GENETIC MODELING OF EXPLOSION-INDUCED DEEP DRAWING PROCESS

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ABSTRACT

Modeling, simulation and optimization of technological processes is continually present in technologically advanced industries where by applying these methods huge savings in material and energy are achieved and working systems' burden reduced, that is, a technological-economic level of working processes is upgraded. In this paper a genetic algorithm for explosion-induced deep drawing process modeling will be applied, thereby enabling forecasts in real process as early as in the stages of design and simulation with increased reliability and stability of the process in the implementing phase. The achieved mathematical model was modified into three different forms expressed with equations with pertaining coefficients, modeling of those forms was performed and the results were compared.

Key words: genetic modeling, explosion-induced deep drawing

1. INTRODUCTION

To present the work of genetic algorithm or to perform the modeling by genetic algorithm, we will modify the achieved mathematical model (1), which adequately describes the pressure of shock wave in explosion-induced drawing, in three different forms presented by equations (2), (4) and (5) with the associated coefficients and we will perform the modeling of these forms. [1]

 $p_V = 287,2739 \ln G + 322,6927 \ln V_E - 682,0897 \ln R - 1866,4059$

(1)

(2)

Further, in the form from the example one or equation (2) we will perform the restricting of limits and compare the achieved results. We will also genetically model and present the model presented by equation (1) and compare the results with other models.

2. GA MODELING

Results achieved by genetic modeling or the values of model coefficients are presented in Figure (1) for the exponential form defined in advance, which is presented in the following equation:

$$p_{v} = C G^{\alpha_{I}} V_{E}^{\beta_{I}} R^{\gamma_{I}}$$
 (bar)

Coefficients are given in Figure (1) and they have the following values: C = 740,33066, $\alpha_1 = 0,39415$, $\beta_1 = 0,20668$ and $\gamma_1 = -0,0447$. GA modeling was done by program MATLAB R2006a. A model with medium deviation error from experimental values of 8,66% was achieved for 10000 generations and population of 100 individuals within limits from [-1000, +1000]. The goal function through generations for the example from equation (2) is presented in Figure (2).

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Figure 1. Coefficients value of the presented GA in Matlab for example 1.



Figure 2. Goal function through generations for example 1.

In this example (example No. 2) the model is the same like in the example 1 the difference being only in the model's width of limits. In this example the limits are significantly narrower for the 2., 3. and 4. coefficient [-1000, -1, -1, -1] to [1000, 1, 1, 1] because in the previous example it was shown that such wide limits are not required. The coefficients have the following values: C=20,91275, α_1 =0,38038, β_1 =0,44881 and γ_1 =-0,85385.

The modeling was performed for 10000 generations and population of 100 individuals and the achieved model has the medium deviation error from experimental values of 2,31% which is significantly better than in the example 1. and for the limits width of [-1000, +1000] with the associated coefficients. Deviation of 2,31% was achieved in the very beginning after 200 generations. In this example (example No. 3) the start model was changed so it looks like this:

$$p_{v} = C + \alpha_{1} \ln G + \beta_{1} \ln V_{E} + \gamma_{1} \ln R \quad \text{(bar)}$$
(3)

The form of this model is the same like the form of the model achieved in equation (1). The values of coefficients of the model amount to: C= -1705,38958, α_1 =296,11539, β_1 =314,89275 and γ_1 =-649,59211.

The modeling was performed for 10000 generations and population of 100 individuals and the achieved model has the medium deviation error from experimental values of 1,09% which is significantly better than in the presented example 1 and example 2. It is also better than the deviation achieved by mathematic modeling because medium deviation in that model is 1,21%. Deviation of 1,09% was achieved in the first process quarter or after 2000 generations, which can be seen in Figure (3). These are the limits where the required model coefficients are: [-2000, -1000, -1000, -1000] to [2000, 1000, 1000, 1000].



Figure 3. Goal function through generations for example 3.

In this example (example No. 4) a model with only one unknown coefficient was changed and it has the following form:

$$p_{v} = C \ln\left(\frac{G \cdot V_{E}}{R}\right) \quad \text{(bar)} \tag{4}$$

The value of model coefficients amounts C=129,19491.

Modeling was performed for 10000 generations and population of 100 individuals and the achieved model has the medium deviation error significantly higher than experimental values. The error which this model provides amounts to 11,28% which is worse than in example 3, but the model has a more concise form which was responsible for the worse approximation.

In this example (example No. 5) changes are similar to the previous example. This model also has a concise form and it is presented by equation (5). The difference between equation (5) and equation (4)

lies in the fact that in the last one a coefficient C was added which is added to the rest of the amount in equation (5) while in the previous equation this was not the case.

$$p_{v} = C + \alpha_{1} \ln \left(\frac{G \cdot V_{E}}{R} \right)$$
 (bar) (5)

The values of model coefficients amount to: C= -1188,40672 and α_1 = 345,07485 and the goal function is presented in Figure (4). Modeling was performed for 10000 generations and population of 100 individuals and the achieved model has the medium deviation error from experimental values 4,19%, which is worse than in example 3 where the genetically modelled expression was achieved by mathematic model (1) or (3) but significantly better result or smaller deviation error than the model from the previous model or example No. 4. The amount of medium deviation error of this model in relation to deviation from experimental values is found in the conciseness of the model or in the smaller number of coefficients.



Figure 4. Goal function through generations for example 5.

3. CONCLUSION

Based on the presented it is noticeable that it is necessary to approach to each problem to be solved and to deal with all its specific qualities to make the modeling work and for us to be satisfied with the achieved result. For successful optimisation it is necessary to define successfully the goal function which needs to copy the problem being solved. In practice there are often certain limitations which need to be overcome in some way. In its work the genetic algorithm generates generations or population whose fitness is better from cycle to cycle, in what we convinced ourselves in this work also. The reliability of results can be increased by repeated repetitions, and with good selection of coefficients or model limits time of work can be significantly reduced with the same or even better results.

4. REFERENCES

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