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Setup of a Parameterized FE Model for the Die Roll Prediction in Fine Blanking using Artificial Neural Networks

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Abstract. Die roll is a morphological feature of fine blanked sheared edges. The die roll reduces the functional part of the sheared edge. To compensate for the die roll thicker sheet metal strips and secondary machining must be used. However, in order to avoid this, the influence of various fine blanking process parameters on the die roll has been experimentally and numerically studied, but there is still a lack of knowledge on the effects of some factors and especially factor interactions on the die roll. Recent changes in the field of artificial intelligence motivate the hybrid use of the finite element method and artificial neural networks to account for these non-considered parameters. Therefore, a set of simulations using a validated finite element model of fine blanking is firstly used to train an artificial neural network. Then the artificial neural network is trained with thousands of experimental trials. Thus, the objective of this contribution is to develop an artificial neural network that reliably predicts the die roll. Therefore, in this contribution, the setup of a fully parameterized 2D FE model is presented that will be used for batch training of an artificial neural network. The FE model enables an automatic variation of the edge radii of blank punch and die plate, the counter and blank holder force, the sheet metal thickness and part diameter, V-ring height and position, cutting velocity as well as material parameters covered by the Hensel-Spittel model for 16MnCr5 (1.7131, AISI/SAE 5115). The FE model is validated using experimental trials. The results of this contribution is a FE model suitable to perform 9.623 simulations and to pass the simulated die roll width and height automatically to an artificial neural network.

1. Introduction

Initial situation. Fine blanking enables the production of components with a completely smooth sheared edge in one single work step [1]. Due to a high quality of the fine blanked components, it is possible to use the sheared edge as a functional surface [2]. Therefore, fine blanking is an economical manufacturing process for the production of high-quality components and is important for the automotive and aerospace industry as well as for mechanical engineering [3]. However, the usable size of the sheared edge is reduced by a die roll. Therefore, the key parameter describing the die roll is the die roll height h_E , cf. Fig. 1. Because the usability of the sheared edge of fine blanked components is the exceptional advantage of this technology, a minimization of the die roll height has a high relevance for



the improvement of fine blanked sheared edges. Due to a large number of influencing variables on the die roll, its control is still challenging.

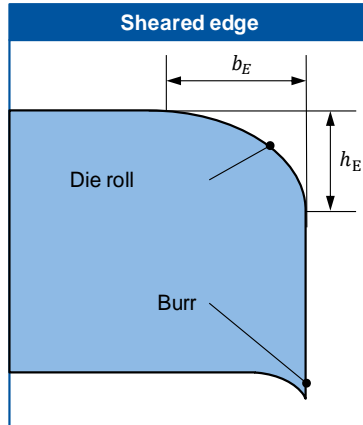


Figure 1. Sheared edge of a fine blanked component, legend: b_E : die roll width, h_E : die roll height

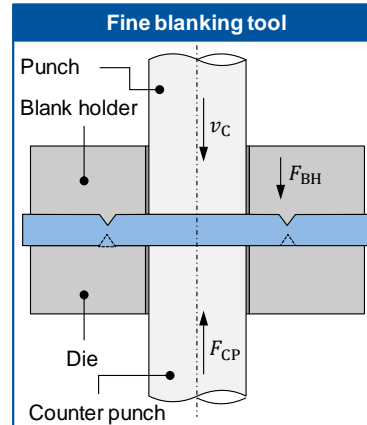


Figure 2. Fine blanking tool sketch with process variables, legend: v_C : cutting speed, F_{BH} : blank holder force, F_{CP} : counter punch force

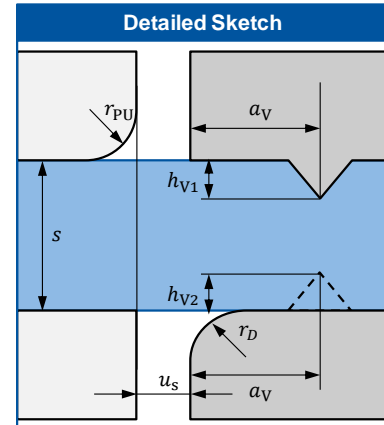


Figure 3. Geometric variables on the die roll, legend: u_s : clearance, r_{PU} : edge radius, r_D : edge radius, a_V : V-ring position, h_{V1} : V-ring height, h_{V2} : V-ring height, s : thickness

In order to design an industrial fine blanking process for a particular component, empirical know-how is usually employed [4]. The die roll height is strongly influenced by the blank holder and counter punch force [4], the cutting speed [1] (cf. Fig. 2), the die plate and the punch radius [2], the V-ring height as well as its position (cf. Fig. 3). The workpiece thickness, geometry and material determine the degree of difficulty of the fine blanking operation. Furthermore, they affect the sheared edge quality and the die roll [5].

