

Multiobjective Genetic Algorithm Optimization of Machining AISI 52100 Hardened Steel

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Abstract—This paper presents an elegant Multiobjective optimization by the Genetic Algorithm (GA) approach, using the Multiple Linear Regression (MLR) model, in the hard turning of AISI 52100 bearing steel, with a Cubic Boron Nitrides (CBN) cutting tool. AISI 52100 is a hardening steel with high carbon, chromium and manganese content, which has applications in several rotating parts, such as drive shafts, cams, bearings, gears, etc. For accurate optimization of hard machining, it is very crucial to know the material characteristics of the workpiece under the extreme conditions imposed during cutting. The bearing steel is studied in various metallurgical states characterized by the presence or absence of carbides in a bainitic or martensitic matrix by scanning electron microscopy (SEM). Both states are studied for identical hardnesses between 45 Hardness Rockwell C (HRC) and 59 HRC. The purpose of the MLR is to establish the mathematical models of the objective function and the constraints used. The dependent variables to be explained by the MLR models are the components of the machining forces such as feed force F_f , radial force F_r , and tangential force F_t and the independent variables are the machining parameters such as workpiece hardness HRC, cutting speed V_c , feed rate f , and cutting depth a_p . Multiobjective GA optimization is used to identify the optimal combination of machining parameters to minimize the machining force components. The outcomes demonstrated that the proposed GA approach outperformed other optimization techniques in terms of performance.

Keywords—AISI 52100, Genetic Algorithm, Hard turning, Multiobjective, Multiple-Linear-Regression, Optimization.

I. INTRODUCTION

The technology of hard machining is largely applied in various applications, including mechanical finishing of

hardened components such as drive shafts, cams, bearings, gears, etc.

Hard turning has many advantages that allow the machining of hardened steels with a hardness of over 45 HRC. Without lubrication, it allows parts to be produced with a level of precision and surface quality similar to that obtained by conventional grinding.

In hard turning, cutting tool materials with enhanced performance, such as ultrafine-grained cemented carbides, ceramets, ceramics, cubic boron nitrides (CBN), polycrystalline cubic boron nitrides (PCBN) and polycrystalline diamonds, have been investigated and implemented [1].

The effects of different machining parameters on cutting forces, surface roughness and tool wear during hard turning of different steel grades using CBN cutting tools have been studied and optimized by several authors [2].

The determination of optimal process parameters is of particular relevance for economic machining by minimizing particular operating errors such as tool fraction, wear and chatter.

The primary objective of this paper is to achieve the optimal hard turning process parameters of an AISI 52100 bearing steel, using a CBN cutting tool.

The bearing steel is studied in various metallurgical states characterized by the presence or absence of carbides in a bainitic or martensitic matrix. Both states were studied for identical hardness ranging from 45 HRC to 59 HRC.

To achieve this objective, we developed a methodology based on two steps:

1. Develop mathematical models of the objective function and the constraints using MLR. The dependent variables to be exposed by the MLR models are the machining force components such as feed force F_f , radial force F_r and tangential force F_t and the independent variables are the machining parameters such as workpiece hardness HRC, cutting speed V_c , feed rate f , and cutting depth a_p .

2. Find the optimal combination of machining parameters to minimize the cutting force of the process with Multiobjective optimization by the GA.

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II. 2. MATERIAL CHARACTERISTIC OF AISI 52100

52100 is a high-carbon, high-chromium, high-manganese, through-hardening steel. The chemical composition and the principal physical and mechanical properties of AISI 52100 are indicated in Table I and Table II. The chemical composition of AISI 52100 has been verified by spark emission spectroscopy. The obtained results are in accordance with those recommended on AFNOR [3].

TABLE I
CHEMICAL COMPOSITION OF AISI 52100 STEEL.

