Predicting Forming Forces and Lack of Volume with Data Mining Methods for a Flange Forging Process

Neelam Frederike Rasche, Jan Langner, Malte Stonis, and Bernd-Arno Behrens

***Abstract*—In the forging industry, like in many other economic sectors, it is common to simulate forming processes before executing experimental trials. An iterative simulation process is more economic than trials only but still takes a lot of time. A simulation with realistic parameters takes many hours. For an economical production the idea of predicting some main results of the simulation by Data mining was developed. Within this paper, the use of four different Data mining methods for the prediction of certain characteristics of a simulated flange forging process are presented. The methods artificial neural network, support vector machine, linear regression and polynomial regression are used to predict forming forces and the lack of volume. Both are important parameters for a successful simulation of a forging process. Regarding both, forging forming forces and lack of volume after the simulation, it is revealed that an artificial neural network is the most suitable.**

***Index Terms*—Data mining, artificial neural network, linear regression, polynomial regression, support vector machine.**

I. Introduction

Today, it is common to use finite element method (FEM) simulations instead of trials within industry, especially the forging industry. The development of the software is well advanced so almost every forging process and its characteristics can be calculated with results very close to reality. However, the development and the design of a process chain for a new forging product still takes a lot of time and many attempts are needed until the desired result regarding for example process time, amount of flash and energy consumption is achieved. At first, the engineer designs a geometry with Computer Aided Design (CAD). Then he develops a suitable forging sequence to form the desired geometry. The tools and the initial billet are designed and afterwards implemented into FEM. The developed process chain is simulated and examined. In case the simulated result is not as desired, e. g. folds appear, the process has to be modified and simulated again. In practice, many iteration loops have to be done to achieve the final process chain, which is used to forge the part in reality. Therefore, the aim of the research project, ongoing at IPH Hannover in Germany, is to develop a method that is able to predict parts of the simulated result within seconds by use of artificial intelligence algorithms. Based on a wide spectrum of investigated flange forging processes the method deals with six different input parameters that are varied. For predicting the result of a simulated forging process, two significant factors for a successful forging operation, the lack of volume and the forming forces are investigated. The corresponding process is a flashless flange forging process. No matter, if it is forged with or without flash, within simulations the parts volume afterwards is lower than at the beginning of the process. The single volume elements in which a part is divided into during the simulation have certain shape functions. If the volume element becomes too distorted the shape function are not valid anymore. Before a critical value of distortion is reached all volume elements of the billet are remeshed. Each remeshing decreases a little bit of volume to preserve the shape functions. Within this paper, the creation of an automatically executed simulation database is described and the first Data mining results are presented.

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II. State of the Art

A. Time Savings within Forging Process Design

The quality of simulations is very high due to developments in the past years. However, a higher quality goes along with a significant increase of simulation duration to some extent. To shorten the duration of process and product development many approaches exist. Some examples are briefly presented in the following.

SCHONGEN ET AL. proposed how to shorten the computing time without significant quality losses at a single FEM simulation by implementing a FEM/BEM (Boundary element method) application for the press-tool-workpiece interaction for a lateral extrusion process [1]. KNUST ET AL. developed an evolutionary algorithm for a cross wedge rolled preform of a connecting rod [2]. The aim was to avoid a lack of form filling and folds. Additionally, the amount of surplus material was reduced to a minimum. This leads to an optimized preform which needs less iterations loops and therefore shortens the simulation phase. SHAO ET AL. showed an approach by implementing a strain-based element addition and removal criterion within a 2D simulation to improve the material flow of a preform [3]. Within a small amount of iterations and therefore less time, a robust and suitable preform was generated. MOGHADDAMI ET AL. proposed an iterative algorithm for short circuit forces on the high current busbars of electric arc furnace transformers [4]. Compared to complex FEM algorithms the computational effort could be reduced by a

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significant amount of time.

In all the papers, no approach including Data mining was investigated. Furthermore, predicting parts of the simulated result by using Data mining was not addressed.

B. Data Mining Methods for Forming Processes

Data Mining methods describe a systematical way to find trends and patterns within a huge amount of data [5]. Some of the common methods are shown below.