Empirical-analytical description models exist for the definition of the process and tool parameters as a function of the workpiece properties. The tool parameters, however, are not precisely defined by these description models but are based on empirical tacit knowledge and are restricted to specific ranges. Therefore, in order to minimize the die roll height, further investigation of the cause-effect relationships between the influencing variables and the die roll is necessary. Several authors have already investigated the effect of different influencing variables on the die roll.

Literature review. KWAK et al. investigated the effect of the die clearance [6] and the position and the size of the V-ring [7] on the die roll of a workpiece for the automotive industry using FE simulation and experiments. KWAK et al. found that the die roll height and width increases with increasing die clearance. An enlargement of the V-ring height as well as a positioning of the V-ring closer to the punch resulted in smaller die roll heights and widths. KIM et al. investigated the influence of the shape of the die chamfer on the die roll height of a workpiece [8]. KIM et al. found out that the die roll height decreases with the decreasing die chamfer angle. In addition, KIM et al. investigated the influence of the V-ring height and the workpiece shape on the die roll using a combination of experiments and FE simulation [9]. The investigations confirmed that the die roll height decreases as the V-ring moves closer to the cutting line. KIM et al. investigated the influence of the shape angles and shape radii of the workpiece and found that the die roll height increases with a sharper angle and a smaller radius. LIU et al. determined the influence of the workpiece geometry on the die roll height using FE simulation and experiments [10]. LIU et al. found that a convex workpiece shape increases the die roll height and a concave workpiece shape reduces the die roll height. The disadvantage of the previous approaches is that only a single or a few of the large number of influencing factors on the die roll have been considered at once while others factors were neglected.

Problem. The reviewed investigations of the effects of the process parameters on the die roll were carried out by means of FE simulations and experiments. The validity and transferability of the results for parameter combinations, which were not covered in the investigations, is still unknown. For a process optimization, a large number of experiments or FE simulations are necessary, which must be repeated as soon as one of the parameters has changed [11]. Thus, a method is needed which gives a reliable prediction of the process result without the need of time costly experiments or FE simulations.

Motivation. If it is possible to derive a model, which can determine the process result without having previously investigated it in the FE simulation or in the experiment, then this fine blanking process could be optimized using this model. The only necessity for the model is that the boundary conditions are within a valid range. One method that could make this possible is machine learning.

Machine learning is already used in many areas. Spam filter learn to filter undesired e-mails, digital cameras learn to recognize faces, and assistance systems on smartphones learn to understand voice commands [12]. Manufacturing technology is an area in which the use of machine learning also offers a great potential [13]. By using machine learning, unknown patterns can be recognized in data [14]. This can help to predict the behavior of a system and to improve its productivity. Compared to conventional procedures, such as statistical process control, the methods of machine learning are more powerful in the detection of defective components in production [15]. This is due to the ability of the machine learning algorithm to account for nonlinear relationships. A method of machine learning that has shown great success in imitating human cognitive abilities are artificial neural networks.

Artificial neural networks (ANN) are inspired by the structure of the brain [16]. ANN can be used to develop models that express the interrelationship between the input and the output of very complex systems [17]. They work on an inductive approach to generalize the input-to-output interrelationship and to approximate the desired function [4]. ANN have already achieved good results in the field of manufacturing technology and, in particular, in sheet metal working. HAMBLLI successfully used a combination of FE simulation and ANN model to determine the optimum die clearance for a blanking process [18]. The ANN served as a substitute for the simulation after the learning phase with FE simulation data. DJAVANROODI et al. have used FE simulations of a fine blanking process to teach an ANN and, thus, predict the die roll on the workpiece [4]. As influencing factors, DJAVANROODI et al. considered the V-ring geometry, the blank holder force and the counter punch force. The predicted values of the ANN model showed very good agreement with the calculated values of the FE model. DJAVANROODI et al. concluded from their results that ANN in combination with FE simulation is a powerful tool for the design of the fine blanking process. AL-MOMANI et al. have succeeded in developing a very fast and accurate model with ANN for the prediction of burrs height in blanking process [19]. The ANN model was more accurate than a model of multiple regression analysis. The explanation for this is that ANN are better suited to detect hidden non-linear relationships. YIN et al. developed a model for prediction of the fine blanking die wear [20]. YIN et al. also used an ANN model, which is trained on FE simulation data. With the model, YIN et al. succeeded in demonstrating an inherent law between the process parameters and the die wear and predicting wear over the entire service life of the tool. The results of the model were in very good agreement with experimental data. Common to all works described above is that they considered only a small subset of the influencing variables.

