Regression-based compensation of part inaccuracies in incremental sheet forming at elevated temperatures

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Abstract

Incremental sheet forming is a sheet forming process for small lot sizes due to its dieless principle. One of its process variants includes local heating of the sheet to counteract some of the process restrictions (formable materials, forming forces, achievable deformations). Although forming at elevated temperatures provides various advantages, the geometric accuracy of the formed part remains low due to shrinking effects caused by local heating and cooling. This publication presents a data-driven approach where process data is gathered and used in regression learning to predict the geometric accuracy resulting from the shrinking effects. To successfully apply regression learning, a big amount of process data is needed covering a wide range of possible process states. Therefore, a specific experimental series, consisting of 54 individual forming experiments, is designed and carried out. Based on the 3D digitization of the formed parts, a process database is built up comprising 408,296 records, each representing a toolpath point. This process database is used to train 19 different regression models. The performance of their ability to predict the geometric deviations is investigated. A compensation approach is presented that improves the geometric accuracy through a prediction-based modification of the toolpath. Validation experiments demonstrate the improvement of the geometric accuracy of the formed part and the generalizability of the approach.

Keywords Double sided incremental sheet forming · Roboforming · Industrial robots · Hot forming · Regression learning

1 Introduction and state of the art

Incremental sheet forming (ISF) is a promising process for the production of sheet metal parts in small batch sizes. Its dieless principle results in high flexibility, as part changes can be executed purely software-based without the need for additional tooling. Furthermore, the needed investment costs of ISF machines are low compared with conventional sheet forming setups. While the process' potential is enormous, it still suffers from a couple of problems. Those are primarily the still low geometric accuracy and the limited formable sheet thicknesses and materials. One solution approach is the extension of the process to forming at elevated temperatures. Heating the sheet yields various advantages similar to conventional sheet forming processes.

1.1 Sheet heating principles in ISF

In ISF heating is achieved by several different principles. These can be divided into local and global heating depending on the heated area. In 2007, Duflou et al. presented laser assisted single point incremental forming (SPIF) which belongs to the local heating variants. In this case the heating is achieved by a laser beam on the backside of the sheet that is moved ahead the forming tool [1]. Göttmann et al. used a similar approach directly integrating the laser beam into the forming tool [2]. While most forming tools in ISF are rotational beared to reduce the forming forces, they can also be actively rotated to heat the sheet due to friction [3]. Another widely spread concept is the local electrical resistance heating where an electric current flows through the forming tool and the sheet, heating it in accordance to Joule's first law. In SPIF the electric circuit is closed by the clamping frame [4]. While this is also possible in double sided ISF (DSIF), the application of a supporting tool on the backside of the sheet enables the use of an electric circuit through both tools and the sheet [5]. This results in a smaller heating zone. During the forming process the electric current needs to be controlled

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Fig. 1 Setup for robot-based incremental sheet forming (Roboforming) at elevated temperatures used in the experimental series to build up the process database and in the validation experiments [20]

to achieve a constant temperature. While it is possible to use thermal models to predict the necessary electric current [6, 7], most controllers depend on temperature measurement by infrared cameras [8] or thermocouples [9]. In 2010, Ghiotti et al. demonstrated the global electrical resistance heating in which the electric current flows only through the clamping frame and the sheet [10]. Other approaches for global heating include the application of warm fluids [11], hot air streams [12], external electric heater bands [13] and induction heating [14].

1.2 Advantages and problems of ISF at elevated temperatures

Similar to conventional sheet forming, ISF at elevated temperatures reduces the required forming forces. Duflou et al. observed a halving of the axial force with a temperature increase to 300 °C compared with forming at room temperature [1]. This way, both subsequent deformation and springback, which are the main causes for geometric deviations in ISF, are reduced. Therefore, the geometric accuracy of the formed part is increased, especially if the forming tool is guided by an industrial robot instead of a NC machine. As industrial robots have a comparable low stiffness, their positioning accuracy improves with decreasing forming forces [15]. Furthermore, sheets have a better formability if they are heated. This