An artificial neuronal network (ANN) consists of a certain number of layers in which the single neurons are located [6]. Each neuron is a computing unit that is able to make a decision based on input information and calculates output information. In each layer, all neurons are connected, interact and work parallel. Each neuron can be connected to all other neurons while the knowledge is described by the weights of the connections. A neuron takes the input parameter or the result of a neuron of the previous layer and calculates a weighted sum. Within the training phase, the algorithm calculates the connections weights given [6]. The algorithm identifies mathematical rules that describe the data and applies them within the validation phase. At the validation the algorithms minimizes the squared error between the desired output parameter and actual output parameter by adjusting the rules learned before.

The support vector machine (SVM) tries to find a separating hyper-plane that maximizes the margin between the hyper-plane itself and the closest input data points of each class [7]-[9]. If the input data cannot be separated linearly, kernel functions need to be implemented to the SVM. These kernels map the original data to a high dimensional feature space in which the problem becomes linearly separable. The classes and their mathematical borders that are built represent the output data.

Linear regression algorithms consist of input and output parameter, which are connected by a linear equation [10]. The input parameters often each are multiplied with coefficients and added. In most cases, an absolute term – the regression residual – is added, too. Linear regression is suitable to describe short-time phenomena and less complex matters.

If a linear regression does not apply, a polynomial regression can be executed [11]. The data then is described by a curve instead of a linear equation. This allows predicting patterns that are more complex.

A perfect prediction would be equivalent to a correlation with the value 1 [6]. The degree of correlation decreases with decreasing values beginning from 1, which indicates if a certain method might or might not be suitable to predict the pattern.

SEDIGHI and HADI executed simulations and used the results to train a neural network and a genetic algorithm to optimize the forging force of a closed die forging process [12]. The ANN gained a correlation of 0.997 regarding the forging force. The optimized results prove that a reduction of a forging force of 50 % could be achieved in comparison with an initial preform with 10 % extra volume. MARINKOVIC proposed an approach to model the flash land by use of an ANN and compared it with a regression method [13]. As a basis, 34 data sets with a wide spread of input parameters were chosen. With the developed three-layered ANN a higher correlation of 0.971 is achieved than with the regression method (0.946). SHAKIB ET AL. developed a predictive flow stress model for martensitic steel at hot temperatures based on experimental research [14]. The model showed deviations at the Hopkinson Pressure bar tests why an ANN was implemented. The results dramatically improved the prediction through the model at a range of parameters beyond the tests up to $r^2 = 0.997$.

DEHUAI ET AL. employed a prediction model based on SVM to predict the temperature changing during resistance furnace sintering [15]. They compared two approaches, SVM with particle swarm optimization and SVM with simulated annealing, with the existing sintered furnace temperature law. The second approach proved to be a promising alterative to the law. To optimize the quality control of complex parts TSENG ET AL. trained a SVM to predict binary whether the part is good or not [16]. The highest testing quality of 93 % was achieved, when using linear, polynomial and special kernels within the SVM.

PANDA ET AL. investigated surface quality characteristics and afterwards predicted the results by using several multiple linear regressions [17]. The measured arithmetic surface roughness average Ra was influenced by par example depth of cut and feed rate and could be predicted with a correlation between 0.918 and 0.953.

BUSTILLO ET AL. compared abrasive wear at different designs of a threading tool for cold forged steel [18]. The applied data models like multilayer perceptrons, SVMs, regression trees and rotation forest. Rotation forest combined with regression trees led to the most suitable results and therefore is recommended for a long-lasting-tool life.

In all the papers, no approach was shown to predict forming forces and the lack of volume based on a CAD model. In addition, none of the papers found addressed the replacement of FEM by using Data mining instead.

III. Process Development

A. Automatic Creation of FEM Preprocessor-Data

A process chain for a forging part is developed from the final geometry backwards to the initial billet. Therefore, the first thing needed is a geometry with a clear defined parameter field in which the geometry is to be varied. In Fig. 1, the CAD models of the billet and its formed flange geometry are shown.

The flange consists of two cylindrical sections, each with one diameter and one height. The dimensions are chosen according to the ones mostly used for industrial flanges and vary from to 25 mm to 500 mm for the diameters D_a and D_i and from 5 mm to 50 mm for the heights H_a and H_i (see table 1). To investigate the influence of the billet geometry, especially the ratio of the billet diameter and height, are varied, too. Apart from this, the billet temperature as a significant parameter that influences the forming forces at the forging process is varied.