Objective. The aim of this work is the development of a finite element method (FEM) based model, which allows to vary automatically all significant influencing factors affecting the die roll. These factors are the punch edge and die edge radius, the blank holder and counter punch force, the workpiece thickness and the workpiece diameter, the V-ring height and position as well as the cutting speed. The die clearance is kept fixed at the state of the art value of 0.5 % of the workpiece thickness since die clearance values in fine blanking are within the mesh size and thus can't be investigated numerically. The model serves to create a data base for the training of ANN. The FE simulations are carried out according to a full factorial experimental design. In the next step, ANNs are trained by different learning algorithms. The aim is to determine the ANN with the best ability to predict the die roll. This is achieved by verifying the trained ANN with test data sets and validation using experimental data.

2. FE model setup

In order to create a data base consisting of die roll heights to given input variables, a numerical FE model was developed. Since the FE software Abaqus allows for the implementation of FE models using Python scripts, this FE software was used for modeling. The implementation of the model as a Python script allows for an automated creation of FE models with different input variables. Since fine blanking is a dynamic, non-linear process with large deformations, explicit time integration scheme for the process modeling was used. As a result of the dissipation of the forming energy, the workpiece material is heated in the shear zone during fine blanking [21]. Therefore, the FE model is defined as temperature-coupled. A rotationally symmetrical fine blanking process of a workpiece made of the case hardening steel 16MnCr5 (1.7131, AISI/SAE 5115) is modeled numerically. The workpiece is modeled as elasto-plastic. The numerical modeling of a rotationally symmetric FE-model enables the saving of FE simulation time. This allows the creation of a sufficiently large database for the training of ANN within a reasonable time frame. The penalty method is used for contact modeling. A constant coefficient of friction $\mu = 0.1$ is defined for the contact between the tool and the workpiece. Contact between tools is not considered. The tools are defined as rigid because the influences of tool deformations in the process are negligible compared to other influencing variables, see Fig. 4.

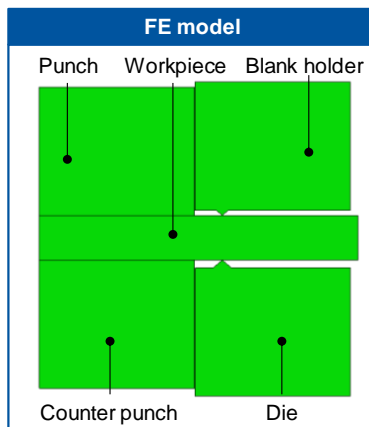


Figure 4. FE model of the fine blanking process

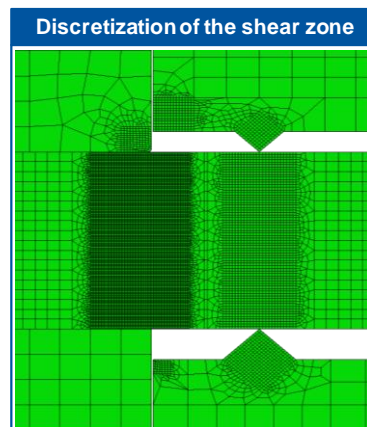


Figure 5. Discretization of the shearing zone

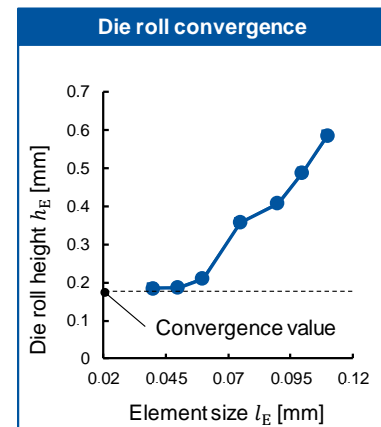


Figure 6. Convergence analysis of the die roll height h_E as a function of the element size l_E