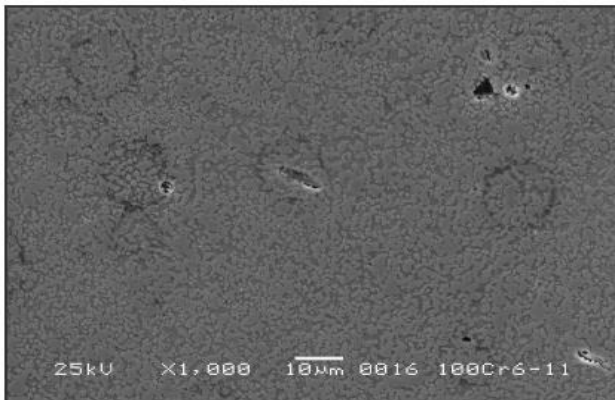
Element	AFNOR value	Measured value
% C	0.95-1.1	1.05
% Cr	1.35-1.6	1.481
% Cu	< 0.35	0.033
% S	< 0.025	0.018
% Si	0.15-0.35	0.239
% Mo	< 0.10	0.01
% Mn	0.2-0.4	0.365
% P	< 0.03	0.009

TABLE II
MECHANICAL AND PHYSICAL PROPERTIES OF AISI 52100 STEEL.

Young's modulus (GPa)	210
Poisson ratio	0.3
Mass density ($\text{kg} \cdot \text{m}^{-3}$)	7853

The Fig. 1(a) and (b) indicates that the structure of the AISI 52100 steel in the initial state before treatment is made up of carbides dispersed in a ferritic matrix with a low carbon content and with a low inclusion content.

(a)



(b)

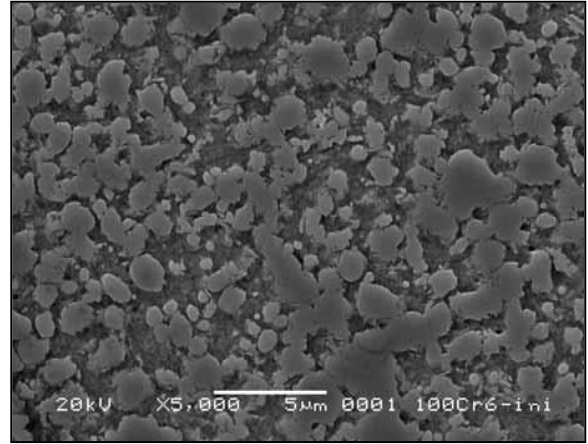


Fig. 1. SEM microstructure of AISI 52000 steel in the initial state [3].

Two different metallurgical states were investigated for identical hardness between 45 HRC and 60 HRC.

A. AISI 52100 steel with carbides

In order to create AISI 52000 steel with the presence of undissolved carbides, the steel was tempered at 850°C in a furnace for 30 minutes, followed by a water quench at 30°C.

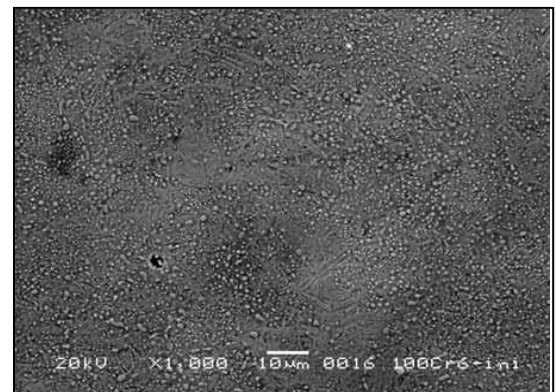
Several tempering temperatures were selected to obtain different hardness values.

TABLE III
TEMPERING TEMPERATURE AND CORRESPONDING HARDNESSES [3].

Tempering temperature (°C) / Maintien (hours)	Hardness (HRC)
500 / (1h)	45
400 / (1h)	50
250 / (1h)	55
Soaked	60

The SEM micrograph in Fig. 2(a) and (b) illustrates the microstructure of AISI 52100 steel with carbides at a hardness of 55 HRC. The results show a martensite matrix with many undissolved carbides; it is the carbides that regulate the hardness of the material.