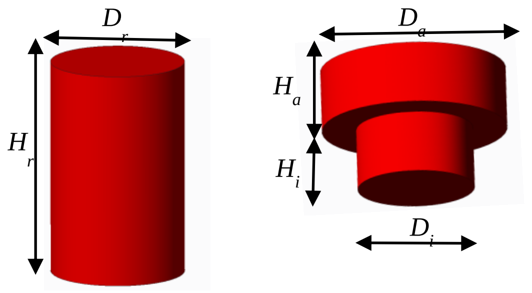

Fig. 1.CAD model of investigated billet (left) and flange (right) with their dimensions.

TABLE I: VARIED DIMENSIONS OF FLANGE, BILLET AND TEMPERATURES AT THE SIMULATIONS

D_a [mm]	H_a [mm]	D_i [mm]	H_i [mm]	D_r [mm]	T [℃] [mm]
50	5	25	5	$D_{r\,min}$	900
100	10	50	10	$D_{r\,min}$ +0,25*($D_{r\,max}$ - $D_{r\,min}$)	1000
200	20	100	20	$D_{r\,min}$ +0,5*($D_{r\,max}$ - $D_{r\,min}$)	1100
300	30	150	30	$D_{r\,min}$ +0,75*($D_{r\,max}$ - $D_{r\,min}$)	1200
400	40	200	40	$D_{r\,max}$	1250
500	50	250	50		

The investigated flange has no radii or other characteristics to simplify the geometry. In addition to the flange, the billet and dies have to be defined. Cylindrical billets are chosen, because they can be defined by a diameter (D_r) and a height (H_r is shown in Fig. 1 only), too. The billets have the same amount of material as the flange because only flashless forging operations are investigated. The equations below show how the minimum value for the billet diameter can be calculated from the flange volume.

$$V_{flange} = H_r \cdot \pi \cdot \left(\frac{D_r}{2}\right)^2 \text{ with } H_r = 1{,}95 D_r \qquad (1)$$

$$D_{r\,min} = \sqrt[3]{\frac{4 \cdot V_{Flansch}}{1{,}95 \cdot \pi}} \qquad (2)$$

The height of the billet can be calculated based on the volume of the flange and the chosen value for Dr. In forging processes the billet must stay within certain proportions or otherwise the billet is not upset into a flange but bends to the side instead. Hence, the height has a maximum of 1.95 times the diameter. The resulting minimum for Dr is shown below. As a maximum value $D_{r\,max}$ = 0.9 D_a is chosen for D_r, thus the billet diameter is always smaller than the larger diameter which guarantees a proper placement within the tool.

The tool consists of an upper and a lower die. The lower die is designed as the invers geometry of the flange while the upper die only consists of a plate. The billet and the tools are constructed with the CAD program and saved as a group so the geometric relations between the three parts are saved, too. This group now serves as a template, which is modified by a VBA macro. The macro needs to receive a range and increments for the parameter field for the named four flange parameters by the constructor. The user also has to define a range and increments for the temperature. After this, the macro creates the CAD models for the billet and the tools for each flange in the stl file format. Flange variants that are not flanges but a block because the two diameters have the same value are filtered out. In this project, 901 out of 1296 combinations that describe a flange were generated. Along with the stl files, a VBA script is created for each flange variant. It is compatible with the FEM program and contains all the data needed for the simulations e.g. the material file for the billet. Each script contains an allocation of the flange geometry to the five different billets and five different temperatures (see Table I and Table II). When loaded into the FEM program Forge NxT each script creates 25 different simulations. The net size of the billet is calculated automatically according to the setting "fine net"; the smallest billet therefore has a mesh size of 1.8 mm while the largest has a mesh size of 13.8 mm. This leads to roughly the same amount of elements for each flange size and guarantees the same quality of the investigated values independently from the flange size.

TABLE II: SETTINGS AT THE SIMULATIONS

FEM parameters	
Material	42CrMo4
Net size billet (edge length)	1.8 – 13.8 mm
Net size tool (edge length)	10 mm
Temperature billet	900 ℃ – 1250 ℃
Temperature tools	250 ℃
Friction	m = 0,3, μ = 0,15
Plasticity of the tool	rigid

To shorten the duration of a simulation only a quarter of the rotation symmetrical billet was simulated. Because of this only a quarter of the flange has been simulated which reduced the duration of the simulation about 60 %. For 22,525 simulations (five times 901), the reduced time adds up to several weeks.