2.1. Model discretization

The FE model was discretized with temperature-coupled elements of type CAX4RT with reduced integration and default hourglass control. The Arbitrary-Lagrangian-Eulerian (ALE) algorithm is used for remeshing in the shearing zone due to the occurrence of large deformations. The workpiece was discretized with finer elements in the shearing zone and in the V-ring indentation area, in order to accurately represent the stress-strain state in these regions. The remaining part of the workpiece was discretized with larger elements. The discretized shear zone is shown in Fig. 5. To determine the necessary element size of the discretization, a convergence analysis of the die roll height as a function of the element size of the discretization in the shearing zone was carried out. The results are shown in Figure 6. The die roll height h_E decreases with decreasing element size. Beginning at the element size of $l_E = 0.06$ mm, the edge feed height begins to converge to a value of $h_E = 0.018$ mm. Based on the convergence behavior of the die roll height, an element size of $l_E = 0.05$ mm was selected.

2.2. Material model

The Hensel-Spittel equation is an analytical function for the description of the yield stress k_f as a function of temperature T , strain ε and strain rate $\dot{\varepsilon}$. This approach is a phenomenological model for an analytical formulation of the flow curve. A flow curve described by means of the Hensel-Spittel

equation is mathematically smoother than the tabular flow curve modeling. Thus, it is numerically more stable. The yield stress k_f is calculated according to the Hensel-Spittel-equation as follows:

$$k_f = A \cdot e^{m_1 T} \cdot e^{m_4 / \varepsilon_f} \cdot \varepsilon_f^{m_2} \cdot \dot{\varepsilon}_f^{m_3} \quad (1)$$

A, m_1, m_2, m_3, m_4 = Material constants of the Hensel-Spittel- equation [-]

The modeled material is the case hardening steel 16MnCr5 (1.7131, AISI/SAE 5115). The material constants of the Hensel-Spittel material model were determined by a regression of experimental data. The parameters of the Hensel-Spittel equation of the modeled case hardening steel are listed in Table 1. The Hensel-Spittel equation was implemented using VUHARD user subroutine in Abaqus.

Table 1. Hensel-Spittel material model parameters of 16MnCr5 (1.7131, AISI/SAE 5115)

A [-]	m_1	m_2	m_3	m_4
789.495	0.0108123	-0.000051	0.144948	-0.005773

2.3. Validation

In order to validate the fine blanking FE Model experimental trials have been conducted on a fine blanking press Feintool XFT2500. 100 rings have been fine blanked, see Table 2 and Figure 7.

Table 2. Workpiece, tool geometry and process parameters used for validation

Workpiece thickness s [mm]	Workpiece diameter d [mm]	Blank holder force F_{BH} [kN]	Counter punch force F_{CP} [kN]	Cutting Speed v_C [mm/s]	Punch edge radius r_{PU} [mm]	Die edge radius r_D [mm]	V-ring h_{V1} / h_{V2} [mm]	V-ring position a_V [mm]
4	65	350	70	20	0.01	0.2	0.8 / 0	2.8

After conducting the experimental trials the die roll height has been measured with a tactile method using a HOMMEL-ETAMIC nanoscan 855 at three different points 120° apart for each part. The three measurements per part were averaged. After the experimental trials a numerical simulation with the derived FE-model has been conducted with the same workpiece, tool geometry and process parameters. The resulting die roll height has been compared with the experimental results and the relative difference of the results has been determined. It has been observed that the worst relative difference is 9.7 % and the average relative difference is 5.3 %. Since those values are within acceptable range the derived FE model is considered a valid model.

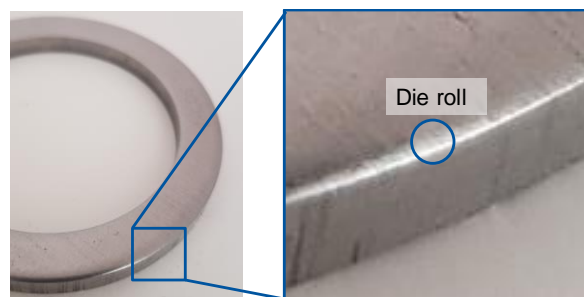


Figure 7. Fine blanked ring with die roll

3. Results

For the creation of a predictive model of fine blanking by means of the methods of machine learning, a large amount of data is required to teach the algorithms. Therefore, by implementing a full factorial experimental plan, a data base is created using 8,748 FE simulations. The experimental plan is shown in Table 3. In addition to the simulations of the experimental plan, a test data set is generated. This has approximately 10% of the size of the learning data set. This yields a total number of 9.623 FE simulations. The parameter combinations for the generation of the test data set are created randomly. The

boundaries of the randomly generated parameters are formed by the boundaries of the parameters from the experimental plan.

