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Genetic programming method for modelling of cup height in deep drawing process

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A B S T R A C T

Genetic programming method for modelling of maximum height of deep drawn high strength sheet materials is proposed in this paper. Genetic programming (GP) is an evolutionary computation approach which uses the principles of Darwin's natural selection to develop effective solutions for different problems. The aim of the research was the modelling of cylindrical cup height in deep drawing process and analysis of the impact of process parameters on material formability. High strength steel sheet materials (DP1180HD and DP780) were formed by deep drawing using different punch speeds and blank holder forces. The heights of specimens before cracks occur were measured. Therefore, four input parameters (yield stress, tensile strength, blank holder force, punch speed) and one output parameter (cup height) were used in the research. The experimental data were the basis for obtaining various accurate prediction models for the cup heights by the genetic programming method. Results showed that proposed genetic modelling method can successfully predict fracture problems in a process of deep drawing.

A R T I C L E   I N F O

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1. Introduction

Deep-drawing processes are frequently used in the sheet metal forming industry, because of the achievable formability. In deep drawing the sheet blank is deformed by tensile and compressive loads in different directions of action. The sheet thickness should remain as constant as possible. Many parameters influence the deep drawing process and should be carefully selected for effective and economical production. Among them, the influence of punch speed and blank holding force are of great importance, since the shortened process duration leads to an increase in productivity. Therefore, gaining knowledge of the influence of these parameters is of great interest when achieving the greatest possible productivity in producing fault-free parts. Accurate models, which describe the influences of different parameters in deep drawing, can be obtained by many different modelling methods, and serve for optimization and prediction purposes in the process.

In widely used deterministic methods like multi regression method, the form and size of a model is determined in advance. These modelling methods have one common feature: all of them optimize a given model of a problem. That is, each genotype determines a particular combination of values of free variables of the model, and the interpretation of those variables within a model is fixed. When applied to a different problem instances, they often turn out to be infeasible or obtain much worse fitness. Much better results are often achieved by non-deterministic modelling methods, such as genetic programming method (GP). In GP the model is not known in advance, and only the constraints of the model are given, e.g., instruction set, the maximum size of organisms etc. [1]. Hence GP creates and optimizes entire model of the problem. In other words, GP evolves an executable code that inputs a given problem instance and outputs a solution to the instance. In this sense GP's solutions are active, i.e. adapt to the given problem instance [2].

Majority of papers dealing with modelling methods in metal forming processes, describing neural network and genetic algorithms (GA) methods while only a few are dealing with GP. In paper [3] authors describe prediction and optimization of sealing cover thinning in deep drawing process by using GA as very accurate and effective method. In [4] GA have been used to develop an optimization strategy for choosing blank holder force and punch force for enable fracture free and wrinkle-free production of deep drawn cups while in [5] optimum blank shape and process parameters were defined and calculated for deep drawing process using Taguchi optimization method and GA. Pareto optimal solution search techniques in GA to reduce excessive thinning and wrinkling occurrence was described in [6] and [7]. An evolutionary structural optimization method for the sheet blank shape optimization in deep drawing process was presented in [8]. Many authors have used combination of neural network and GA approach for modelling and predicting deep drawing parameters and some properties of drawn products [9, 10]. In [11], the effect of hydro-mechanical deep drawing process parameters was investigated by FE simulations and neuro-fuzzy modelling method to predict the maximum thinning of sheet material, while in [12] a fuzzy control algorithm for optimization of loading profiles and drawing ratio was proposed.

An overview of recent applications of evolutionary computing in manufacturing industry was presented in [13]. Very few papers (and especially sheet forming processes) dealing with modelling by the GP modelling method. In papers [14, 15] authors compared genetic algorithm models and GP models for the distribution of effective strain and stress and also some mechanical properties in forward extruded alloy. GP method performed well in developing more accurate genetic models. In [16] authors described the application of bi-objective GP modelling for prediction of the size of austenite grain as a function of heating time. GP method was also used very successfully for modelling of bending capability of titan-zinc sheet in [17]. Different bending parameters and their impact on bending capability were analysed and optimized and a variety of accurate models were developed by GP.