B. Analysis of the Simulations

Each finished simulation now contains data concerning the forming force and the amount of volume at the end of the forging process. The two files, which included the information and their position within the file, were detected each. Afterwards the information was written by another VBA-macro into a Microsoft Excel table that contained every single combination that was simulated in one line. The macro systematically went through the single simulation result files determined before and transferred the required value into Excel. In Excel, the forging forces were multiplied with factor 4 because only a quarter was simulated. In this way, a table with all input and output data was created. This table is the basis for the Data mining algorithms.

IV. Results for Predicting the Forming Force

For Data mining the program RapidMiner is used. The input parameters are the four dimensions of the flange D_a, D_i, H_a and H_i as well as the billet diameter D_r and the billet temperature T. After this, the output parameter is determined; the maximum forming force and the flange volume at the end of the forging process. One line within the table represents one simulation with its input and output parameters. According to many researchers in the past, 80 % of the data is used for training, the rest for validation. This is a common relation, which proved to be suitable for many different patterns in the past, and therefore leads to comparable results. The lines within the table are randomized so the training for the Data mining model is independent from the order of the executed simulations. The training data now includes a wide spread of input parameters. The Data mining models used in the following are according to the state of art; namely ANN, SVM, linear regression and polynomial regression.

For the Data mining method an ANN, a three-layered back propagation algorithm, is used. Fig. 2 shows the relation between the measured values, namely the simulated forming forces and the predicted forming forces by the Data mining method. The values roughly follow a line but show scattering. A correlation of 0.911 was achieved, which is low for an ANN algorithm. In case of a perfect result, namely a correlation of 1, all the points would lay on one line without any scattering. The correlation within the pictures is measured by the amount of scattering so an increasing scattering leads to a decreasing correlation.

To investigate the reason for the scattering the table with the data is filtered by the billet diameter Dr being higher or lower than the flange diameter D_i. Then the Data mining is executed again. The filtered results are shown for $D_r < D_i$ in Fig. 3 and for $D_r > D_i$ in Fig. 4. The figures reveal that the scattering lowers dramatically for $D_r < D_i$. Depending on which value is higher, the billets position inside the tools is different (Fig. 5). The material flow therefore differs and causes other forming forces. Hence, two figures for each Data mining method are presented in the following. The scattering for $D_r > D_i$ can be explained by the amount of billet material which is in contact with the plane between H_a and H_i. An investigation of the forming forces depending on the material flow is not part of this paper. The correlation for ANN at $D_r > D_i$ is 0.932 while it is 0.996 for $D_r < D_i$. The correlation values for ANN are close to 1 for $D_r < D_i$, which means that ANN is generally suitable to predict the forming force of a forging process.

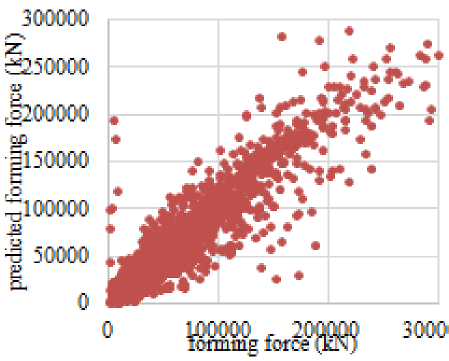

Fig. 2. Predicted forming force with ANN.

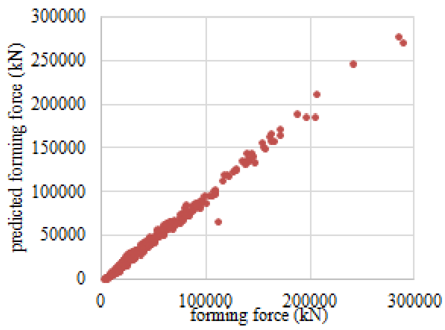

Fig. 3. Predicted forming force with ANN for $D_r < D_i$.

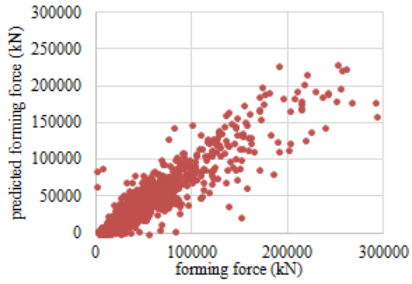

Fig. 4. Predicted forming force with ANN for $D_r > D_i$.

