bar{\Phi} \cdot \bar{\mathbf{A}}$. Now the force curve data can be stored as a set of $N_{reduced}$ coefficients instead of the average size of 62 force increments needed to compute the first bending step. To determine how many coefficients are needed for a good predictive model of the force, 100 extra simulations have been run for cross-validation, and the R^2 -values for the *variation of the force curve* have been determined as a function of the number of used coefficients (Table 2). The chosen number of coefficients $N_{reduced}$ is 8.

Table 2: Number of coefficients for POD model versus R^2 value of the force curve variation.

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|-------|-------|-------|-------|-------|-------|-------|-------|
| 0,785 | 0,904 | 0,942 | 0,966 | 0,974 | 0,976 | 0,976 | 0,977 |

2.3 METAMODELS

After reducing the result space with the POD method, a set of 8 coefficients describing the full force curve of the first bending stage and the final angle after the second bending stage have been computed for all 1677 simulations. These results have been fit to 9 separate metamodels. The used interpolating function is a Multiquadric Radial Basis Function, based on its good global predictive accuracy [14]. A more extensive description of the used implementation can be found in [15].

With these 9 predictive models and the 8 eigenvectors of the force curve, a prediction of the final angle and of the full force curve can be made for any combination of input parameters within the ranges defined in Table 1. This ‘virtual process’ can be used to mimic a real thin sheet bending process and to assess the different control approaches.

2.4 PROCESS VARIATION

To model the sheet bending process, assumptions on the variations of the input parameters have to be made. These assumptions are essential for the assessment of the effectiveness of the control approaches. In the field of robust optimization, it is common to model input variations as a normal distribution with a mean and a standard deviation. In the case of process control, the rate at which the input parameters changes is of great importance. Long-term variations (e.g. material properties) and short-term variations (e.g. material thickness) have to be treated differently in the control of a production process [10].

Furthermore it has to be noticed that the delay between measurement and feedback leads to loss of

information about the short-term variations. In the case of our thin strip bending process, the only angle measurement available before the second bending stage of product number n , will be the angle measurement of product $n-2$. Hence, when only using the angle measurement in the control scheme, no information will be available on the changes in the process between product $n-2$ and the current product. Therefore a good estimate of the product-to-product variation is needed to assess the added value of the force curve information in the control scheme.

The rate of variation is modelled with the autocorrelation factor ρ . Therefore, given the mean μ and standard deviation σ of an input parameter x (e.g. material thickness), the probability of the value x^n of product n , given the value x^{n-1} of product $n-1$, is given by conditional probability of the bivariate normal distribution:

$$x^n \sim N\left(\mu + \rho \cdot (x^{n-1} - \mu), (1 - \rho^2) \cdot \sigma^2\right) \quad (2)$$

Furthermore, values have been assumed for the uncertainty of the force measurements and the angle measurement in the process. An overview of the assumed statistics of the process is given in Table 3. Smaller correlation values indicate faster fluctuations. A low correlation value for the sheet thickness has been assumed, which corresponds to measured values during tests. On the other hand, it is assumed that material properties only vary on long-term. With these assumptions the ‘virtual process’ can be used to simulate and compare different control approaches.

Table 3: Assumed values for the mean μ , the standard deviation σ and the autocorrelation factor ρ for all process parameters.

| | μ | σ | ρ |
|---------------------------|-------|-----------|--------|
| Yield stress [Mpa] | 295 | 6 | 0.99 |
| Elasticity modulus [GPa] | 210 | 3 | 0.998 |
| Sheet thickness [mm] | 0.3 | 0.002 | 0.8 |
| Friction coefficient [-] | 0.12 | 0.01 | 0.9 |
| Punch 1 end distance [mm] | 0.32 | $2e^{-4}$ | 0 |
| Force sensor error [N] | 0 | 1 | 0 |
| Angle sensor error [°] | 0 | 0.05 | 0 |

3 CONTROL SCHEME

For control of the thin sheet bending process, force curves of the first bending step and angle measurements are available to control the depth of the punch stroke at the second bending step. Two approaches will be compared: feedback control and predictive model control. These approaches will be discussed in Sections 3.1 and 3.2. The results will be compared with the case that no control is applied. For the case without control, the punch depth

is set to the optimal setting, based on a robust optimization approach.