This paper proposed a GP modelling of maximum height of cup deep drawn high strength steel specimens. Maximum height achieved in deep drawing process depends on many parameters and is excellent indicator for formability level of chosen material. Experimental data measured during the deep drawing processes served as an environment for evolution process in genetic programming. Blank holder force, punch speed, tensile and yield stress were used as independent input variables, while maximum height of deep drawn specimens before first cracks occur was a dependent output variable.

2. Materials and methods

2.1 Genetic programming

Genetic programming is a sub brunch of evolutionary computation (EC) emulating the natural evolution of species and is probably the most general approach among EC methods. To imitate the evolutionary process in GP, certain components must be defined, such as mathematical functions, problem variables and genetic operations like reproduction, mutation or crossover [1].

The GP process starts with random generation of initial population of organisms (computer programmes). Terminal genes, such as variables and constants, and function genes (arithmetic operations) compose each programme and must be carefully selected. After that the fitness function must be determined for evaluation of programme adaptation to the environment (e.g., to the experimental data). Adaptation is a main force in natural selection. The change and improvement of programmes fitness during GP process is enabled by genetic operations, such as reproduction, mutation and crossover. The right selection of genetic operations and their probability is of vital importance for successful GP process (and often vary regarding the problem to be solved), because genetic operations provide an increasing diversity and genetic exchange among computer programmes. The mutation also introduces new code fragments into population and is used as a common workaround for loose of diversity and stagnation, especially in small populations.

The last step of the process is the definition of termination criterion which is usually prescribed number of generations. If the termination criterion is fulfilled the evolution is then terminated. In general, many independent GP runs are needed for successful and accurate problem solutions.

2.2 Experimental details

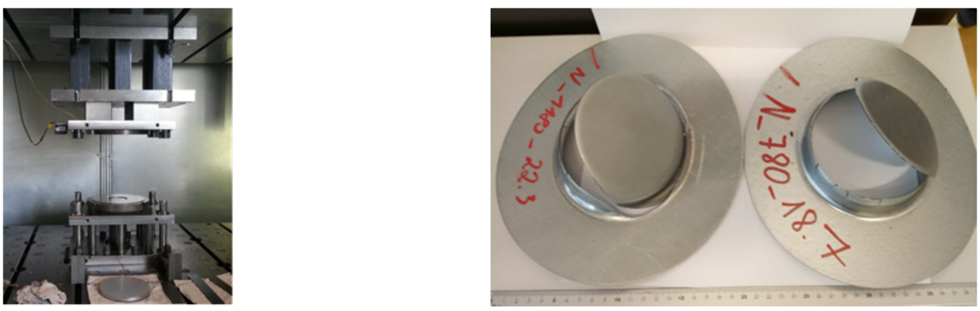
The main goal of the experiments was determination of the impact of punch speed and blank holder force on the maximum height of deep drawn sheet metal cups before crack occurs. The two chosen parameters are very important for efficient and quality process of deep drawing. Deep drawn cups are cylinders that are closed on one end and open on the other, with or without a flange on the open end. Two different sheet materials were used (DP1180HD and DP780) which are new advanced high strength steels with good cold formability developed for automotive industry. These two materials are also suitable for welding and show excellent characteristics by crash tests.

With the help of tensile tests two important mechanical characteristics were determined: R_m (tensile strength) and yield stress $R_\mathrm{p0.2}$ for DP1180HD ($R_\mathrm{p0.2}$ = 1077 N/mm^2, R_m = 1269 N/mm^2) and for DP780 ($R_\mathrm{p0.2}$ = 490 N/mm^2, R_m = 840 N/mm^2). Material thickness was s = 1.5 mm, diameter of round sheet specimens was D = 215 mm and punch diameter was d = 100 mm. For deep drawing process special experimental tool with a cylinder shaped punch and hydraulic press SHC-400 were used [18], Fig. 1(a).