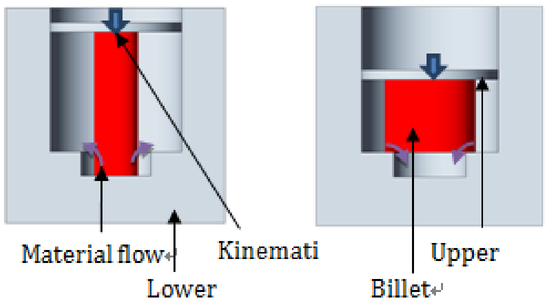

Fig. 5. Direction of the different material flows at forming.

The linear regression calculates a balance line from the FEM data. The correlation, as before at the ANN is based on the distance from a single value to the balance line. For the linear regression at $D_r < D_i$ the correlation is 0.888 (Fig. 6) and 0.741 for $D_r > D_i$ (Fig. 7). The higher value for correlation for $D_r < D_i$ goes along with the observations made in Fig. 3 and Fig. 4.

The polynomial regression calculates a curve instead of a linear function. The correlation for $D_r < D_i$ is 0.889 (Fig. 8) and 0.662 for $D_r > D_i$ (Fig. 9). The correlation values however are lower than with the linear regression. This and the increased scattering can both be explained by the complexity of the polynomial function, which predicts less precise if the data correlates linearly.

The SVM used within this paper is the LIBSVM, which is a common variant of SVMs that uses quadratic functions within its algorithm to solve usually binary problems. The current case is not a binary problem because six different input parameters are varied and therefore all of them influence the output parameter “forming force”. The correlation for the LIBSVM at $D_r < D_i$ is 0.923 (Fig. 10) and 0.852 for $D_r > D_i$ (Fig. 11). The reason for the scattering at Fig. 10, as before is the influence of the material flow depending on how much billet surface is in contact with the lower die.

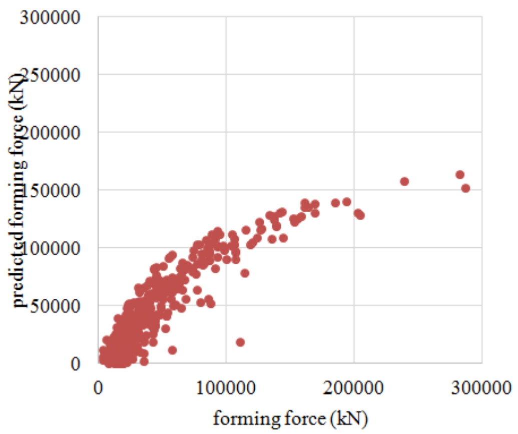

Fig. 6. Predicted forming force with linear regression for $D_r < D_i$.

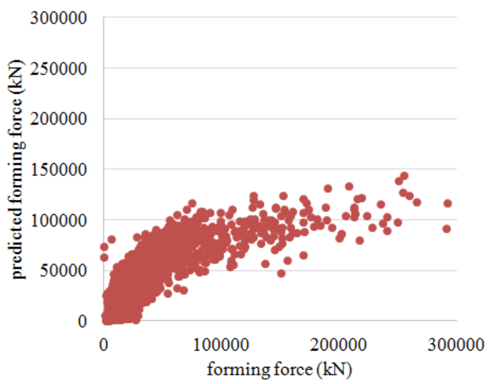

Fig. 7. Predicted forming force with linear regression for $D_r > D_i$.

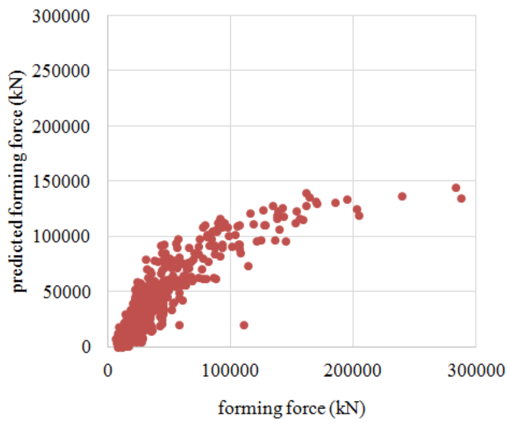

Fig. 8. Predicted forming force with polynomial regression for $D_r < D_i$.