results in a higher formable part depth [2, 16] and an increased formable wall angle [1, 10]. Additionally, ISF at elevated temperatures enables the forming of materials that are hardly or not at all formable at room temperature. This includes magnesium [10] and titanium [8] alloys. Furthermore, complex phase [17] and high-strength steels [14] can be precisely formed due to the fact that their springback is greatly reduced. As the material recrystallizes as a result of the heating up to a full recrystallization of the microstructure [11], residual stresses remain small, which can reduce the post processing expenditure as annealing might become obsolete. Although ISF at elevated temperatures is capable of reducing subsequent deformation and springback, the geometric accuracy of the formed part remains low. Magnus demonstrated that such parts tend to be smaller as a result of shrinking effects during the cooling phase [17]. This applies especially for flat faces, typically at the sides of an incrementally formed part, due to their lower stiffness. While the phenomenon of inward bent side faces can also be observed in ISF at room temperature, it is greatly increased by tensile stresses induced through local heating [18]. While globally heated parts do not suffer from the bending, complex phase and high-strength steels can only be formed by local heating as the springback would be nearly identical to forming at room temperature otherwise. Therefore, to effectively utilize the advantages of ISF at elevated temperatures, it is

Fig. 2 Principle of local electrical resistance heating used in Roboforming. The electric current flows through forming tool, sheet metal and clamping frame. Adapted from [23]

necessary to predict and afterwards prevent the geometric deviations, especially the inward bending of the side faces. To achieve this, a data-driven approach to predict and compensate the geometric deviations is presented in this publication. In the first step, process data is gathered in a systematic experimental series to build up a process database. Various regression models are trained using the process database. These regression models can predict the resulting geometric deviation based on process parameters and part geometry. Their performance is investigated afterwards using various performance coefficients. The prediction of the best regression model is applied to modify toolpaths for improving the geometric accuracy of the formed parts. Validation experiments, carried out using a robot-based ISF setup for forming at elevated temperatures, demonstrate applicability and generalizability of the developed approach.

2 Experimental setup

To generate the process data required for regression learning, an experimental series is carried out using a robot-based DSIF process (Roboforming). In Roboforming hemispherical tools (forming and supporting tool) are mounted on industrial robots, specifically two KUKA

Fig. 3 Technical drawing of the varied part geometry used in the experimental series. Dimensions are given in millimeters

KR360 with KUKA KRC2 controllers (see Fig. 1). This way, the process benefits from the availability and flexibility of industrial robots. Furthermore, it is possible to change the roles of the forming and supporting tool during the forming process, enabling forming in two directions. Therefore, Roboforming is capable of producing complex parts with even undercuts [19].

As industrial robots have a comparable low stiffness, they show positioning errors depending on the forming forces. Laurischkat measured a displacement of the forming tool of over 3 mm at an axial force of 2000 N while forming 1 mm thick DC04 steel [21]. Therefore, the industrial robot's stiffness needs to be compensated. During the

Table 1 Values of the factor levels taken into account in the design of experiments. The radii describe consecutive convex and concave curve radii with a concave one in the middle

Forming temperature (°C)	Step depth (mm)	Wall angle (°)	Curve radii (mm)
25	0.25	40	20
300	0.5	50	30
600		60	40
			50

Table 2 Specifications of the reference geometries A, B and C formed to build up the process database. Each base geometry is extruded with three different wall angles leading to nine individual parts

Geometry	Wall angle WA (°)	Upper radii RU (mm)	Convex-concave curve radii RC1 — RC2 — RC1 (mm)
A	40 / 50 / 60	30	50 — 30 — 50
B	40 / 50 / 60	20	40 — 40 — 40
C	40 / 50 / 60	40	30 — 50 — 30

forming process, the industrial robot carrying the supporting tool is exposed to forces around ten times smaller. Although current research investigates the simultaneous stiffness compensation, the supporting industrial robot is not stiffness compensated during the experimental series. As the displacement is force dependent, measurement of the forming force is inevitable for an online stiffness compensation. Accordingly, both industrial robots are equipped with ATI Omega190 force torque sensors (FTS; see Fig. 1). The compensation itself is executed by a flexible joint multibody dynamics system model of the industrial robot. Based on the beforehand measured joint stiffnesses and the forces and torques acting at the forming tool, the displacement of the industrial robot is calculated and compensated [22]. Laurischkat managed to reduce the mean displacement from -1.35 to -0.08 mm forming 1-mm-thick DC04 steel [21]. While this is sufficient in context of the positioning accuracy of the industrial robots, 1% of the displacements still exceed ± 0.6 mm due to model errors rising with the forming force. Therefore, the reduction of the forming force in ISF at elevated temperatures is especially important for robot-based ISF, in addition to the in Section 1.2 mentioned advantages of the process.