Table 3. Experimental plan for the generation of the data base for teaching the ANN containing the workpiece, tool geometry parameters and process parameters, legend: l_V : V-ring length, R_m : Tensile strength of the workpiece material, A_q : Area of the workpiece, SOA: State of the art, $h_V = h_{V1} + h_{V2}$

Workpiece thickness s [mm]	Workpiece diameter d [mm]	Blank holder force F_{BH} [kN]	Counter punch force F_{CP} [kN]	Cutting Speed v_C [mm/s]	Punch edge radius r_{PU} [mm]	Die edge radius r_D [mm]	V-ring height h_{V1} / h_{V2} [mm]	V-ring position a_V [mm]
3	10	$2 \cdot l_V \cdot h_V \cdot R_m$	$A_q \cdot 20$	100	$0.01 \cdot s$	$0.01 \cdot s$	-20 % from SOA	-20 % from SOA
7	20	$4 \cdot l_V \cdot h_V \cdot R_m$	$A_q \cdot 50$	200	$0.05 \cdot s$	$0.05 \cdot s$	SOA Value +20 % from SOA	SOA Value +20 % from SOA
12	40	$8 \cdot l_V \cdot h_V \cdot R_m$	-	-	$0.1 \cdot s$	$0.1 \cdot s$		

The FE simulations are started automatically one by one by means of a batch file. After a FE simulation has been completed, the die roll height of the simulated workpiece is also calculated automatically using a postprocessing Python script. The calculated die roll height, together with the associated tool and workpiece geometry as well as the process parameters, are written into the non-relational NoSQL database MongoDB suitable for large data sets. The result of the variation of the die edge radius is presented in this chapter. Three radii are examined: a die edge radius of $r_D = 0.07$ mm, $r_D = 0.35$ mm and $r_D = 0.7$ mm. The remaining geometry and process parameters of the experiment are kept constant and summarized in Table 4.

Table 4. Workpiece, tool geometry and process parameters of the simulated die edge radius variation

Workpiece thickness s [mm]	Workpiece diameter d [mm]	Blank holder force F_{BH} [kN]	Counter punch force F_{CP} [kN]	Cutting Speed v_C [mm/s]	Punch edge radius r_{PU} [mm]	V-ring h_{V1} / h_{V2} [mm]	V-ring position a_V [mm]
7	20	995	63	200	0.35	0.8 / 1.2	3.5

The value $r_D = 0.07$ mm represents a quasi-sharp-edged die edge with a minimum die edge preparation, the radii $r_D = 0.35$ mm and $r_D = 0.7$ mm correspond to 5 % and 10 % of the workpiece thickness and thus reflect the current state of the art in die edge preparation. Figure 8 and Figure 9 show the results of the variation of the die edge radius.

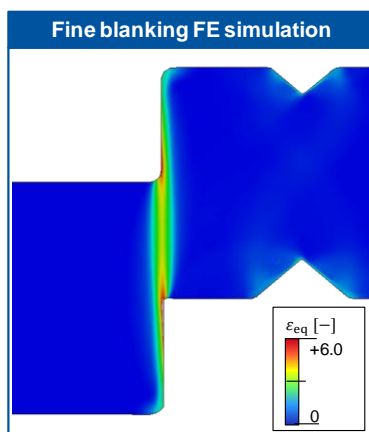


Figure 8. Fine blanking simulation with a die edge radius of the $r_D = 0.07$ mm after 50 % of the cut

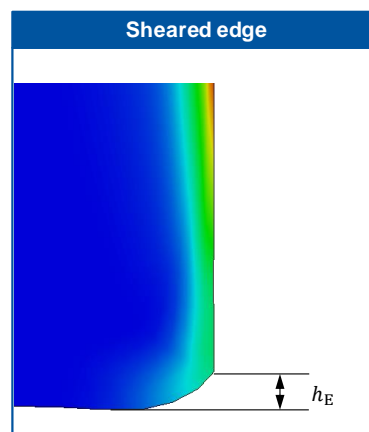


Figure 9. Simulated sheared edge of the workpiece with formed die roll

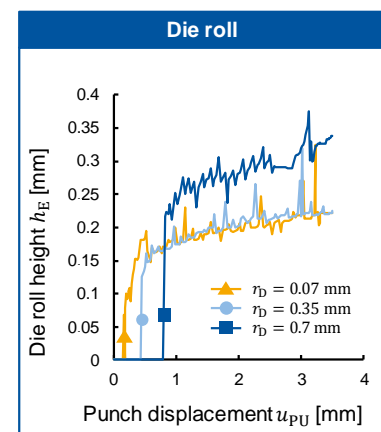


Figure 10. FE simulation results of the die roll to three different die edge radii