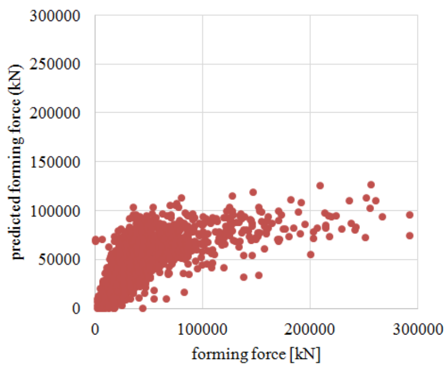

Fig. 9. Predicted forming force with polynomial regression for $D_r > D_i$.

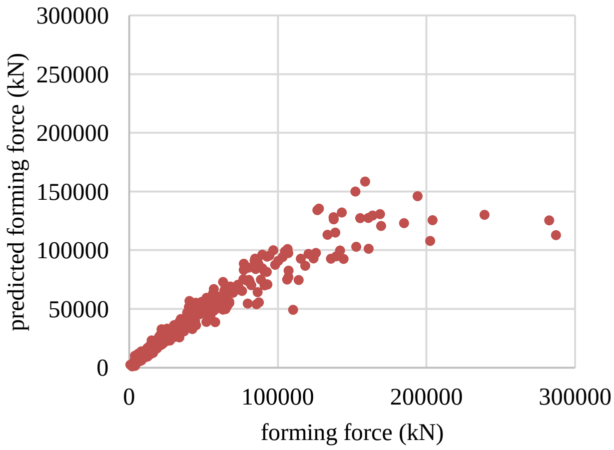

Fig. 10. Predicted forming force with LIBSVM for $D_r < D_i$.

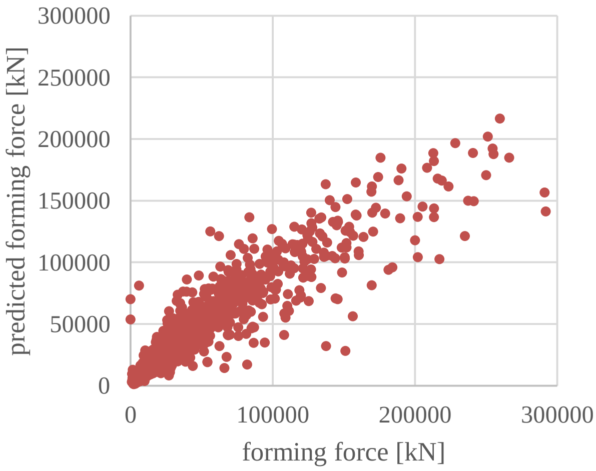

Fig. 11. Predicted forming force with LIBSVM for $D_r > D_i$.

The ranking of the result can be explained by the complexity of the methods. Complex methods mostly lead to predictions that are more accurate. The data is split for the prediction of the forming force, which improves the results significantly. The reason for this is not an inaccurate Data mining process but different directions of the material flow, which highly influence the forming forces.

V. Results for Predicting the Volume

Data mining was executed again for the prediction of the volume lack after the simulated forming process. As before, the figures all show the relation between the values measured by the FEM software on the x-axis and the predicted values by a certain Data mining method on the y-axis.

Regarding the prediction of the lack of flange volume by using ANN, Fig. 12 reveals a correlation close to 1, namely 0.998. The lack of volume, as written above, results from critical values within the algorithm of the FEM software during the forming process. Critical values within the FEM should be avoided to receive a result, which is closer to the forging process in reality. The lack of volume is a significant factor at the FEM and therefore predicted. The scattering as seen in chapter 4 is not evident. The material flow influences the forming forces but not the volume, which is the reason the data is not split. The predicted volume using linear regression is shown in Fig. 13 and has a correlation of 0.91. The polynomial regression, shown in Fig. 14, shows similar characteristics but slightly more scattering. The reason for the increased scattering is the same as at the forming forces. The style of the function follows a curve and not a line, which is not favorable when a linear relation of the measured data is assumed. However, the correlation still is 0.891. The LIBSVM shows a completely different prediction than the other methods because the LIBSVM is the only method that tries to separate the data given into clusters. The volume of the flange roughly increases linearly with increasing values for D_a, D_i, H_a and H_i. The huge number of data with values that are close to one another cannot be divided by the LIBSVM because the distances between the single values are almost the same. As a result only two possibilities exist: one cluster for each value or one cluster for all values. As shown in Fig. 15 the LIBSVM algorithm calculates one single cluster and predicts single value. Therefore, the LIBSVM is not suitable to predict the flange volume.

