Tool Wear Modeling in Drilling Process of AISI1020 and AISI8620 using Genetic Programming

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Abstract: In manufacturing industry, it has been acknowledged that tool wear prediction has an important role in higher quality of products and acceptable efficiency. Being an emerging area of research in recent years, drilling tool wear is an important factor which directly affects quality parameters of machined hole such as hole centring, roundness, burr formation and finished surface. In this paper, the genetic equation for prediction of drilling tool flank wear was developed using the experimentally measured wear values and genetic programming for two different materials, AISI1020 and AISI8620 steels. These equations could be used to compare the behaviour of wear in both mentioned materials and analyse the effect of materials characteristics on wear rate and wear pattern. The suggested equations have been shown to be corresponding well with experimental data obtained for flank wear when machining in various cutting conditions. The results of experiments and equations showed that properties of work material can affect drill bit flank wear drastically. It was concluded that greater toughness and strength of AISI8620, compared to AISI1020, lead to higher cutting stresses and temperatures, resulting more flank wear.

Keywords: Drilling operation, Flank wear, Genetic programming, Tool wear

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1 INTRODUCTION

In order to achieve improved efficiency in manufacturing industry and higher quality of products in metal cutting processes such as drilling, prediction of wear, especially flank wear, is of great importance. The reason for acquiring drill wear state information is to enhance the predictive capability of drilling process and detecting tool state during cutting process. This capability allows the machine operator to schedule tool change or regrind just in time to avoid underuse or overuse of tools, avoid shutdown of machines due to damage, and to minimize scrap or rework [1]. Furthermore, drill wear has a remarkable effect on drilled hole quality such as roundness, burr formation at drill exit, centring and finished surface roughness [2]. In the majority of researches relating to drill tool wear prediction, progressive flank wear is the dominant failure mode and has been extensively investigated [1]. A typical view of drill flank wear, *VB*, is shown in Fig. 1.

The most performed researches in the literature are techniques applied to online tool wear monitoring by using some process variables such as force [3], torque [3], acoustic emission [4], Vibration [1], etc. However it must be said that sometimes it is really difficult to decide on the most proper parameters to sense and measure. The cost of selected sensory system is another problem which in most cases is not justifiable for production shops. Therefore, offline wear prediction still remains highlighted, though there is a little research in the field of drilling flank wear prediction before applying tool in drilling process. The main reason of this shortage is the complexity of behaviour of different materials in specific machining conditions which makes it difficult to predict tool wear in various conditions.

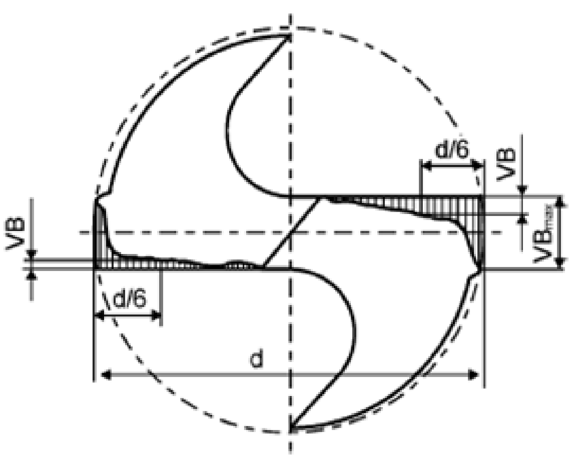

Fig. 1 A typical view of drill flank wear, *VB*

In the field of analysing cutting parameters on tool wear, A. Taskesen and K. Kutukde investigated the effect of various parameters in drilling process of reinforced alloys and introduced optimized condition based on performed tests and presented models [5]. Chethan, Ravindra, Gowda, and Kumar considered EN-8 material as the workpiece and used machine vision applied with Taguchi method, tried to present a model and optimize cutting parameters [6]. Considering the effect of work material on tool wear, V. P. Astakhof compared W5 and Inconel 718, and realized that the influence of cutting speed on the contact characteristics at the flank-workpiece interface cannot be generalized, because it differs considerably from one work material to another [7].