Only a half of the cut is simulated, since the die roll has already been fully formed when shearing of the material begins. This starts at about 25% of the workpiece thickness s . Subsequently, deformation takes place only in the shearing zone. The die roll curves shown in Figure 10 shows a sustained slight increase after a sudden increase in the die roll height. This is a numerical effect because the discretization elements are permanently stretched over the course of the cut what increases the die roll height h_E . The noise in the curves is also caused by numerical effects. It was also found that the larger the die edge radius is, the later the beginning of the increase in die roll height is. This is caused by the fact that at a larger radius the workpiece does not lie over a larger surface. As a result, a stronger deflection of the workpiece occurs and the shear begins later. The results show that a die edge radius of $r_D = 0.35$ mm produces an approximately equal die roll height of $h_E = 0.225$ mm, similar to a quasi-sharp-edged die edge. For a cutting edge radius of $r_D = 0.7$ mm, the die roll height is significantly increased to $h_E = 0.325$ mm.

4. Interim findings regarding artificial neural networks

The FE simulation data is used to teach an ANN. The input variables of the ANN are the variation parameters of the experimental plan (workpiece thickness, workpiece diameter, blank holder force, counter punch force, cutting speed, punch edge radius, die edge radius, V-ring height and V-ring position). The die roll height is set as the output variable of the ANN. After a successful learning phase of the ANN, the ANN will be able to predict the resulting die roll height to any input values within the range of validity.

ANN may have different types, learning algorithms and architectures. For the case being investigated, feed forward neural networks (cf. Fig. 11) are considered [19]. They are suitable for supervised learning and are usually taught by a back-propagation network [22]. In this case the error between output and the desired output is being back-propagated and the weights between the neurons are changed in a way, which minimizes the error. Other important learning algorithms are the conjugate gradient method and the Levenberg-Marquardt method, which in some cases are much faster than the backpropagation algorithm [18]. Another possible type of ANN for the prediction of the die roll is the deep feed forward neural network. Those are similar to the regular feed forward neural networks but consist of more hidden layers and number of neurons per layer. Special care has to be taken when choosing the activation function of the neurons, the initialization of the weights, and the learning algorithms for this type of network [23]. Their advantage is that their architecture is closer to the human cognition and hence, is supposed to have a better ability to learn complex interdependencies. Support vector networks can be considered for the prediction of the die roll too [24]. They are well suitable for classification problems. They showed good performance in text recognition.

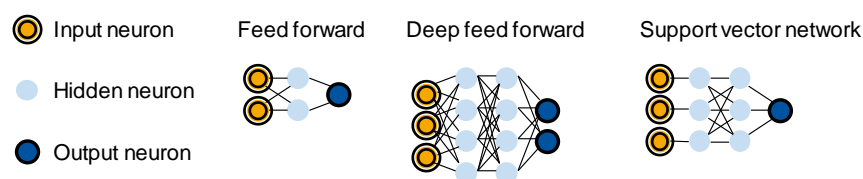


Figure 11. Different types of artificial neural networks suitable for modeling the die roll [25]

The mentioned types of ANN will be trained in the future with the generated FE simulation data. This way, ANN with different architectures will be created. Using the test data sets from FE simulations which are not included in the teaching data set, the predictability of the ANN will be tested and subsequently validated with an experimental fine blanking data. The result will be the determination of the ANN with the best ability to model the die roll.

5. Summary and conclusion

While artificial neural networks have already been applied successfully to imitate human cognitive abilities, e.g. board games [26] or autonomous driving [27], this has not yet been fully achieved in the field of manufacturing technology. Therefore, the goal is to transfer this potential to manufacturing

processes, such as fine blanking. To train the ANN, data from a FE model of a rotationally symmetrical fine blanking process is to be used. The FE model enables the automated variation of significant influencing variables of the fine blanking process. These factors are the punch edge and die edge radius, the blank holder and the counter punch force, the workpiece thickness and the workpiece diameter, the V-ring height and position as well as the cutting speed. The ANN will be used to predict the die roll height according to given input values.

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