(a)



(b)

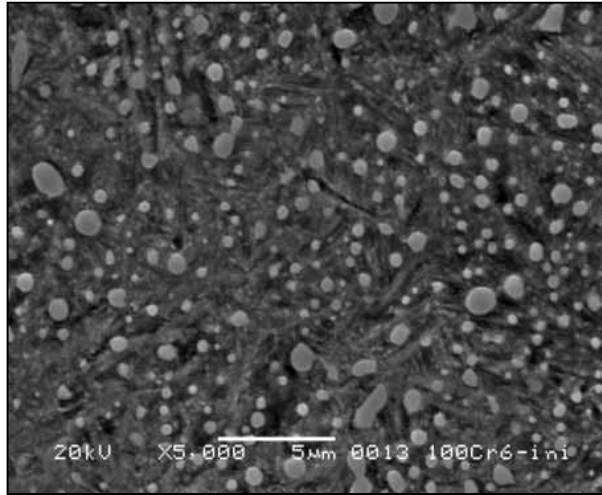


Fig. 2. SEM microstructure of AISI 52100 steel with carbides [3].

(b)

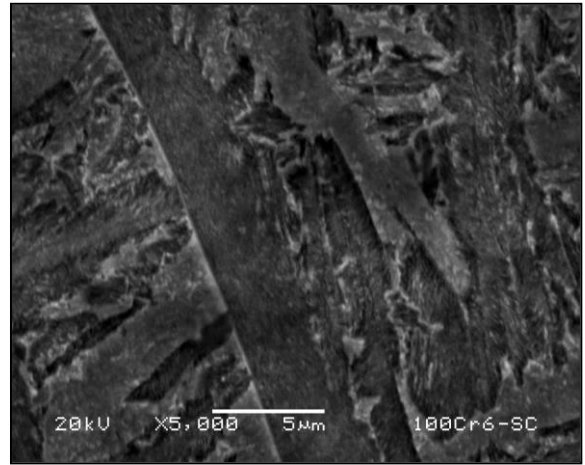


Fig. 3. SEM microstructure of AISI 52100 steel without carbides [3].

B. AISI 52100 steel without carbides

The samples were austenitized at 1000°C (dissolution temperature of all carbides) and isothermally transformed in a salt bath furnace at 225°C for 7 hours to obtain a hardness of 55 HRC. Other temperatures were held to obtain different hardnesses.

TABLE IV
TRANSFORMATION TEMPERATURE AND RELATIVE HARDNESS [3].

Staged quenching temperature	maintaining time	Hardness (HRC)
350	2 h 45 min	45
275	5 h	50
225	7 h	55

As can be seen in the following SEM Fig. 3 (a) and (b) the microstructure after this heat treatment is a bainitic structure.

(a)

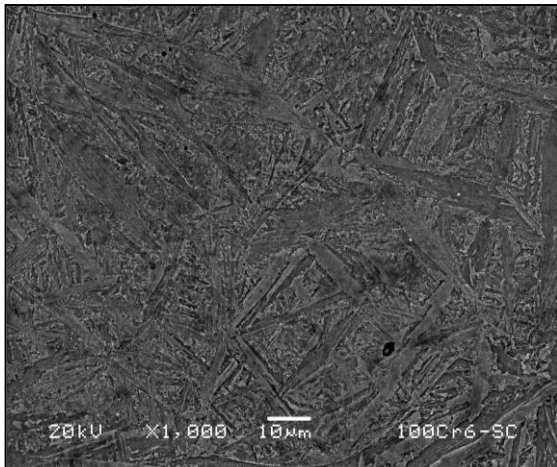
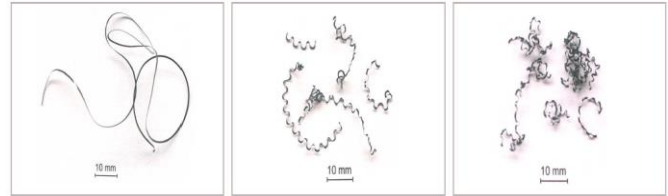


Fig. 4 represents the various macrographic and micrographic morphologies of the chips produced for different hardnesses [3]. The morphology of the chips is strongly dependent on the hardness of the material being machined. With a hardness of 45 HRC, the chips observed are continuous. However, as the hardness increases (55 HRC), more and more discontinuous chips appear with the formation of intense shear bands.