The process starts with the application of the same amount of Wisura FMO 5020 lubricating oil on both sides of the specimens. Because of cup geometry, anisotropy doesn't have any influence so position of the blank doesn't have to be considered. The measurement of the deep drawn cup's height was executed by laser and acoustic measurement devices. Laser measures drawing height and acoustic sensor device, which was attached in the inner side of the die, detects the moment when crack occurs. With the interaction of these two devices and special software it is possible to detect exact drawing height of the cup just before first crack occurs.

For punch speed the experimental range was set from 50 mm/s to maximum speed of 150 mm/s. The latter is usually the highest punch speed tolerated in praxis for successful and economical deep drawing process of high strength steel. Blank holder force was set to 200 kN and 600 kN respectively.

In order to provide reliable results, three experiments for the same parameters were performed (60 experiments for both materials) and then average value of the height was calculated. The shape of deep drawn cups for both materials after the experiment is shown in Fig. 1(b). Therefore, we obtained a total of 20 combinations of experimental data. The results for measured cup's height are listed in Table 1.



(a) (b)

Fig. 1 (a) Experimental tool for deep drawing, (b) deep drawn cups (v = 125 mm/s, F_b = 200 kN)

Table 1 Experimental results of deep drawing process

Experiment No.	Yield stress $R_{p0.2}$ (*X1*) (N/mm²)	Tensile strength R_m (*X2*) (N/mm²)	Blank holder force F_b (*X3*) (kN)	Punch speed v (*X4*) (mm/s)	Cup height H (mm)
1	490	840	200	50	20.086
2	1077	1269	200	50	15.596
3	490	840	200	75	20.043
4	1077	1269	200	75	15.360
5	490	840	200	100	19.853
6	1077	1269	200	100	15.220
7	490	840	200	125	19.423
8	1077	1269	200	125	14.626
9	490	840	200	150	18.623
10	1077	1269	200	150	13.073
11	490	840	600	50	19.863
12	1077	1269	600	50	15.580
13	490	840	600	75	19.667
14	1077	1269	600	75	15.140
15	490	840	600	100	19.370
16	1077	1269	600	100	14.500
17	490	840	600	125	18.936
18	1077	1269	600	125	14.293
19	490	840	600	150	18.360
20	1077	1269	600	150	13.256

Fig. 2 shows the influence of punch speed v and blank holder force F_b on maximum cup height. It is obvious that an increase of the punch speed leads to a decrease of the maximum drawing height, i.e. to decrease of the formability. This is valid for both examined high strength steels. The highest difference between measured height when blank holder force F_b = 200 kN was used was 7.2 % for DP780. The difference was much higher for DP1180HD, i.e. 16 % decrease of height when punch speed v = 150 mm/s was used compared to the height achieved at v = 50 mm/s.

The increase of blank holder force also leads to a decreasing drawing height but to a smaller extent. A change of the blank holder force does not affect the shape or tendency of the curve. Since increasing punch speed has confirmed the tendency of the formability to decrease, but high speeds are needed to achieve a certain level of productivity, it is important to optimize the process parameters with the goal to improve the efficiency and quality of the deep drawing process.

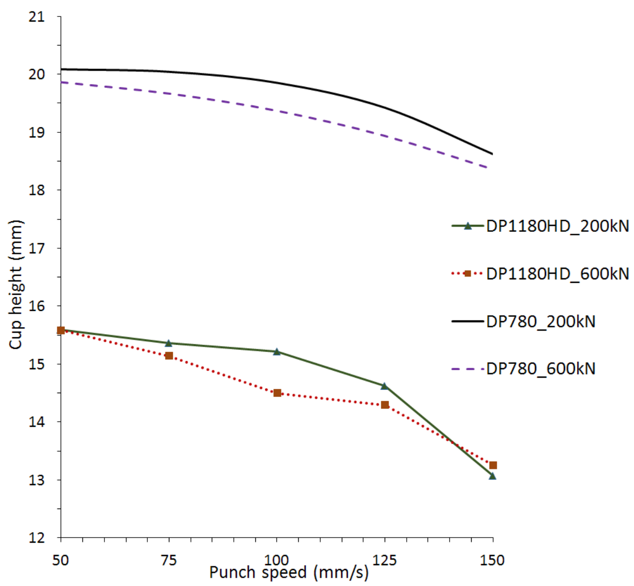


Fig. 2 The influence of punch speed v and blank holder force F_b on maximum cup height