In another work, Lim C. Y., Lau, and Lim S. C. investigated the flank wear pattern of AISI1045 and AISI4340 during machining with a TiC coated tool insert. They found an optimum condition for tool wear regarding with various cutting speeds and different materials [8]. Considering performed research in this field, it can be concluded that developing an analytical model to predict tool wear is extremely a difficult task since a wide variety of parameters in various cutting conditions can affect the wear pattern. Furthermore, high strain rate in the cutting zone applies more complexity to the modelling of wear. Due to these shortages and difficulty in developing a practical model, there is a great need to implement intelligent methods such as Artificial Neural Networks (ANN) and Genetic Programming (GP) which can connect the influential input to output parameters.

In the last decade, various ANNs with different structures and learning algorithms have been utilized widely in tool wear prediction, e.g. selective artificial neural network ensemble model [2], multilayer perceptron [9], back propagation networks (BPN) [10], radial basis function networks [11], learning vector quantization (LVQ)[12], fuzzy LVQ (FLVQ) [12], fuzzy forward connected neural network (FFCNN) [13] and neural network with differential evolution learning [14].

Among mentioned intelligent methods, only a few have acceptable accuracy and relatively high convergence speed to be used in online operations. In addition, ANNs, which are used to model processes only act as a black box and do not offer an explicit objective model. On the contrary, by applying genetic programming, GP, in modelling of processes, not only acceptable accuracy is accessible for a given data set, but also it is possible to develop a mathematical equation on the basis of independent input parameters and dependent output parameters. In this paper, a precise numerical way to predict drill flank wear has been proposed by the use of genetic programming which will be applied into manufacturing process for the determination of flank wear with a small number of experiments. Allowing the optimization of extremely difficult structures, GP can be applied to a wide variety of problems [15]. This relatively new automatic programming technique was first described by Koza [16]. In engineering, especially manufacturing engineering, GP is frequently used to model various processes and conditions. Some applications of GP have been reported in prediction of tool chip contact length in orthogonal cutting [17], prediction of surface roughness [18], nonlinear system modelling [19], investigation of the cutting force in ball end milling [20], machine scheduling problems [21] and tool wear prediction in turning process using chip geometry [22].

According to shortages mentioned about the applicability and correctness of analytical and intelligent methods in modelling of machining processes, in this paper GP is utilized to model and predict the flank wear in drilling process. Two independent data sets were obtained for both AISI1020 and AISI8620 steels on the basis of experimental measurements: training data set and testing data set. Spindle speed (or cutting speed in other means), feed rate and drill bit diameter were used as the independent input variables, while the value of flank wear was the dependant output variable. An equation of flank wear was developed on the basis of training data set and the accuracy of obtained model was proved on the testing data set by using fitness functions. The overview of the methodology used in this paper is shown in Fig. 2.

2 GENETIC PROGRAMMING

Being one of the most applicable members of evolutionary computation methods, genetic programming, GP, was first introduced by Koza in 1990s [18]. GP can be considered as a domain-independent method that creates computer programs for solving complicated problems using the principles of Darwinian natural selection [16]. This computer programs are called chromosomes or organisms and their form change during process of evolution. In GP, the structural blocks, terminal set and function set, are defined first, and subsequently, the evolutionary process tries to find the best computer program or, in other words, optimal mathematical equation with relevant coefficient.

The set of terminal genes can be defined as T={a_1,a_2,…,a_n} where n is the number of terminal genes and the set of function genes can be specified as F={F_1,F_2,…,F_m} where *m* is the number of function genes. The set of terminal genes T can include various constants such as numerical and logical constants or it may contain various variables. The set of function genes F includes basic arithmetical functions, relation functions, Boolean functions, and functions defined regarding with the problem [17]. GP triggers with randomly created of initial population or computer programs, consisting of T, the set of terminal genes, and F, the set of function genes. In the next step, fitness for each member of population is calculated [18].

In the process of genetic evolution, computer programs are subject to some operations such as reproduction, crossover, and mutation. The reproduction operation or natural selection has a selective nature and transmits specified number of successful computer programs to the next generation.