(a)



(b)

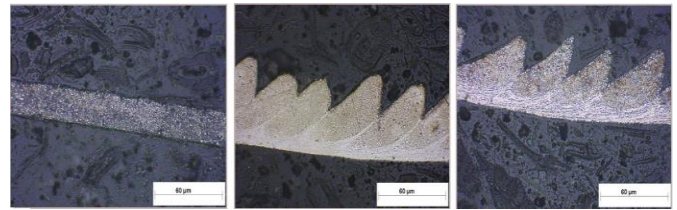


Fig.4. Chips morphology according to the hardness of AISI 52100/100Cr6 steel with carbides.

(a) Macrographic observation, (b) Micrographic observation
($V_c = 150$ m/min, $f = 0.1$ mm/rev, and $ap = 0.2$ mm).

The recent studies have shown that the two main parameters affecting chip morphology and segmentation are material hardness and cutting speed and that shear localization in the chip in hard steels occurs for hardness values above 53 HRC. Nevertheless, it is also reported that shear segmentation also occurs when machining medium hard steel at higher cutting speeds [4].

III. MULTIOBJECTIVE OPTIMIZATION USING THE GENETIC ALGORITHM APPROACH

Using the GA-based Multiobjective optimization technique, the objective is to find the optimal machining parameters to minimize the machining force components in hard turning.

Fig. 5 shows the cutting parameters and machining force components in the turning process.

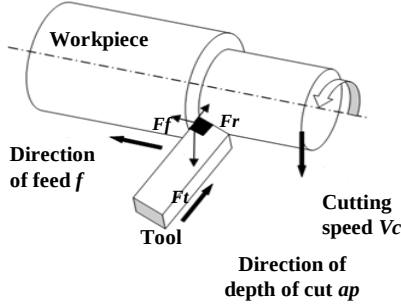


Fig. 5. Machining force components in turning process.

A. Mathematical modelling

The model, formulated in terms of several explanatory variables, takes the following form:

$$y_i = a_0 + a_1 x_{i1} + a_2 x_{i2} + a_j x_{ij} + e_i \quad (1)$$

Where y_i ($i = 1, Q$) is the endogenous or explained variable, ($x_{i1}, \dots, x_{ij}$) are the exogenous or explanatory variables, ($a_0, \dots, a_j$) are the parameters of the model, and e_i is the model error which expresses or summarises the missing information in the explanation.

In explicit form, (1) can be written as follows:

$$\left\{ \begin{array}{l} y_1 = a_0 + a_1 x_{11} + \dots + a_j x_{1j} + e_1 \\ y_2 = a_0 + a_1 x_{21} + \dots + a_j x_{2j} + e_2 \\ \vdots \\ y_Q = a_0 + a_1 x_{Q1} + \dots + a_j x_{Qj} + e_Q \end{array} \right. \quad (2) \quad (3) \quad (4)$$

The models provided by Multiple Linear Regression (MLR) to predict the components of the cutting force in hard turning are expressed by the following equations

$$F_f = a_{01} + a_{11} HRC + a_{21} V_c + a_{31} f + a_{41} a_p \quad (5)$$

$$F_r = a_{02} + a_{12} HRC + a_{22} V_c + a_{32} f + a_{42} a_p \quad (6)$$

$$F_t = a_{03} + a_{13} HRC + a_{23} V_c + a_{33} f + a_{43} a_p \quad (7)$$

Mathematical correlations between the dependent variables (F_f , F_r , and F_t) and the independent variables (HRC , V_c , f , and a_p) are achieved using MLR with the experimental results [3].