3. Results and discussion

Evolutionary parameters that were used for GP modelling processes were: population size was 400 for all GP runs, maximum number of generations varied from 500 to 1000, reproduction probability was set to 0.1, probability of crossover varied from 0.1 to 0.3, while probability of mutation varied from 0.6 to 0.8. Such a high probability of mutation has been chosen because of the relatively small allowable maximal depth of organisms. In this way, sufficient diversity of organisms in the population is preserved. Maximum allowed depth for organisms created in the initial generation was 6 and maximum depth after crossover was 10 (in some cases only 8). Experimental results from Table 1 were used as a training data set for GP process. Additional experiments were also performed for testing data purpose and were not used in training data set.

Three different function sets were applied for GP modelling. Each function set contained function genes. First set contained three operations (function genes): addition, subtraction and multiplication, i.e. *F* = {+, -, *}, while division operation was added to the second function set, i.e. *F* = {+, -, *, /}. In third function set, natural exponential function was added to the second function set {+, -, *, /, ZEXP}. All function genes were protected against extreme values that can be occurred during simulated evolution process [1].

Terminal set comprised of terminal genes. In our case, the terminal consisted of four input variables, and random real numbers, i.e. *T* = {*X1*, *X2*, *X3*, *X4*, ℝ}. *X1* is yield strength ($R_{p0.2}$), *X2* is tensile strength (R_m), *X3* is blank holder force (F_b), *X4* is punch speed (v), and ℝ are random generated real constants from the interval -1 to 1.

By applying the first function set and terminal set, the most accurate genetically developed model for a cup height *H* developed by genetic programming was:

(+ (* -8.71014 -2.13249) (* (+ (* (+ (- (+ (- (* -9.70734 *X1*) (* *X1 X4*)) (* (- *X2 X1*) (+ *X2* 9.80336))) (+ (* (+ 9.80336 *X4*) (+ *X1 X1*)) (* *X1* (+ *X4 X1*)))) (+ (- (- (* -9.70734 *X1*) (* *X4 X3*)) (+ (* *X3 X4*) (* *X4 X4*))) (- (- (* -9.70734 *X1*) (* *X4 X4*)) (* (+ 9.80336 *X4*) (+ *X1 X3*))))) (- -2.07369 -2.07544)) (- (+ (+ (- (- *X2* 1.62782) (* -0.0546093 *X4*)) (+ 9.76417 1.167)) (- (+ (- (- *X2* 1.62782) (* -0.0546093 *X4*)) (+ 9.76417 1.167)) *X1*)) (- (- (- (+ *X1* (* -0.0546093 *X4*)) 9.80336) 9.80336) (- (- (- *X2* 1.62782) (* -0.0546093 *X4*)) (+ *X1* (+ (* 3.08974 -6.87342) (- -7.08458 4.51225))))))) (- -2.07369 -2.07544))))

The above model is presented in prefix notation of programming language LISP. After simplifying, the above model for a cup height *H* can be written as the mathematical expression (please note that in Eq. 1 instead of variable names *X1*, *X2*, *X3*, *X4* original symbols are used):

$$\begin{aligned}&18.6958 - 3.0625 * 10^{-6} {R_p}^2 + 0.00528002\, R_m + 3.0625 * 10^{-6} {R_m}^2 - 0.0000300228\, F_b\\&+R_p(-0.00545928 - 3.0625 * 10^{-6}\, R_m - 0.0000153125\, v) + 0.000382265\, v\\&-9.1875 * 10^{-6} F_b v\; - 6.125 * 10^{-6}\, v^2\end{aligned} \tag{1}$$