In Roboforming local electrical resistance heating is used to heat the sheet metal. The required electric current is generated by a Sinus HWI inverter unit of Harms & Wende GmbH & Co. KG. Downstream of the inverter unit, the transformer MF4-13,2/6,3-3,0-TM-M8-1B of Expert Transformatorenbau GmbH transforms the electric current to up to 13.2 V and 3000 A. For electrical resistance heating, this electric current flows through the forming tool, the sheet metal and the clamping frame (see Fig. 2). As it is a DSIF process, it is also possible to close the electric circuit with the supporting tool. To prevent overheating of the system, inverter unit, transformer, the electric cables connected to the clamping frame and both tools are water cooled. Due to positioning deviations of the two industrial robots, it is possible that the supporting robot loses contact to the sheet metal resulting in arc welding. This can be prevented by force controlling the supporting robot to ensure the contact. As this would result in bad surface quality, the electric circuit is closed by the clamping frame. A PI160 infrared camera with a O23 lens of Optris GmbH is mounted on the supporting industrial robot next to the supporting tool to measure the sheet temperature (see Fig. 1). In combination with a CYHCS-K2C3000A electrical current sensor of Chen Yang Technologies GmbH & Co. KG, the measured sheet temperature is used to control the initial electric current of the inverter unit, hence the forming temperature. To ensure visual contact of the infrared camera to the heated forming zone regardless of the forming direction, the camera is mounted on a positioning unit which can rotate the camera around the supporting tool.

Table 3 Full factorial experimental design covering a wide range of possible forming process states. The base geometry is extruded with the corresponding wall angle and formed with the given step depth and forming temperature

Experiment no.	Geometry	Wall angle (°)	Step depth (mm)	Forming temperature (°C)
1	A	60	0.5	25
2	A	50	0.25	25
3	A	60	0.25	25
4	A	40	0.25	600
5	A	50	0.25	600
6	A	60	0.5	600
7	A	60	0.25	600
8	A	40	0.5	300
9	A	60	0.25	300
10	A	50	0.25	300
11	A	50	0.5	600
12	A	40	0.25	25
13	A	50	0.5	25
14	A	40	0.5	25
15	A	40	0.25	300
16	A	50	0.5	300
17	A	60	0.5	300
18	A	40	0.5	600
19	B	40	0.25	600
20	B	60	0.5	300
21	B	50	0.25	25
22	B	40	0.25	25
23	B	50	0.25	300
24	B	50	0.5	25
25	B	60	0.25	300
26	B	40	0.5	25
27	B	60	0.25	600
28	B	50	0.25	600
29	B	50	0.5	600
30	B	40	0.5	300
31	B	50	0.5	300
32	B	60	0.5	600
33	B	60	0.25	25
34	B	40	0.5	600
35	B	40	0.25	300
36	B	60	0.5	25
37	C	40	0.25	600
38	C	60	0.25	300
39	C	40	0.5	300
40	C	50	0.25	25
41	C	50	0.25	300
42	C	40	0.5	600
43	C	40	0.25	300
44	C	60	0.25	600
45	C	50	0.5	300

Table 3 (continued)

Experiment no.	Geometry	Wall angle (°)	Step depth (mm)	Forming temperature (°C)
46	C	50	0.5	600
47	C	60	0.5	600
48	C	50	0.25	600
49	C	40	0.25	25
50	C	60	0.25	25
51	C	60	0.5	300
52	C	40	0.5	25
53	C	60	0.5	25
54	C	50	0.5	25

3 Experimental series

Parts formed with Roboforming at elevated temperatures exhibit an inward bending of the flat side faces. Aim of this publication is to predict and compensate this bending with a data-driven approach utilizing regression models. The quality of this prediction directly depends on the quality of data used for training of the regression models. To ensure a generalizability of the results, the data should cover a wide range of possible forming process states. This process data needs to be collected in an experimental series. The experimental series needs to take a big amount of process parameters into account covering a wide range of combinations. Thyssen et al. identified a strong dependency of the phenomenon of inward bending on forming temperature, step depth and part geometry [24]. In this experimental series the part geometry will be represented by varying wall angles and radii respectively curvature. The design of experiments covers the in Table 1 listed factor levels.