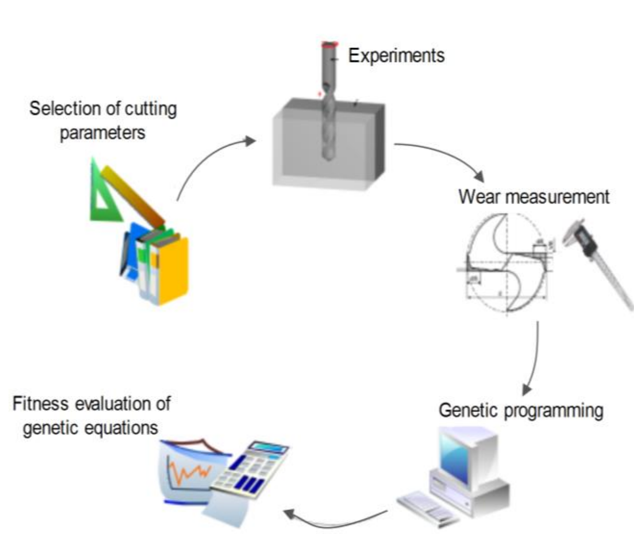

Fig. 2 Overview of the methodology used in this paper

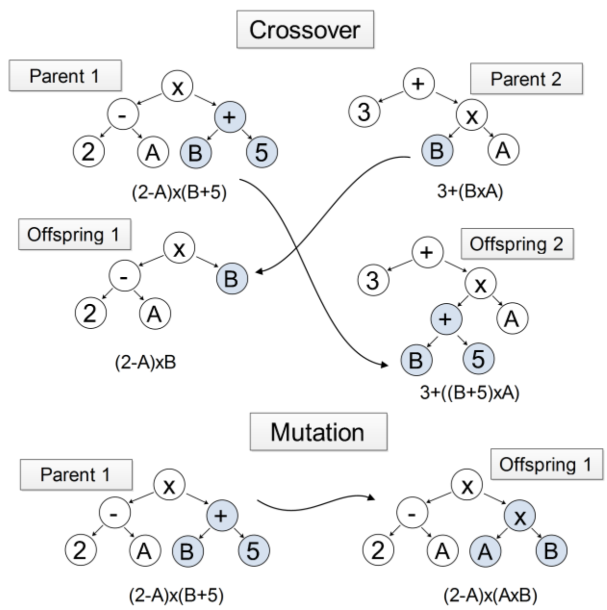

Fig. 3 Schematic process of crossover and mutation in GP [17]

By using crossover operation, a node in two computer programs is selected randomly and then the set of terminals and functions from the two programs are swapped to create two new offspring or new computer programs. The mutation operation increases the population diversity by changing a function or terminal from a computer program at random [16]. Fig. 3 presents the schematic process of crossover and mutation.
The following steps are performed in each step of GP:

I. Generation of initial random population.
II. Determination of population fitness for all members in the population. Furthermore, if a specified criterion is reached, such as certain fitness or certain number of generations, the process is terminated and the member with the best fitness is introduced as the final result.
III. Applying genetic operators (reproduction, cross over, and mutation) to current population and replacing the current population by new population.
IV. Return to step II [17].

A graphic representation of the GP method is depicted in Fig. 4.

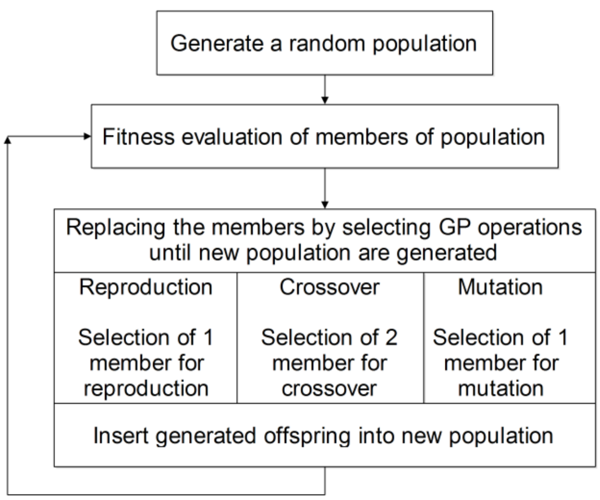

Fig. 4 Schematic flowchart of GP method

In this paper, for determination of the relationship between cutting parameters and flank wear of drill bit, genetic equations with genetic programming have been proposed. On the basis of experimental data and with the selection of proper algorithm settings, the genetic equation for flank wear is developed as Eq. (1).

$$VB=F(s,f,d) \tag{1}$$

Where F is a function which relates input parameters of spindle speed, *s*, feed rate, *f*, and drill bit diameter, *d*, to output parameter which is flank wear, *VB*. Various parameters are involved in GP algorithm. It is obvious that the selection of parameters affects the model performance and its accuracy. These parameters are selected based on values obtained from trial and error approach or from some previously suggested values [17]. The parameter settings are shown in table 1. Two data sets are used for training and validation of presented GP model. The training data are utilized for learning step of evolution and the validation or testing data are used to measure the performance and accuracy of obtained genetic equations.