These correspondences are represented by the following equations; where R^2 is the coefficient of determination:

1) The component F_f with $R^2 = 92.5 \%$:

$$\ln(F_f) = 7.31419 + 0.17844 \cdot \ln HRC - 0.21268 \cdot \ln V_c + 0.60292 \cdot \ln f + 1.25507 \cdot \ln a_p(8)$$

2) The component F_r with $R^2 = 82.2 \%$:

$$\ln(F_r) = 7.11439 + 0.29941 \cdot \ln HRC - 0.17022 \cdot \ln V_c + 0.78193 \cdot \ln f + 0.70274 \cdot \ln a_p(9)$$

3) The component F_t with $R^2 = 96.6 \%$:

$$\ln(F_t) = 8.02677 + 0.12830 \cdot \ln HRC - 0.15214 \cdot \ln V_c + 0.82226 \cdot \ln f + 0.81963 \cdot \ln a_p(10)$$

B. Genetic Algorithm Approach

GA is a solution finding method based on natural selection, the process begins with an initial set of random solutions known as a population. Every single member of the population is called a chromosome, representing a solution to the problem at hand. These chromosomes grow in successive iterations, called generations. Throughout each generation, the chromosomes are evaluated, using some measure of fitness. To generate the solutions for the next generation, new chromosomes, called children, fuse two chromosomes from the current generation using a mutation operator. A new generation is formed by selecting some of the parents and discarding the others, based on their fitness values, in order to keep the population size constant. The most suitable chromosomes have a higher probability of being selected. After dealing with several generations, the algorithm converges on the best chromosome, which hopefully represents the optimal solution to the problem. The process that leads to biological evolution. GA employs three main types of rules at each step to generate the following generation from the current population [5]:

- 1) Selection.
- 2) Crossover.
- 3) Mutation.

a) Objective function

In this paper, the cutting force is considered in the formulation of the objective function. The cutting force is calculated using (11):

$$F_c = \sqrt{F_f^2 + F_r^2 + F_t^2} \quad (11)$$

Cutting force is one of the most important physical phenomena in the metalworking process, directly impacting cutting heat, tool wear, tool life and machined surface quality. In order to achieve this, it is necessary to be able to use the same tools as those used in the production process.

b) Machining constraints

Machining parameters are regarded as constraints for the optimization of the objective function. Therefore, they are

limited by the permissible lower and upper limit and expressed by:

$$HRC \min \leq HRC \leq HRC \max \quad (12)$$

$$VC \min \leq VC \leq VC \max \quad (13)$$

$$f \min \leq f \leq f \max \quad (14)$$

$$ap \min \leq ap \leq ap \max \quad (15)$$

Furthermore, the constraints for the maximum components of the machining force are given by the following equations:

$$7.31419 + 0.17844 \cdot \ln HRC - 0.21268 \cdot \ln Vc + 0.60292 \cdot \ln f + 1.25507 \cdot \ln ap \leq \ln(Ffmax) \quad (16)$$

$$7.11439 + 0.29941 \cdot \ln HRC - 0.17022 \cdot \ln Vc + 0.78193 \cdot \ln f + 0.70274 \cdot \ln ap \leq \ln(Frmax) \quad (17)$$

$$8.02677 + 0.12830 \cdot \ln HRC - 0.15214 \cdot \ln Vc + 0.82226 \cdot \ln f + 0.81963 \cdot \ln ap \leq \ln(Ftmax) \quad (18)$$

The machining parameters are optimized by the GA optimization code which was developed in Matlab.

Fig. 6 shows the running of the GA-based search algorithm in Matlab.