Due to the amount of factor levels of the part geometry, it is difficult to fit them in a single part. Therefore, a dedicated base geometry is designed. The geometry itself is surrounded by a stiffening structure. This base geometry features various convex and concave curve radii. To cover all factor levels, three variants of the same base geometry with different radii are built, ensuing referenced as geometry A, B and C (see Fig. 3). Each of those three base geometries is extruded with three different wall angles (see Table 2).

Table 4 Constant process parameters used in the experimental series to build up the process database

Sheet metal material	Tool material	Lubricant	Forming velocity
DC04, 0.8 mm	KXF	MoS2	25 mm/s

Therefore, nine variants of the same part are constructed for the experimental series. To gain the maximum amount of process data, a full factorial design of experiments is chosen. This leads to 54 individual forming experiments (see Table 3). While part geometry, step depth and forming temperature are varied, the rest of the process parameters are kept constant (see Table 4). All formed parts' geometric accuracy is measured after the forming process using a Comet 5 2M 3D-digitization system of Steinbichler Optotechnik GmbH (nowadays part of Carl Zeiss Optotechnik GmbH).

4 Regression learning

After finishing the experimental series, the complete process data of all 54 forming experiments with 408,296 individual toolpath points is available in a process database for regression learning. This includes the part geometry, influenceable process parameters (e.g. forming temperature) and the resulting geometric accuracy. To create a connection via regression learning, the process data needs to be transferred in a usable input format. As it is only possible to influence the forming process at the toolpath points, the corresponding process data of each toolpath point is chosen as input for the regression learning. This includes the forming temperature. Additionally, the relative position of the toolpath point on the toolpath length is taken into account. Due to the local heating of the sheet and the small step depth, toolpath points at the beginning and ending of the forming process are heated less times. This also depends on the step depth which is a regression learning input as well. Furthermore, the local part geometry is abstracted by the local surface normal vector, wall angle and curvature.

These parameters are identical for every toolpath point on flat side faces although the geometric deviation typically has its maximum in the middle of the face. Therefore, two additional parameters are used which specify the relative position of the toolpath point on the face in depth and circumference direction (see Fig. 4). The last considered parameter and output of the regression learning is the measured or predicted geometric deviation in surface normal vector direction. Summarizing, these are the parameters taken into account for regression learning:

- Forming temperature
- Toolpath point position relative to the toolpath length
- Step depth
- Surface normal vector of the toolpath point
- Wall angle
- Curvature
- Relative position of the toolpath point on the face in depth and circumference direction

Fig. 4 Exemplary ID-based representation of a toolpath point on a flat side face of the part in depth and circumference direction to take the higher inward bending in the face center into account

– Geometric deviation in surface normal vector direction

Result of the 54 forming experiments is a process database consisting of 408,296 individual records, each representing a unique toolpath point with its parameters. To calculate a relation between the inputs and the output respectively the resulting geometric accuracy of the toolpath point, 19 different regression algorithms are investigated utilizing MATLAB's Regression Learner. They belong to the categories multiple linear, regression trees, support

Table 5 Performance coefficients of the investigated regression models utilizing cross validation assigning 4/5 of the records to training and 1/5 of the records to testing

Regression model	RMSE	R^2	MSE	MAE
Multiple linear				
Linear	0.38068	0.40	0.14492	0.29499
Intersections linear	0.34972	0.50	0.12231	0.26888
Robust linear	0.38115	0.40	0.14527	0.29412
Stepwise linear	0.34974	0.50	0.12232	0.26890
Regression trees				
Fine tree	0.15627	0.90	0.02442	0.08812
Medium tree	0.16939	0.88	0.02869	0.10500
Coarse tree	0.19192	0.85	0.03683	0.12925
Support vector machine				
Linear SVM	0.38202	0.40	0.14594	0.29396
Quadratic SVM	0.32024	0.58	0.10255	0.24163
Cubic SVM	0.28495	0.66	0.08119	0.20814
Fine gaussian	0.18191	0.86	0.03309	0.10238
Medium gaussian	0.24729	0.75	0.06115	0.16945
Coarse gaussian	0.30872	0.61	0.09531	0.23120
Gaussian process				
Rational quadratic	0.18779	0.85	0.03526	0.12605
Quadratic exponential	0.22600	0.79	0.05107	0.16641
Matérn	0.19933	0.84	0.03973	0.13918
Exponential	0.15275	0.90	0.02333	0.08980
Ensemble learning				
Boosted trees	0.30510	0.62	0.09309	0.23376
Bagged trees	0.15362	0.90	0.02360	0.10177