Table 1 The evolutionary parameter settings for the GP algorithm in this paper

Parameter	Setting
Function set	+, -, x, X^2, X^3, exp
Population size	300
Number of generations	1000
Mutation rate	0.044
Crossover rate	0.5
Reproduction rate	0.25
Maximum tree depth	4
Maximum number of genes	7
Elitism	0.01% of population

The best models are selected on the basis of following criteria:

- Simplicity
- Fitness

The both objectives can be reached by selecting proper parameter selection (e.g., number of genes or number of generations). Absolute fraction of variance, R^2, root mean squared error, *RMSE*, and mean absolute error, *MAE*, are used to evaluate the fitness of the proposed equations. These statistical measures are defined as below:

$$R^2 = 1 - \frac{\sum_{m=1}^{n} (Y_{predicted,m} - Y_{experimental.m})^2}{\sum_{m=1}^{n} (Y_{experimental.m})^2} \tag{2}$$

$$RMSE = \sqrt{\sum_{m=1}^{n} \frac{(Y_{predicted,m} - Y_{experimental.m})^2}{n}} \tag{3}$$

$$MAE = \frac{\sum_{m=1}^{n} (Y_{predicted,m} - Y_{experimental.m})}{n} \tag{4}$$

Where n is the number of data points, *Y predicted, m* and *Y experimental, m*, respectively, indicate the predicted value and the target value from experimental data of point m.

3 EXPERIMENTAL WORK

All the experimental tests were performed on milling machine (M.S.T. Group, FP4M model) and under dry condition. In order to establish the genetic equation, various combinations of spindle speed, *s*, federate, *f*, and drill diameter, *d*, were chosen for the experiments based on full factorial method from values illustrated in table 2. The obtained sets are used to train genetic model.

Table 2 The cutting parameters limitations

Spindle speed [rev/min]	224	560	710	1120
Feed rate [mm/rev]	0.05	0.12	0.19	0.3
Drill diameter [mm]	4	6	8	10

Table 3 The composition and relevant mechanical properties of AISI1020 and AISI8620

	Element weight [%]								Tensile strength [MPa]	
	C	Mn	P	S	Si	Cr	Ni	Mo	Ultimate	Yield
AISI1020	0.20	0.6	0.02	0.02	-	-	-	-	393.4	290
AISI8620	0.19	0.72	0.02	0.02	0.16	0.55	0.53	0.15	533.1	380.4

Table 4 Testing data set

No.	Spindle speed [rpm]	Feed rate [mm/rpm]	Drill diameter [mm]
1	224	0.05	4
2	560	0.12	4
3	710	0.19	4
4	1120	0.3	4
5	224	0.12	6
6	560	0.05	6
7	710	0.3	6
8	1120	0.19	6
9	224	0.19	8
10	560	0.3	8
11	710	0.05	8
12	1120	0.12	8
13	224	0.3	10
14	560	0.19	10
15	710	0.12	10
16	1120	0.05	10

High speed steel standard twist drills were used in these tests as the cutting tool. The wear on the flank side of the tool is known as the flank wear. For the measurement of the flank wear, drill bits were examined thoroughly using an optical microscope equipped with image processing software.

In order to evaluate the effect of work material on the flank wear of drill bit, two different steels, AISI1020 and AISI8620, were selected as the workpiece material. The actual chemical composition has been analysed using a Spectro Spark Analyzer. The composition and relevant mechanical properties were given in table 3. The cutting parameters selected for testing step of genetic equations are shown in table 4. Before entering the training dataset into GP, the dataset pre-processing (i.e., standardization) must be implemented. Standardization is to make input training data into a constant range through a linear transformation process. The standardization is needed, because GP can be trained on a certain range of data. In this study, the normalization is used for pre-processing of dataset, which makes the input data to be between 0.1 and 0.9.