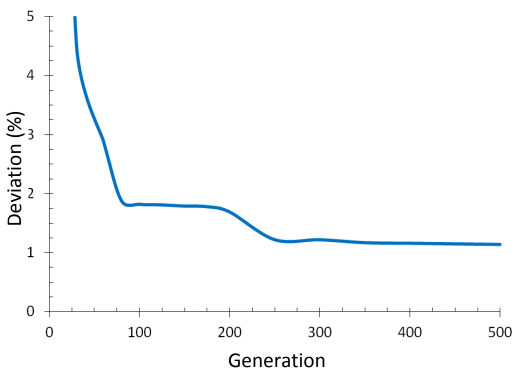


Fig. 3 Deviation of best GP model using first function set {+, -, *} and training data

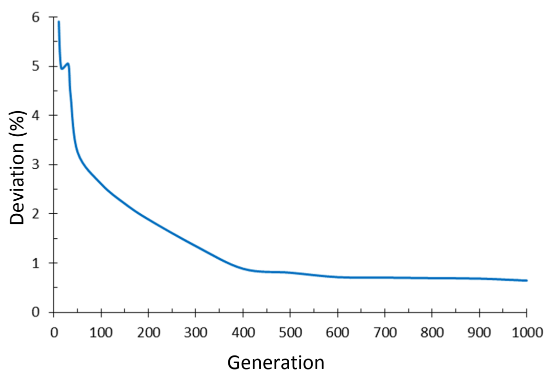


Fig. 4 Deviation of best GP model using second function set {+, -, *, /} and training data

The model in Eq. 1 was generated in generation 500. It has a total of 127 genes, 63 functional genes and the depth of this model is 10. Probability of reproduction was 0.1, probability of mutation 0.6, and probability of crossover 0.3. Maximal allowed depth after crossover was 10. The average difference between experimental results and the results predicted by the genetic developed model in Eq. 1 was δ = 1.14 % and δ = 1.18 % for training data set and testing data set, respectively.

Fig. 3 presents the average deviation (error) of best GP models when applying first function set. In first few generations there is a large deviation between the prediction results of the GP developed model and experimental data but after several generations natural selection randomly added new genes. Thus, diversity get bigger and deviation becomes better, i.e. lower. After generation 250, the deviation of best models improves very slowly and does not change much until final generation.

The most accurate GP model of all experiments for modelling of cup height was developed by applying the second function set (+, -, *, /). In the prefix LISP form it can be expressed as:

(+ (/ (+ (- (/ (- (* 9.40782 *X2*) (* *X2* -5.06327)) (+ (- *X3* 9.69337) (* -0.346372 *X3*))) (+ (+ (- 3.49304 5.8424) -8.94781) (+ (- *X1* 0.583014) -8.27698))) (- (/ (- (- *X2* -5.60735) (- *X3* 9.69337)) 4.48845) (+ (/ (* *X3* 3.73772) (- *X2 X1*)) (+ (- -9.68001 3.38485) (- *X4* -0.0676581))))) (+ (+ (/ (+ (* *X1* 3.13824) (* *X1* 3.13824)) (- (+ 7.6819 5.58638) (- *X3 X4*))) (+ (/ (+ *X2 X3*) (- *X1 X2*)) (+ -1.18787 *X2*))) (/ (+ (- (* *X1* -8.97815) (* *X1 X4*)) (* (- *X4* -8.75927) (* *X1* -2.32527))) (- (* (- *X2* 8.5169) 0.560745) (+ (/ *X1 X4*) (/ *X1 X4*)))))) (+ (/ 5.35335 (/ (+ (- (+ *X1* -8.27698) (/ *X2 X4*)) (/ (+ *X2* 5.21486) -9.66085)) (+ *X2* (/ (* *X1* 8.08171) (+ -6.90552 *X3*))))) 8.66904)))