vector machines, gaussian process regression and ensemble learning (see Table 5). For performance evaluation of the trained regression models, cross validation is used assigning 4/5 of the records to training and 1/5 of the records to testing. By comparing the predicted geometric accuracy of the toolpath point with the measured one, various performance coefficients are calculated for every regression algorithm. Specifically, these are root mean square error (RMSE), coefficient of determination (R^2), mean square error (MSE) and mean absolute error (MAE). The performance validation shows that fine tree, bagged trees and exponential gaussian process regression have nearly identical and overall the best performance coefficients. As regression trees tend to overfitting, exponential gaussian process regression is chosen for further investigations. The calculated MAE of 0.0898 indicates a good performance quality. By plotting the predicted and the measured geometric deviation of every of the 408,296 records respectively toolpath points, it becomes clear that both are in good agreement (see Fig. 5). Solely at the extremes a higher prediction error can be observed. These mainly result of the toolpath points at the beginning and end of the forming

Fig. 5 Comparison of the measured (blue) and the predicted (yellow) geometric deviation of the exponential gaussian process regression

Fig. 6 Comparison of the measured and the predicted geometric deviation of the exponential gaussian process regression

process. While the forming parameters used for prediction are nearly identical to the rest of the toolpath points in the corresponding face, the sheet has a different stiffness at the top and bottom of the part due to the roundings (see Fig. 3). This effect should have been covered by considering the toolpath point position relative to the toolpath length during regression learning. As the prediction errors show, this representation needs to be improved. Future research will feature methods for surface representations usable for regression learning to improve the prediction quality at the beginning and end of the toolpath. Figure 6 shows the predicted deviation over the measured deviation for all records. While some scattered higher errors can be seen, representing the before mentioned toolpath points, it is to note that all 408,296 records are plotted. Therefore, the point density is way higher towards the center line confirming the good prediction quality of the calculated exponential gaussian process regression model.

5 Validation experiments

The developed regression model is capable of predicting the resulting geometric deviation of a toolpath point based on forming temperature, forming parameters and part geometry. This information can be used to improve the geometric accuracy of parts formed with ISF at elevated temperatures. To achieve this, every toolpath point is shifted in the opposite direction of the predicted geometric deviation in surface normal vector direction. This way, the

geometric deviations, especially the inward bending of the flat side faces, are compensated. The geometric accuracy of parts formed with a modified toolpath is verified in forming experiments. Although the process database was built up using the DSIF process variant, the validation experiments are carried out with SPIF due to technical difficulties. While the forming results differ quantitatively, they resemble qualitatively. As parts formed with SPIF and DSIF at elevated temperatures show similar shrinking behavior, the developed regression model is still applicable. In the validation experiments three parts are formed that were used to train the regression model in order to test the general viability of the compensation approach. Each of the three geometries is formed one time with a standard toolpath and one time with a modified toolpath. To test the generalization of the regression, in two further experiments an independent part is formed that was not used during the training process.

5.1 Validation against parts used for training

For validation of the functionality of the compensation approach, three of the experiments for building up the process database are repeated. These cover the whole range of process parameters including varied wall angle, curvature, step depth and forming temperature (see Table 6). All three parts are formed with and without compensation, leading to a total of six experiments. Comparing their 3D digitization, the effectiveness of the compensation becomes clear (see Fig. 7). Huge improvements can be observed, especially on the flat side faces. The parts formed without compensation have their highest deviations on the side faces due to the inward bending caused by the shrinking. This applies especially for the experiment carried out with a forming temperature of 600 °C (see Fig. 7c) as the tensile stress increases with the local heating. The performance coefficients confirm the performance of the approach with a decrease of the side faces' MAE of up to 69% (see Table 7, Fig. 7d). All mean values are calculated based on the measured deviations at the individual toolpath points. Therefore, the big improvements of the flat area in the