3.1 FEEDBACK CONTROL

First, a feedback control scheme will be used, controlling the punch depth for product n based on the angle measurement of product $n-2$. Note that the angle measurement of product $n-1$ is not yet available since the angle measurement of product $n-1$ occurs at the same time as the second bending step of product n . Proportional feedback control for the punch displacement u is used:

$$u^n = u^{n-1} + (1 - \eta) \cdot K_p \cdot e^{n-1} \quad (3)$$

The error of the angle of product $n-1$ is e^{n-1} . The proportional control gain factor K_p is identified as the derivate from punch displacement to final angle $\delta u / \delta \alpha$. A damping factor η is included to the control to prevent instability. The optimal damping factor depends on the error of the angle measurement and on the rapid fluctuations of the process. Therefore every investigated scenario is run with different damping factors, but only the best feedback results of each scenario are presented in the results section.

3.2 PREDICTIVE MODEL CONTROL

In the case of feedback control, only the angle measurement of product $n-2$ is used to control product n . However, the punch force of the first bending stage has been measured and obviously this curve carries information about the variations of the current product. The main question is to identify this information and implement it in a control approach. Some researchers attempt to identify some characteristics of the force curve and build a predictive model of the final angle based on fuzzy models [4] or neural network models [5]. The approach in this work is based on the approach of Müller-Duysing for an air bending process, published in 1993 [1,2]. The force curves and final angles for multiple products were measured and fit to regression models. These regression models were updated after every new measurement and used for control of the process. The selected force curve characteristics were the forces at certain predefined moments in time.

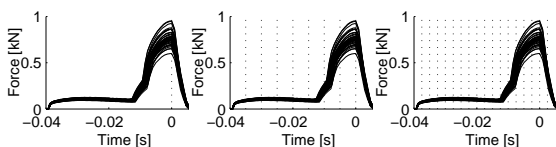


Fig 3: Force curves, with the 1, 8 or 17 'support points' of the predictive model.

For the current thin sheet bending process, it is chosen to evaluate the force curve at 1, 8 or 17 points in time (Figure 3), from now on called 'sup-

port points'. The forces at these support points and the angle measurement of product $n-2$ are used as input of the predictive model. A linear model is fit with the data of the last N_p products, leading to the following predictive model of the angle:

$$\hat{\alpha}^n = \left(1 \quad f_1^n \quad \dots \quad f_{N_f}^n \quad u^n \quad \alpha^{n-2} \right) \cdot \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_{N_f+3} \end{pmatrix} \quad (4)$$

The coefficients β are updated after each new measurement. The choice of the number of support points N_f and the number of products N_p used to fit the model strongly influence the quality of the predictive model. Furthermore, adding interactions between input parameters or adding non-linear terms to the model could improve the quality of the model. However, this is not investigated in this work.

The punch displacement u^n for the current product can be determined by setting the predicted angle $\hat{\alpha}^n$ to the target angle 41.5° , and solving Equation 4 for u^n .

The predictive model approach is closely related to the virtual metrology approach developed for the semiconductor manufacturing industry [16]. The main idea is that certain quality parameters cannot be constantly measured during production. Therefore the quality parameters are only measured for some products and the correlation of these quality parameters with other easy-to-measure secondary process parameters is determined. After gathering sufficient process data with in-line measurements, a predictive model of the quality parameters can be built based on the data of the secondary parameters. Such models potentially lead to major improvements of the production quality.

4 RESULTS

A large set of scenarios has been built and evaluated with feedback control and with different sets of input data for the predictive model control. The nominal process settings are given in Table 3, and the nominal value for the number of products used to fit the predictive model (N_p) is 2000. For each scenario, 200.000 products have been 'produced' with the 'virtual process'. Within each scenario, only one parameter is changed from the nominal values, to investigate the influence of the separate parameters on the control efficiency. The investigated parameters are listed in Table 4.

4.1 NOMINAL SETTINGS

The results for the different scenarios are shown in Figure 4. The scrap rate is shown as a function of the allowed error. All products with an error larger than the allowed error are regarded as scrap.

Hence, an allowed error of 0° yields a scrap rate of 100%, and a large allowed error yields a scrap rate of almost 0%. Every plot represents one scenario, and for each scenario the results of different control approaches are shown: the case without control (thick solid line), the best result (see Section 3.1) for all cases with feedback control (thick dashed line) and the cases with the predictive model approach (square markers). The scrap rate plots are computed with the *real* final angle, meaning that the error of the inline angle measurement is not included in the results.