The above model can be written in the infix mathematical expression as:

$$8.66904+\frac{5.35335\left(R_{\mathrm{m}}+\dfrac{8.08171\,R_{\mathrm{p}}}{-6.90553+F_{\mathrm{b}}}\right)}{-8.81677+R_{\mathrm{p}}-0.103511\,R_{\mathrm{m}}-\dfrac{R_{\mathrm{p}}}{v}}+\frac{\left(36.5633-R_{\mathrm{p}}+R_{\mathrm{p}}\left(0.222794-\dfrac{14.4711}{9.69337-0.653628\,F_{\mathrm{b}}}\right)-0.222794\,F_{\mathrm{b}}+\dfrac{3.73772\,F_{\mathrm{b}}}{R_{\mathrm{p}}-R_{\mathrm{m}}}-v\right)}{-1.18787+R_{\mathrm{m}}+\dfrac{R_{\mathrm{p}}+F_{\mathrm{b}}}{R_{\mathrm{p}}-R_{\mathrm{m}}}+\dfrac{6.27648\,R_{\mathrm{p}}}{13.2683-F_{\mathrm{b}}+v}+\dfrac{R_{\mathrm{p}}(-29.3458-3.32527\,v)\,v}{-2R_{\mathrm{p}}-4.77581\,v+0.560745\,R_{\mathrm{m}}\,v}} \tag{2}$$

In this process we increased the highest allowed number of generations from 500 to 1000. Also the values of probability for some genetic operations were changed. The obtained model (Eq. 2) has an average error of δ = 0.65 % (δ = 0.68 % for testing set) and was generated in generation 1000, has a total of 139 genes, 69 functional genes and the depth of this model is 8 which was also the highest allowed depth after crossover. In this case the values of main evolutionary parameters were: probability of reproduction was 0.1, probability of crossover 0.1 while mutation probability was set to 0.8. This model is more complicated compared to GP model in Eq. 1 but it is also much more accurate.

Fig. 4 presents the average deviation (error) of the best GP model when second function data set was applied for GP process. It can be seen that after generation 50 all calculated average errors of best GP models are smaller than 3 % and after generation 360 they are all under 1 %. From that point and up to final generation the percentage deviation decreases very slowly. If more generations would be used in genetic programming the accuracy of the models would not increase significantly, but processing time would be much longer.

Some very simple genetic models were also obtained by GP process. One of the best simple model with average error of 1.31 % was developed with first function set (+, -, *) and is presented in Eq. 3.

$$-0.30418-0.0469128\,R_{\mathrm{p}}+0.0532937\,R_{\mathrm{m}}-0.000797616\,F_{\mathrm{b}}-0.0170231\,v \tag{3}$$

The above model is the evidence that GP process is capable of developing not only complex genetic models, but also very simple models with satisfactory accuracy. Simple models are easy to use, but when accuracy of the model is priority, such as in our research, the more complex and more accurate models should be used for prediction and simulation purposes.

We have also performed a few runs of GP modelling with third function set by adding natural exponential function (ZEXP) to four basic math functions. The best obtained genetic models were complex but not so accurate. It was obvious that adding ZEXP function does not results in getting better genetic models, in some cases natural selection in GP even eliminates exponential function and so the best developed models were without ZEXP function. The reason for this happening could be in relatively simplicity of the studied problem.

4. Conclusion

In the paper a GP modelling method for maximum height of cup deep drawn high strength steel specimens, which is an indicator for cold formability level of the material, was presented. The research showed that an increase of the punch speed and blank holder force leads to a decrease of the maximum drawn height. By GP modelling it was possible to develop many different and very accurate genetic models. By using and combining different values for evolution parameters the optimal and most suitable GP models were developed. In our case, a high probability of mutation was vital for good convergence of the algorithms, because it preserves high diversity of a population. With lower value of probability of mutation, the convergence becomes either very slow due to low diversity of organisms in a population or organisms do not even converge to a sufficiently good solution. In the paper only three of the best developed genetic models were presented. The most accurate GP model was also very complex, but this is not an obstacle because modern production processes are all supported by high performance computers, so it is easy to use even the most complex models for accurate prediction of chosen parameters.

In mass production processes, such as deep drawing, sometimes even the tiny improvement in optimization of process parameters can lead to massive reduction of production costs and consequently highly accurate models are desired. In our future work we intend to perform experiments with much more different materials and also additional parameters with the goal to optimize the input parameters for achieving better formability in deep drawing process.

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