Table 6 Parameters of the carried out validation experiments

Experiment no.	Geometry	Wall angle (°)	Step depth (mm)	Forming temperature (°C)
1	A	60	0.5	25
2	B	50	0.5	600
3	C	40	0.25	300

All experiments are carried out one time with a normal toolpath and one time with a modified one based on the prediction of the exponential gaussian process regression model

Fig. 7 Measured geometric accuracy of validation experiments number 1/2/3 ((a, b)/(c, d)/(e, f)) without ((a), (c), (e)) and with ((b), (d), (f)) compensation of the geometric deviations based on the prediction of the regression model

middle of the parts does not count towards the MAE of the complete part as it is not actively formed and has no toolpath points on it. However, the overall MAE still decreased in all three forming experiments (−38%, −22%, −2%). The same effect can be observed regarding the maximum geometric error which also decreased in all forming experiments (−23%, −37%, −60%). Furthermore, in validation experiment 1 the minimum geometric error could be decreased by −23% (see Fig. 7a, b). However, a slight increase could be observed in the other experiments (3%, 4%; see Fig. 7c, d, e and f). These deviations can be measured at the feet of the geometries. As explained in detail in Section 4, the prediction quality at the foot of the geometry exhibits occasional errors what results in the slight worsening of the achieved geometric accuracy in these areas. In ISF at elevated temperatures, side faces tend to show the biggest geometric deviations. This could also be observed in the validation experiments without regression-based compensation as they exhibit big geometric errors on their side faces (Fig. 7a, c, e). Their reduction was the initial aim of the developed approach. Especially on the left (−69%, −37%, −67%) and upper (13%, −43%, −36%) side faces, big improvements can be observed (see Fig. 7). Experiment 1 builds an exception as the accuracy of the upper side face worsened by 13% though this comprises of only 0.07 mm. While the MAE of the left and upper side face improved in all experiments with one exception, the right face worsened. Due to the initially small deviation, the percentage change turns out rather high. This cannot be explained with the gathered process data as the input of the regression model is similar for all side faces. One possible explanation is the acceleration behavior of the industrial robot before and after the radii. A longer contact in the corresponding areas will lead to an increased recrystallization due to the longer heating. The recrystallization could be reduced by lowering the forming temperature in these areas. Though, this will also influence the forming behavior. In further research, the validation experiments will be repeated using a newer forming setup, currently in development, with a faster acceleration behavior to reduce the contact time in the corresponding areas. Nevertheless, the viability of the compensation approach can still be taken as granted in the current state as the overall geometric accuracy was improved.

5.2 Validation against an independent reference geometry

To test the applicability of the regression model for parts that were not used for training, another two forming experiments are carried out with an independent geometry. This geometry features similar side faces and radii, but

Table 7 Evaluation of the performance coefficient of the validation experiments

Performance coefficient	Without compensation	With compensation	Difference
Experiment 1			
MAE Geo _{overall}	0.67 mm	0.42 mm	− 38%
Geo _{max}	1.74 mm	1.12 mm	− 36%
Geo _{min}	− 2.24 mm	− 1.72 mm	− 23%
MAE SF _{overall}	0.70 mm	0.50 mm	− 28%
MAE SF _{left}	1.41 mm	0.44 mm	− 69%
MAE SF _{right}	0.27 mm	0.45 mm	66%
MAE SF _{top}	0.51 mm	0.58 mm	13%
SF _{max}	1.74 mm	1.12 mm	− 36%
SF _{min}	− 0.58 mm	− 0.35 mm	− 30%
Experiment 2			
MAE Geo _{overall}	0.74 mm	0.58 mm	− 22%
Geo _{max}	1.69 mm	1.07 mm	− 37%
Geo _{min}	− 2.86 mm	− 2.96 mm	3%
MAE SF _{overall}	0.75 mm	0.68 mm	− 10%
MAE SF _{left}	1.19 mm	0.75 mm	− 37%
MAE SF _{right}	0.29 mm	0.90 mm	206%
MAE SF _{top}	0.77 mm	0.44 mm	− 43%
SF _{max}	1.68 mm	1.07 mm	− 36%
SF _{min}	− 1.08 mm	− 1.38 mm	28%
Experiment 3			
MAE Geo _{overall}	0.64 mm	0.63 mm	− 2%
Geo _{max}	1.26 mm	0.50 mm	− 60%
Geo _{min}	− 2.97 mm	− 3.07 mm	4%
MAE SF _{overall}	0.46 mm	0.50 mm	9%
MAE SF _{left}	0.60 mm	0.20 mm	− 67%
MAE SF _{right}	0.38 mm	0.94 mm	149%
MAE SF _{top}	0.39 mm	0.25 mm	− 36%
SF _{max}	1.21 mm	0.45 mm	− 63%
SF _{min}	− 1.47 mm	− 1.45 mm	− 1%