Table 4: The effect of the following parameters on the control efficiency has been investigated. The nominal settings are shown with bold numbers.

| Parameters | Values |
|--|-------------------------|
| Sheet thickness correlation ρ [-] | 0.8 / 0.9 / 0.99 |
| Standard deviation of force sensor error σ [N] | 0 / 1 / 5 |
| Standard deviation of angle sensor error σ [°] | 0 / 0.05 / 0.5 |
| Number of products used for predictive model N_p [-] | 25 / 500 / 2000 |

Regarding the results with the nominal settings, it can be seen that the feedback control only gives a slight improvement to the product quality. However, it can be seen that adding information from the force curve to the control strongly improves the product quality. The improvement can already be seen when only the maximum force is used (one support point), but a stronger improvement can be seen for the cases with 8 and 17 support points.

4.2 SHEET THICKNESS CORRELATION

A larger value of sheet thickness autocorrelation leads to slower process fluctuations. Hence, there are less changes in the process between product $n-2$ and product n . Therefore it can be said that the relevance of the angle measurement of product $n-2$ increases. This can clearly be seen when larger values for the sheet thickness correlation are used: the effectiveness of the feedback control increases. However, the predictive model control is hardly influenced by the correlation change, especially for the case with 17 support points. It can be observed that the predictive model approach has the highest advantage to the feedback control when the fluctuations within the process are relatively fast.

4.3 FORCE SENSOR ERROR

It is expected and observed that the effectiveness of the predictive model approach decreases with increasing error of the force sensor. However, it can be noticed that the predictive model case with one support point is hardly influenced by the increased amount of force sensor noise. This is caused by the location of this support point, which is set to the deepest point of the punch, where the punch force is maximal. Hence, the error is relatively smaller compared to the maximum force than to the force at the other support points (see Figure 3).

4.4 ANGLE SENSOR ERROR

Obviously the quality of the angle measurement has a high impact on the effectiveness of the process control. It is observed that the feedback control is not effective with an angle measurement

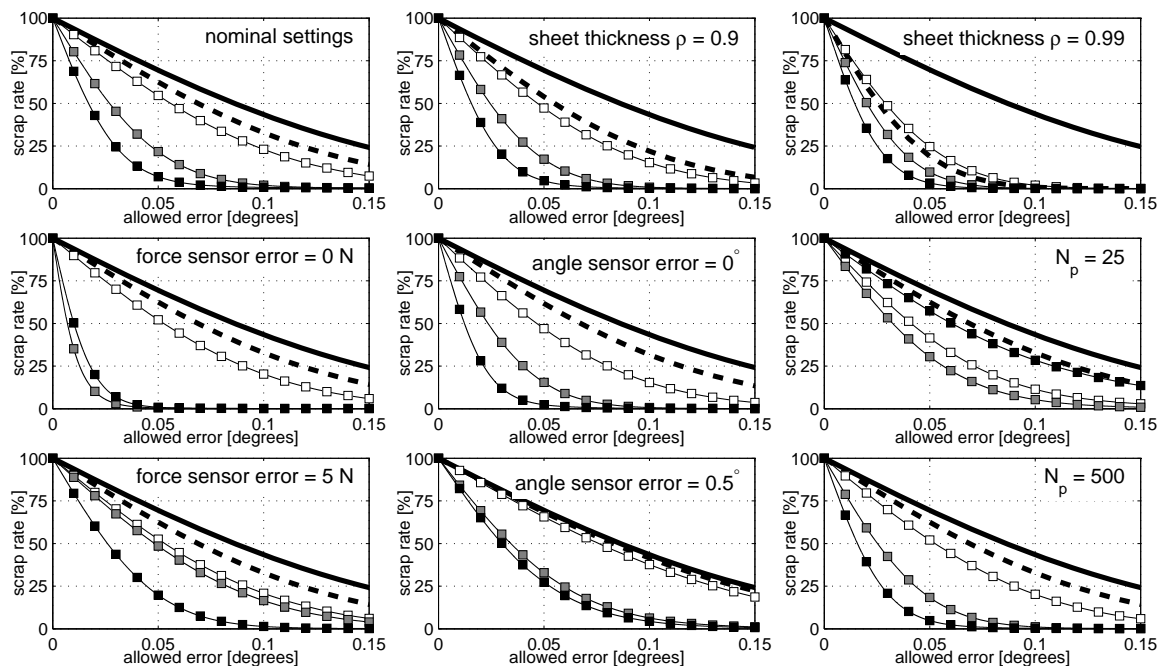


Fig. 4: Scrap rate versus allowed error for different scenarios. Thick solid line for the case without control. Thick dashed line for the feedback case with optimal damping settings. Square markers for predictive model control: 1 support point \square , 8 support points \blacksquare and 17 support points \blacksquare .

uncertainty of 0.5° . However, the accuracy can still be improved with the predictive model approach even with a large angle sensor error. This is possible because a large dataset is used to fit the predictive model, averaging out the error of the sensor.

