OPTIMIZATION OF AN ORTHOGONAL CUTTING PROCESS BY COMBINING FUZZY LOGIC AND GENETIC ALGORITHMS

Dirma Yanes[*a], Mercedes Pérez[a], Ramón Quiza[b], Marcelino Rivas[b]

a) Department of Mathematics, University of Matanzas, Cuba.
b) Department of Mechanical Engineering, University of Matanzas, Cuba.

Abstract: The work presents the multiobjetive optimization of an orthogonal cutting process, where two mutually conflicting objectives are considered: unit cutting time and tool wear rate. The relationship between the tool wear rate and the decision variables (cutting parameters and tool geometry) is modeled by using a Sugeno-type fuzzy inference system, fitted from finite element-based simulations. Optimization is carried out by using a multiobjective genetic algorithm, through an a posteriori approach, where the non-dominated solutions set is firstly obtained and, then, the most convenient solution is chosen depending on the specific workshop conditions.

Keywords: Optimization, fuzzy logic, genetic algorithm, orthogonal cutting.

Introduction

Optimization plays a key role in designing efficient highly competitive manufacturing processes. Nevertheless, it is not a simple task as it requires the use of accurate and reliable models relating, on the one hand, the so-called decision variables and, on the other hand, the optimization targets and process constraints. Due to the complex nature of the physical phenomena involved in the manufacturing processes, these relationships are highly nonlinear and noisy. Consequently, the corresponding models (often based on artificial intelligence techniques, such as neural networks or fuzzy logic [1]) usually do not fulfill the mathematical requirements (continuity, smoothness, unimodality, etc.) of the analytical and numerical optimization techniques [2]. On the contrary, heuristic optimization techniques are more flexible in their prerequisites [3] and, therefore, they have been successfully applied to a wide set of engineering problems, including most of the manufacturing processes [4].

The advantages of using heuristic optimization techniques rise when considering a posteriori multiobjective optimization problems, because they can obtain the set of optimal solutions (the so-called Pareto front) in a single run [5]. It must be pointed out that these solutions can be considered optimal, in the wide sense that no other solution, in the feasible search space, is superior to them when all optimization objectives are simultaneously considered [6].

The following work presents the multiobjective optimization of a micromilling process of a titanium alloy. The proposed approach combines a fuzzy inference system for modeling one of the optimization target and a genetic algorithm for carrying out the optimization process.

[*] Corresponding author: Dirma Yanes, E-mail: dirma.yanes@umcc.cu, Phone: +(52)(45)256782

Problem description and modeling

The considered process was an orthogonal cutting process of an AISI 1045 steel [2]. Three decision variables were selecting: the cutting speed, V; feed, f; and rake angle, γ. Two optimization objectives were simultaneously considered: the unit cutting time, τ_0, and the wear rate, wr. While the first objective can be analytically determined from the cutting parameters, $\tau_0 = 1/(VFa_P)$ (where the depth of cut is considered as a constant, $a_P = 1.0$ mm), the second must be empirically modelled from some data. In this case, these data were obtained by simulation, though the finite element method and the Usui's equation.

In order to obtain the models relating the wear rate to the decision variables, a Sugeno-type fuzzy inference system was used. The model was generated by using subtractive clustering. Three Gaussian membership functions (low, medium and high) were used for each input variable. The following code show the obtained inference rules:

```
IF (V is LOW) AND (f is LOW) AND (γ is LOW) THEN (z is 0.011)
IF (V is LOW) AND (f is LOW) AND (γ is MED) THEN (z is 0.018)
IF (V is LOW) AND (f is LOW) AND (γ is HIG) THEN (z is 0.046)
IF (V is LOW) AND (f is MED) AND (γ is LOW) THEN (z is 0.116)
IF (V is LOW) AND (f is MED) AND (γ is MED) THEN (z is 0.192)
IF (V is LOW) AND (f is MED) AND (γ is HIG) THEN (z is 0.216)
IF (V is LOW) AND (f is HIG) AND (γ is LOW) THEN (z is -0.037)
IF (V is LOW) AND (f is HIG) AND (γ is MED) THEN (z is -0.295)
IF (V is LOW) AND (f is HIG) AND (γ is HIG) THEN (z is -0.605)
IF (V is MED) AND (f is LOW) AND (γ is LOW) THEN (z is 0.119)
IF (V is MED) AND (f is LOW) AND (γ is MED) THEN (z is 0.205)
IF (V is MED) AND (f is LOW) AND (γ is HIG) THEN (z is 0.228)
IF (V is MED) AND (f is MED) AND (γ is LOW) THEN (z is 0.901)
IF (V is MED) AND (f is MED) AND (γ is MED) THEN (z is -0.354)
IF (V is MED) AND (f is MED) AND (γ is HIG) THEN (z is 3.075)
IF (V is MED) AND (f is HIG) AND (γ is LOW) THEN (z is 23.525)
IF (V is MED) AND (f is HIG) AND (γ is MED) THEN (z is 42.197)
IF (V is MED) AND (f is HIG) AND (γ is HIG) THEN (z is 64.633)
IF (V is HIG) AND (f is LOW) AND (γ is LOW) THEN (z is 0.090)
IF (V is HIG) AND (f is LOW) AND (γ is MED) THEN (z is 0.111)
IF (V is HIG) AND (f is LOW) AND (γ is HIG) THEN (z is 0.127)
IF (V is HIG) AND (f is MED) AND (γ is LOW) THEN (z is 0.823)
IF (V is HIG) AND (f is MED) AND (γ is MED) THEN (z is 1.940)
IF (V is HIG) AND (f is MED) AND (γ is HIG) THEN (z is 2.792)
IF (V is HIG) AND (f is HIG) AND (γ is LOW) THEN (z is 20.280)
IF (V is HIG) AND (f is HIG) AND (γ is MED) THEN (z is 36.036)
IF (V is HIG) AND (f is HIG) AND (γ is HIG) THEN (z is 61.820)
```

Fig. 1 shows the graphical representation of the obtained fuzzy model for three values of rake angle.