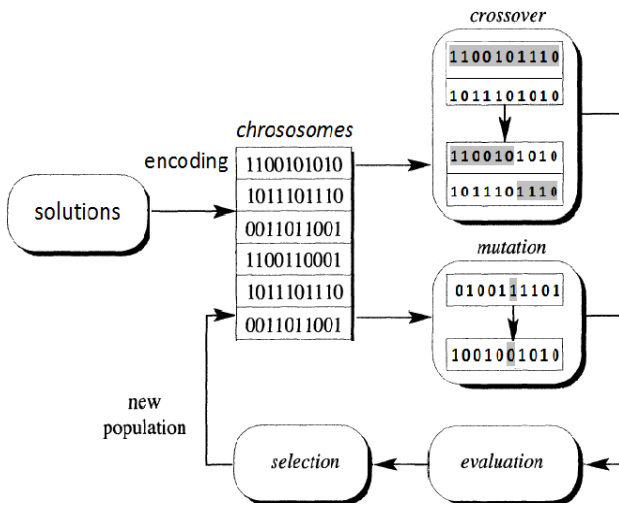


Fig. 6. Genetic algorithm types rules.

for a good optimization according to the above equations, some rules must be followed such as :

- (1) we should create and change options by using the optimoptions function.
- (2) We indicate when GA stopped, furthermore can also return a next argument, Output, which contains information about the performance of the solver.

- (3) The genetic algorithm works on a population using a set of operators that are applied to the population, we run the solver with function FunctionTolerance.
- (4) If you run this example without the *rng* default command, your results can differ, because GA is a stochastic algorithm.

IV. RESULTS AND CONCLUSION

The R^2 values of the MLR modelling of the machining force components yield 92.5%, 82.2% and 96.6% are scored on F_f , F_r , and F_t respectively. This gives an excellent relationship between the response with MLR and the experimental values. Furthermore, the GA approach converges very quickly to define the optimal machining parameters after the evolutionary process. As we can observe: the independent parameters such as $HRC = 45$, $Vc = 50$ m/min, $f = 0.2$ mm/rev, $ap = 0.1$ mm, and the dependent parameter is $Fc = 114.573$ N.

Fig. 7 illustrates a graphical comparison between the experimental cutting forces, those predicted by MLR and the GA approach.

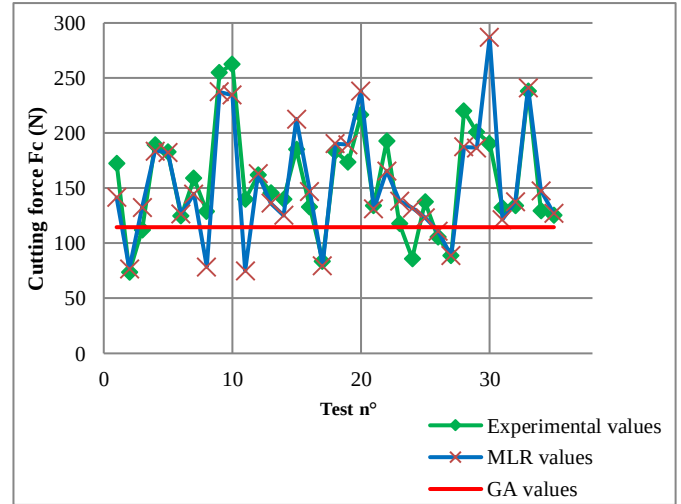


Fig. 7. Correlation between experimental, MLR and GA values for cutting forces.

The genetic algorithm considers the coding of the decision variables as the object of the operation and directly takes the value of the objective function as search information.

For this type of objective function optimization and combinatorial optimization problems, the genetic algorithm exhibits its great superiority, as it avoids the obstacle of function derivation. Compared to other algorithms, the strength of the genetic algorithm makes the influence of parameters on its search effect as small as possible.

Material hardness and cutting forces are ranked among the most important technological parameters to be controlled in the machining process. The obtained results of the GA Multiobjective optimization of the machining of AISI 52100 hardened steel are the optimal solutions, these solutions are

the most appropriate in practice and can be selected for hard machining.

This investigation can be completed and extended by including more constraints, such as cutting surface temperature, etc.

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