4.5 PREDICTIVE MODEL DATASET

The size N_p of the dataset used to build the predictive model is varied. It can be seen that the predictive model with one support point increases in effectiveness with decreasing dataset size. When the predictive model is fit using a large dataset, the relation between the force and the final angle is averaged over more products. However, this relation may vary together with the short-term fluctuations. Hence, fitting the model to a smaller dataset leads to a predictive model which is better adapted to the current state of the process. On the other hand, it can be seen for the case with 17 support points that decreasing the dataset size deteriorates its quality. This is expected, since a large number of coefficients has to be fit, and too few sampling points lead to a poor regression fit. Thus, selection of the dataset size is a balance between restricting to recent data due to process fluctuations and the need for more data points for fitting accuracy.

5 DISCUSSION

It is shown that a predictive model of the final angle of a thin sheet bending process can be made based on the forces measured in the process. This model can be used for control of the process and a huge improvement with respect to the classical feedback approach is observed. However, many factors influence the effectiveness of this approach. The main question for further research is how to maximally exploit the force measurements for production control.

6 ACKNOWLEDGEMENT

The work leading to these results has received funding from the European Community's Seventh Framework Programme under grant agreement n° FP7-285030.



REFERENCES

- [1] Müller-Duysing M.: *Die Berechnung und adaptive Steuerung des Drei-Punkt-Biegens*, ETH Zürich, VDI Fortschritt-Berichte, 1992
- [2] Dallinger F., Roux E., Havinga G.T., et al.: *Adaptive process control strategy for a two-step bending process*. In: SDM 2014. KES Transaction on Sustainable Design and Manufacturing, 2014.
- [3] Heller B., Chatti S., Ridane N., et al.: *Online-process control of air bending for thin and thick sheet metal*, Journal of the Mechanical Behavior of Materials, 15(6): 381-462, 2011.
- [4] Yang M., Kojima N., Manabe K., et al.: *High accuracy V-bending process control with an on-line database and modified fuzzy models*, JSME international journal, 40(1): 157-162, 1997.
- [5] Forcellese A., Gabrielli F., Ruffini R.: *Effect of the training set size on springback control by neural network in an air bending process*. Journal of Materials Processing Technology, 80: 493-500, 1998.
- [6] Longo M., Maccarini G.: *Control System Algorithm for the Prediction of Springback in Air Bending*. Key Engineering Materials, 554: 1382-1387, 2013.
- [7] Siegert K., Ziegler M., Wagner S.: *Closed loop control of the friction force. Deep drawing process*. Journal of materials processing technology, 71(1): 126-133, 1997.
- [8] Lim Y., Venugopal R., Galip Ulsoy, A.: *Auto-tuning and adaptive control of sheet metal forming*. Control Engineering Practice, 20(2): 156-164, 2012.
- [9] Cao J., Solla S. A., Kinsey B.: *Consistent and minimal springback using a stepped binder force trajectory and neural network control*. Journal of engineering materials and technology, 122(1): 113-118, 2000.
- [10] Endelt B., Danckert J.: *Iterative Learning and Feedback Control Applied on a Deep Drawing Process*. International Journal of Material Forming, 3(1): 25-28, 2010.
- [11] Hora P., Heingärtner J., Manopulo N., et al.: *Zero failure production methods based on a process integrated virtual control*. In: NUMISHEET 2011. AIP Publishing 1383(1): 35-47, 2011.
- [12] Buljak V.: *Proper orthogonal decomposition and radial basis functions algorithm for diagnostic procedure based on inverse analysis*. FME Transactions, 38(3): 129-136, 2010.
- [13] Mohamed H., Le Quilliec G., Breitkopf P., et al.: *Surrogate POD models for parametrized sheet metal forming applications*. Key Engineering Materials, 554: 919-927, 2013.
- [14] Franke R.: *Scattered data interpolation: Tests of some methods*. Mathematics of computation, 38(157) : 181-200, 1982.
- [15] Havinga G.T., Klaseboer G., Van den Boogaard A.H. : *Sequential optimization of strip bending process using Multiquadric Radial Basis Function surrogate models*. Key Engineering Materials, 554: 911-918, 2013.
- [16] Khan A. A., Moyne J. R., Tilbury D. M. : *An approach for factory-wide control utilizing virtual metrology*. IEEE Transactions on semiconductor Manufacturing, 20(4) : 364-375, 2007.