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GENETIC BASED APPROACH TO PREDICT MECHANICAL PROPERTIES OF THE MATERIAL

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ABSTRACT
Genetic programming (GP) is probably the most general approach from among evolutionary computation methods. The GP method is most often used for complex system modelling, but it can also be effectively used for the modelling of a relatively simple system, such as the systems described in our paper. In the paper a special genetic approach for the modelling of mechanical properties in formed material is proposed. Special material was formed by using different process parameters and then some mechanical properties of the specimens were determined. On the basis of a training data set, various different genetic models for mechanical properties with great accuracy were obtained during simulated evolution.
Keywords: mechanical properties, genetic programming, modelling.

1. INTRODUCTION

Evolutionary computation *(EC)* harnesses the power of natural selection to turn computers into optimization tools. This is very applicable to different problems in the manufacturing industry [1, 2]. One of most important *EC* methods is genetic programming (*GP*) which is, similarly to a genetic algorithm, an evolutionary computation method for imitating biological evolution of living organisms. Several researches have been carried out using a neural network or genetic algorithms for modelling, thus forming process parameters [3, 4, 5, 6], but only a few dealing with much more general genetic programming method [7, 8,9].
This paper describes an evolutionary computation method approach for the modelling of yield strength. Experimental data obtained during the cold drawing processes under different conditions serves as an environment which, during simulated evolution, models for the yield strength have to be adapted to. Different values for effective strains and coefficients of friction were used as independent input variables (parameters), while yield strength was a dependent output variable. Then, *GP* was used for the evolutionary development of the models for yield strength prediction, on the basis of a training data set.

2. EXPERIMENTAL WORK

The aim of the experimental work was to determine the influence of the effective strain ε_e and coefficient of friction μ during cold drawing on the change of yield strength of cold drawn alloy CuCrZr. Copper alloy rods were deformed by cold drawing under different conditions. Copper alloy rods were drawn from an initial diameter of D=20 mm to six different diameters (i.e. six different effective strains). Three different lubricants with different coefficients of friction (μ=0,07, μ=0,11 and μ=0,16) were used for the drawing process. In order to evaluate the yield strength, standard specimens for tensile tests were prepared from locations in the middles of the drawn rods. In this way we obtained 18 different experimental specimens. The yield strengths of all specimens were

determined by providing three tensile tests for each specimen in order to provide reliable results. The results (average values) for yield strength are presented in Table 1. Experimental data serve as an environment which, during simulated evolution, models for impact toughness have to adapt.

Table 1. Experimental results.

Nr.	Effective strain	Coef. of friction	Yield strength $R_{p0,2}$ [N/mm^2]
initial	/	/	409
1	0.10	0.07	498
2	0.21	0.07	513
3	0.32	0.07	523
4	0.44	0.07	529
5	0.57	0.07	532
6	0.71	0.07	533
7	0.10	0.11	500
8	0.32	0.11	528
9	0.71	0.11	537
10	0.10	0.16	502
11	0.44	0.16	536
12	0.71	0.16	544
13	0.21	0.11	515
14	0.44	0.11	532
15	0.57	0.11	535
16	0.21	0.16	520
17	0.32	0.16	529
18	0.57	0.16	540

3. METHOD USED

Genetic programming is probably the most general approach from among evolutionary computation methods in which the structures subject to adaptation are those hierarchically organized computer programs whose size and form dynamically change during simulated evolution. The initial population in GP is obtained by the creation of random computer programs consisting of available function genes from set *F* and available terminal genes from set *T*. The next step is the calculation of individual's adaptation to the environment. Fitness is a guideline for modifying those structures undergoing adaptation. After finishing the first cycle, which includes creation of the initial population, calculation of fitness for each individual of the population, and genetic modification of the contents of the computer programs, an iterative repetition of fitness calculation and genetic modification follows. The evolution is terminated when the termination criterion is fulfilled. This can be a prescribed number of generations or sufficient quality of the solution. The evolutionary processes were controlled by the following evolutionary parameters: population size 1000, maximum number of generations to be run 50, probability of reproduction 0.15, probability of crossover 0.7, maximum depth for initial random organisms 6, and maximum permissible depth of organisms after crossover 12. Each individual *GP* run started with the training phase by the training data set shown in *Table 1* (Nr.1 to Nr.12). The testing data set (*Table 1*: Nr.13 to Nr. 18) was not included within the training range. Each run lasted up to generation 30 when it was temporarily interrupted. If an average percentage deviation $\Delta(i)$ of at least one prediction model (organism) in the population was smaller than 5%, the evolution of the population continued up to generation 50, otherwise it was terminated. More a 500 independent runs were executed for modelling the yield strength.