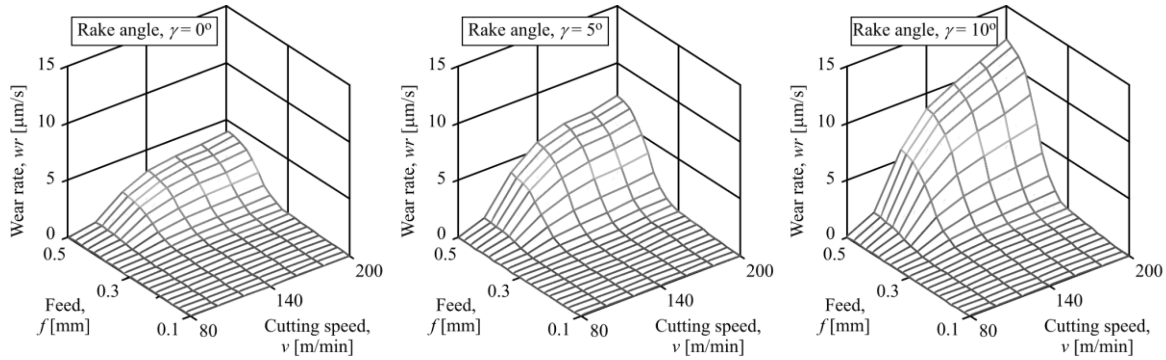

Figure 1 Graphical representation of the fuzzy model of the wear rate

Optimization

The optimization process was carried out by using the Non-dominated Sorting Genetic Algorithm-II (NSGA-II). The values for the population size and the generation number were 500 and 1000, respectively. After the optimization, the following Pareto front was obtained (see Fig. 2):

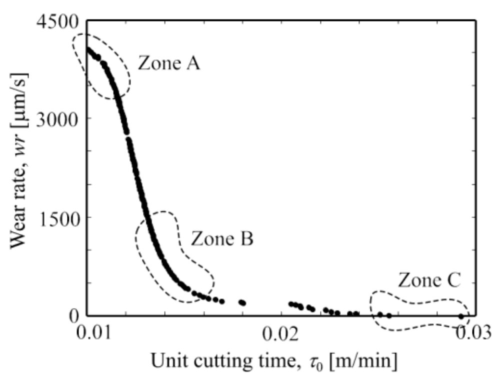

Figure 2 Obtained Pareto front

From the decision making point of view, three zones are especially interesting. Zone A, corresponds to highest wear rate and lowest cutting time, i.e., highest productivity but also highest tool waste. This point is convenient when labor cost is notably higher than tool cost, or when productivity is the only important factor (form example, in war time).

Zone C involves solutions with lowest wear rate but highest unit cutting time. These solutions are proper for conditions where the production load is lower than the machine tool capacity, so time is not an important factor. They can be used, also, when the used tool are especially expensive.

Finally, Zone B includes the compromise solutions where reasonable combinations of productivity and tool waste are achieve. It should be expected that they will be convenient for most of the practical industrial conditions.

It should be pointed out that the final decision involves economic criteria, so costs analysis may complement and enhance the obtained results.

Conclusions

In the work, the fuzzy logic and the genetic algorithms are combined for solving a practical engineering problem. The obtained fuzzy model describes accurately the behavior of the wear rate. On the other hand, the genetic algorithm shows to be able to deal with the fuzzy model in spite of its mathematical characteristics.

The proposed approach can be applied to other machining processes, such as oblique turning, milling or drilling.

Bibliography

[1] P. M. Dixit and U. S. Dixit, *Modeling of metal forming and machining processes by finite element and soft computing methods*. London (UK): Springer-Verlag, 2008.

[2] R. Quiza, O. López-Armas, and J. P. Davim, *Hybrid modeling and optimization of manufacturing: Combining artificial intelligence and finite element method*. Heidelberg (Germany): Springer, 2012.

[3] X.-S. Yang, S. Koziel, and L. Leifsson, "Computational optimization, modelling and simulation: Past, present and future," *Procedia Computer Science,* vol. 29, pp. 754-758, 2014.

[4] R. V. Rao and V. D. Kalyankar, "Optimization of modern machining processes using advanced optimization techniques: a review," *The International Journal of Advanced Manufacturing Technology,* vol. 73, pp. 1159-1188, 2014/07/01 2014.

[5] C. A. Coello, G. B. Lamont, and D. A. Veldhuizen, *Evolutionary algorithms for solving multi-objective problems*, 2nd ed. New York: Springer, 2007.

[6] H. A. Abbass, R. Sarker, and C. Newton, "PDE: A Pareto–frontier differential evolution approach for multi objective optimization problems," in *Congress on Evolutionary Computation*, Piscataway, NJ (U.S.A.), 2001, pp. 971-978.