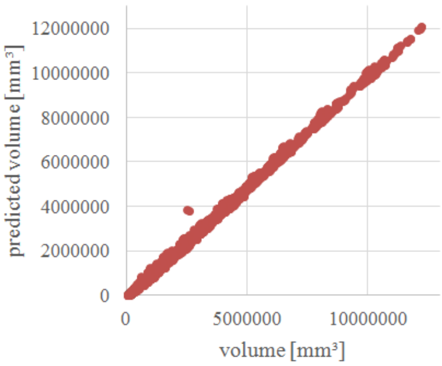

Fig. 12. Predicted flange volume with ANN.

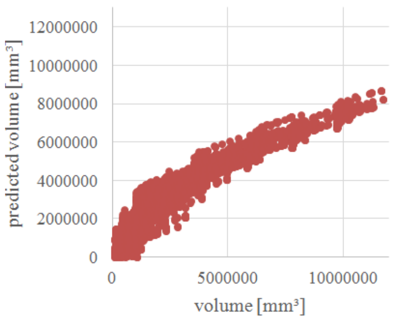

Fig 13. Predicted flange volume with linear regression.

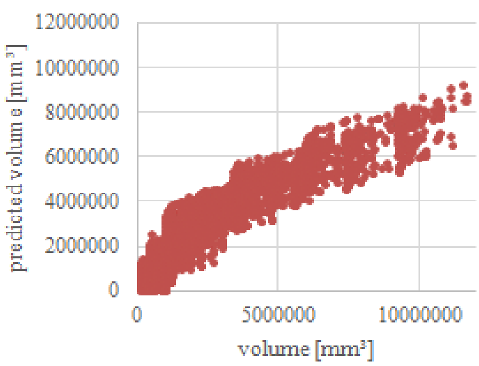

Fig. 14. Predicted flange volume with polynomial regression.

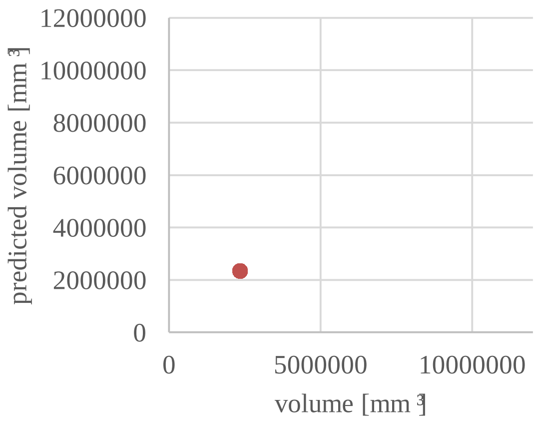

Fig. 15. Predicted flange volume with LIBSVM.

VI. Conclusion

It can be stated, that the ANN is suitable to predict the forming forces and the lack of volume of a flange forming simulation because the correlation of the measured and the predicted values was nearly 1. LIBSVM still produces acceptable predictions with a correlation up to 0.923. Linear and polynomial regression prove to be less suitable. The data is split to differentiate two different material flows. Regarding the prediction of the lack of volume at the end of the simulation the results reveal that the accuracy of the ANN is the best with a correlation of 0.998 while linear and polynomial regression shows similar correlations of 0.91 and 0.891. The LIBSVM is shows only a spot because the method is not able to separate the data and therefore is not recommended for this pattern.

As further investigations, the authors recommend the use of other SVM methods and the prediction of forged parts that are more complex than a flange by all the Data mining methods used within this paper.

References

[1] F. Schongen, F. Klocke, P. Mattfeld, S. Rjasanow, and R. Grzhibovskis, "FEM/BEM simulation of cold forging process considering presstool-workpiece interaction," *Procedia Engineering*, vol. 81, pp. 2403–2408, 2014.

[2] J. Knust, M. Stonis, and B. A. Behrens, "Preform optimization for hot forging processes using an adaptive amount of flash based on the cross section shape complexity," *Prod. Eng. Res. Devel*., 2016.

[3] Y. Shao, B. Lu, H. Ou, F. Ren, and J. Chen, "Evolutionary forging preform design optimization using strain-based criterion," *Int J Adv Manuf Technol*, vol. 71, pp. 69–80, 2015.