These are calculated based on the measured geometric accuracy of all toolpath points except for the minimums and maximums which are the exact values

differs in detail (see Fig. 8). For the forming experiments a temperature of 600 °C is chosen as the influence of the heating rises together with the temperature. Accordingly, the highest geometric deviation was measured with a forming temperature of 600 °C in the first validation experimental series (see Fig. 7c). Furthermore, a step depth of 0.25 mm is used which is common compromise between forming time and surface quality (see Table 8). Analogously to the former validation experiments, the part is formed one time with a standard toolpath and afterwards with a regression-based compensation. The 3D digitizations show an improvement of the geometric accuracy for the whole

Fig. 8 Technical drawing of the independent reference geometry formed in validation experiment number 4. It features similar side faces and radii as Fig. 3 but differs in detail. Dimensions are given in millimeters [17]

part (see Fig. 9). That applies especially for all side faces including the curved ones. Due to the compensation, the MAE of the side faces is decreased by 43% (see Table 9). The sole worsening can be observed in the blue/gray areas at the geometry foot. As these do not belong to the part and will be cut out in subsequent post processing, it can be stated that the generalization of the regression model was successful. This is approved by the overall MAE that improved from 0.91 to 0.61 mm.

Table 8 Forming parameters used in the validation experiments with an independent reference geometry. The part is formed one time with a standard toolpath and one time with a regression-based compensation of geometric deviations

Experiment no.	Geometry	Wall angle (°)	Step depth (mm)	Forming temperature (°C)
4	R	40	0.25	600

6 Summary and conclusions

While the advantages of incremental sheet forming at elevated temperatures are numerous (reduced forming forces, better formability, extended material spectrum), formed parts still suffer from low geometric accuracy. This results from shrinking effects during the cooling phase. Especially on flat side faces of the part, inward bending of the part occurs due to heating induced tensile stress. This publication demonstrates the possibilities of a regression-based compensation of the part inaccuracies. To achieve this, a systematic experimental series has been carried out covering a wide range of process parameters and forming statuses. Thereby, a process database has been built up consisting of 408,296 records, each representing an individual toolpath point. This database has been used to train various regression models. These models use the corresponding process parameters and a geometry representation of every toolpath point to predict the resulting geometric accuracy.

Based on calculated performance coefficients the exponential gaussian process regression has been chosen for an experimental validation. Therefore, the toolpaths of parts used for training and of an independent geometry have been modified based on the prediction. The experimental results show high increases of the geometric accuracy, even for the part not used for the training of the regression model. Accordingly, the generalizability of the approach can be taken as granted. During the experiments a worsening of the geometric accuracy has been observed for one side face. This cannot be explained with the process database as the inputs for the regression model were the same as for the other side face. Presumably, the acceleration behavior of the industrial robot causes these deviations. Subsequent

Table 9 Evaluation of the performance coefficient of the validation experiment with an independent geometry

Performance coefficient	Without compensation	With compensation	Difference
Experiment 4			
MAE Geo _{overall}	0.91 mm	0.61 mm	− 33%
Geo _{max}	2.00 mm	1.21 mm	− 39%
Geo _{min}	− 4.46 mm	− 4.76 mm	7%
MAE SF _{overall}	1.03 mm	0.59 mm	− 43%
MAE SF _{left}	0.75 mm	0.47 mm	− 37%
MAE SF _{top}	1.24 mm	0.68 mm	− 45%
SF _{max}	2.00 mm	1.21 mm	− 39%
SF _{min}	− 0.82 mm	− 0.63 mm	− 23%

These are calculated based on the measured geometric accuracy of all toolpath points except for the minimums and maximums

Fig. 9 Measured geometric deviation of validation experiment number 4 without (a) and with (b) regression-based compensation of the deviations

research will take this into account. Furthermore, the process database and the representation of the part geometry will be extended to increase the geometric accuracy even more.

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