4. GENETIC MODELS – RESULTS AND DISCUSSION

The best accuracy (Δ (i) = 0,175 %, and that of the testing data Δ(i) = 0,18%) of the GP model was obtained when the genes function set which includes the exponent function was used: *F* = (+,-,*, /, ZEXP):

(- (- ((+ (* 8.218 μ) (+ -6.93491 7.17839)) (+ (% (ZEXP μ) μ) (- 2.8788 -9.30543))) (+ (% (ZEXP 5.93875) (* (+ 3.20968 2.16393) (ZEXP ε))) (% (* (- μ -4.38819) (* 8.218 ε)) (% (ZEXP (+ ε 7.35216)) (ZEXP (ZEXP ε)))))) (- (+ (+ (- (% (ZEXP (ZEXP ε)) ε) (% (* (+ 3.20968 2.16393) (ZEXP ε)) (ZEXP ε))) μ) (% (* (+ ε 8.218) (% (* 8.218 μ) (* ε (% 6.56898 (ZEXP μ))))) (- (+ (* 8.218 μ) (+ -6.93491 7.17839)) (* ε -5.45287)))) (+ (ZEXP (- (- 2.8788 -9.30543) (% 6.56898 1.10215))) (% (* (+ (* 8.218 μ) (+ -6.93491 7.17839)) (+ (% (ZEXP μ) μ) (- 2.8788 -9.30543))) (* (+ (* 8.218 μ) (+ -6.93491 7.17839)) (+ (% (ZEXP ε) μ) (- 2.8788 -9.30543)))))))*

The upper GP model can be written as a mathematical expression:

$$513.098 - 70.615e^{-\varepsilon} + 0.023\frac{e^{e^{\varepsilon}}}{\varepsilon} + e^{-\varepsilon e^{\varepsilon}}\varepsilon + e^{\varepsilon}\left(8.218 + \frac{0.243}{\mu} - \frac{10.281\mu + 1.251\varepsilon}{\varepsilon(0.234 + 5.452\varepsilon + 8.218\mu)} + \frac{1}{e^{\varepsilon} + 12.184\mu}\right) + \mu\left(99.13 + \frac{12.184}{e^{\varepsilon} + 12.184\mu}\right) \quad (4.1)$$

The most accurate simple model with model depth 5, containing 7 function genes has average deviation Δ (i) = 1,67 % (testing data Δ(i) = 2,2%) is:

(+ (% -1.85689 ε) (* (- ε -9.72416) (- (+ μ ε) (* 5.39679 -8.66756))))

or

46.76 μ - 454.79 – 1.85/ε (4.2)

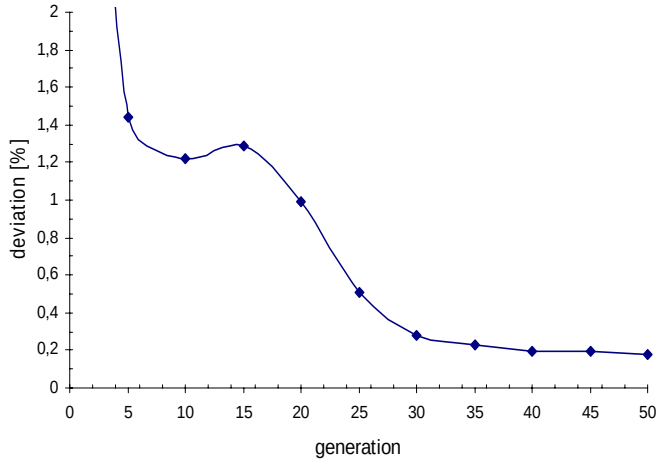

*Figure 1. Percentage deviation curve between the best models regarding individual generation and experimental results (F = +, -, *, /, ZEXP)*

Figure 1 shows the percentage deviation curve (Δ_i) between the best model regarding individual generation and experimental results when using the set of function genes F = {+, -, *, /, ZEXP}. It is obvious that in early generations the best models are not as precise as the models generated in late generations.

5. CONCLUSIONS

The genetic development of models took place on the basis of experimental data. The experimental data in this research were in fact the environment to which the population of models had to be adapted as much as possible. The models presented are a result of the self-organization and stochastic processes taking place during simulated evolution, and not of human intelligence. The accuracies of the models developed during the training phase were also confirmed using testing data not included within the training range. Only two genetically developed models out of many successful solutions are presented here. The accuracies of solutions obtained by *GP* depend on applied evolutionary parameters and also on the number of measurements and the accuracy of measurement. In general, more measurements supply more information to evolution which improves the structures of models.

At the same time, the greater number of measurements causes time-consuming computer processing and the execution of experiments is very expensive and requires much time. Because of the high precision regarding the models developed by the *GP* approach, with the proposed concept, the excessive number of experiments/simulations can be avoided, which leads to the reduction of the product development costs. The research showed that simple, and in the same time, very precise models are often hard to reach. This is due to the fact that evolution is a stochastic process, therefore, rationality in the development of the models is rare. However, in many metal-forming processes the accuracy of prediction is of vital importance, not the model complexity.

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