[4] M. Moghaddami, A. Moghadasi, and A. I. Sarwat, "An algorithm for fast calculation of short circuit forces in high current busbars of electric arc furnace transformers based on method of images," *Electric Power Systems Research*, vol. 136, 173–180, 2016.

[5] R. S. Michalski, I. Bratko, M. Kubat, *Maschine Learning and Data Mining: Methods and Applications*, John Wiley & Sons, Inc. New York, 1998, pp. 71-112.

[6] D. J. Kim and B. M. Kim, "Prediction of de formes Configuration and ductile fracture simple upsetting using neuronal network," *Int j Adv Manuf Technol*, vol. 19, pp. 336-342, 2002.

[7] S. M. H. Bamakan, H. Wang, and A. Z. Ravasand, "Parameters optimization for nonparallel support vector machine by particle swarm optimization," *Procedia Computer Science*, vol. 91, pp. 482 – 491, 2016.

[8] S. M. H. Bamakan, "A new intrusion detection approach using PSO based multiple criteria linear programming," *Procedia Computer Science*, vol. 55, pp. 231-237, 2015.

[9] C. Cortes and V. Vapnik, "Support-vector networks. Machine learning," vol. 20, pp. 273-297, 1995.

[10] E. Ostertagová, "Modelling using polynomial regression," *Procedia Engineering*, vol. 48, pp. 500–506, 2012.

[11] H. Wang, X. Lu, P. Xu, and D. Yuan, "Short-term prediction of power consumption for large-scale public buildings based on regression algorithm," *Procedia Engineering*, vol. 121, pp. 1318 – 1325.

[12] M. Sedighi and M. Hadi, "Preform optimization for reduction of forging force," *Proc. IMechE*, vol. 224, Part B: J. Engineering Manufacture, 2010, pp. 1717-1724.

[13] V. Marinkovic, "Application of artificial neural network for modeling the flash land dimensions in the forging dies," *Journal of Mechanical Engineering*, vol. 55, no. 1, pp. 64-75, Feb. 2009.

[14] M. Shakib, K. M. Perkins, S. E. Bray, and C. R. Siviour, "Development of a high temperature flow stress model for AerMet100 covering several orders of magnitude of strain rate," *Materials Science & Engineering A*, vol. 657, pp. 26–32, 2016.

[15] Z. Dehuai, L. Yuan, Y. Lianbo, L. Li, and X. Gang, "Wick sintered temperature forecasting based on support vector machines with simulated annealing," *Physics Procedia*, vol. 25, pp. 427 – 434, 2012.

[16] T. L. Tseng, K. L. Aletia, Z. Hua, and Y. Kwon, "E-quality control: A support vector machines approach," *Journal of Computational Design and Engineering*, vol. 3, pp. 91–101, 2016.

[17] A. Panda, A. K. Sahoo, A. K. Rout, "Investigations on surface quality characteristics with multi-response parametric optimization and correlations," *Alexandria Engineering Journal*, vol. 55, 1625–1633, 2016.

[18] A. Bustillo, L. N. López de Lacalle, A. Fernández-Valdivielso, and P. Santosa, "Data-mining modeling for the prediction of wear on forming-taps in the threading of steel components," *Journal of Computational Design and Engineering*, pp. 3337–348, 2016.

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- B.-A. Behrens, M. Stonis, N. Rasche, "Influence of the forming angle in cross wedge rolling on the multi-directional forging of crankshafts," *Int J Mater Form.* 2016, doi:10.1007/s12289-016-1326-3.
- B.-A. Behrens, M. Stonis, N. Rasche, „Influence of the cross section area reduction in cross wedge rolling on the multi-directional forging of crankshafts," *Advances in Materials and Processing Technologies*, 2017, doi: 10.1080/2374068X.2017.1328151.

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- J. Langner, M. Stonis, B.-A. Behrens, "Experimental investigation of a variable flash gap regarding material flow and influence of trigger forces," *Production Engineering – Research and Development*, Springer Verlag, Band 9 (2015), H. 3, pp. 289-297.

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- T. Blohm, M. Stonis, B.-A. Behrens "Investigation of Simulation Parameters for Cross Wedge Rolling Titanium and Bainitic Grade Steel," *Applied Mechanics and Materials, Trans Tech Publications*, Switzerland, vol. 736 (2015) pp. 165-170.

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