4 RESULTS

For determining the relationship between cutting parameters and tool flank wear in drilling operation of AISI1020 and AISI8620 steels, the genetic equation was developed with GP approach. Processing of GP starts with the training step on the basis of training data set. The evolution process lasted up to the generation 1000. In every 100 generations, the evolutionary process was stopped to record the model and relevant statistical measures. When the number of generations reached to 1000, the process was terminated and the best model was selected and tested with testing data set. Genetic equations obtained for AISI1020 and AISI8620 steels are as follows:

AISI1020: The best model for drilling flank wear in AISI1020 is presented by Eq. (5).

$$\begin{aligned} VB = {} & 0.4\times d^{3}+(s^{12}-s)^{4} \\ & + [(f-2.81)\times \exp(f-2.66)]^{2} \\ & + [(\exp(f-4.93))^{3}\times f]^{9} \end{aligned} \tag{5}$$

AISI8620: the best model of tool flank wear in drilling of AISI8620 is obtained as Eq. (6).

$$VB = 0.453\times s^4 - s^3 + 0.574\times s + 0.136\times(d+f)^2\times(s^2+2.8) + exp[-(1.241+2.24\times s)^3]-0.078 \quad (6)$$

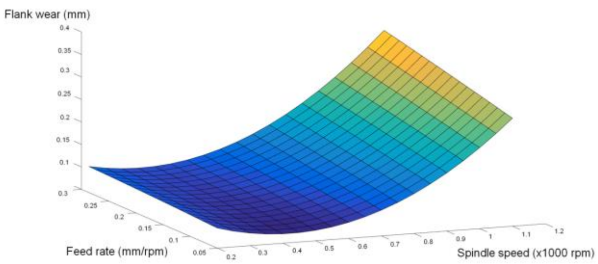

Fig. 5 Variation of flank wear, *VB*, versus spindle speed and feed rate in AISI1020 according to Eq. (5), drill dia. 6 mm

In which *s* is the normalized form of spindle speed, *f* is the normalized form of feed rate and *d* is the normalized form of drill diameter. The variation of the drill tool wear with the input parameters spindle speed, *s*, and feed rate, *f*, for AISI1020 and AISI8620, in drill diameter of 6mm according to Eqs. (5) and (6) are shown in Fig. 5 and Fig. 6. The values of R^2, *RMSE*, and *MAE* for obtained genetic equations are shown in table 5.

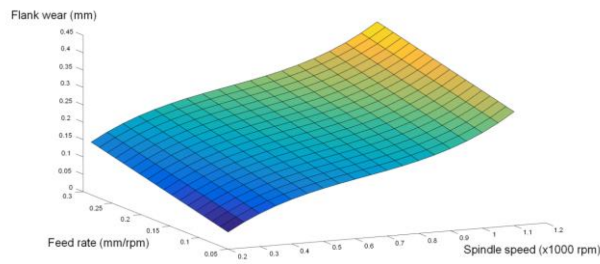

Fig. 6 Variation of flank wear, *VB*, versus spindle speed and feed rate in AISI8620 according to Eq.(6), drill dia. 6 mm

Figs. 7 and 8 show a comparison between the predicted tool wear by genetic programming and the measured tool wear from the testing data of AISI1020 steel and AISI8620 respectively. The results of table 6, Fig. 7, and Fig. 8 indicate that the tool wear predicted by genetic programming closely agrees with the values of measured tool wear, which further approves the good prediction performance of GP.

Table 5 Statistical measures for obtained genetic equations according to Eqs. (2), (3), and (4)

	Training			Testing		
	R^2	*RMSE*	*MAE*	R^2	*RMSE*	*MAE*
AISI1020	0.97	0.014	0.012	0.96	0.015	0.012
AISI8620	0.98	0.017	0.013	0.97	0.022	0.019

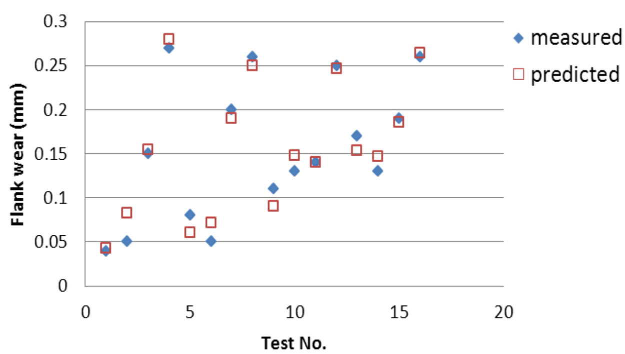

Fig. 7 Comparison of Measured and predicted results for AISI1020 testing data set

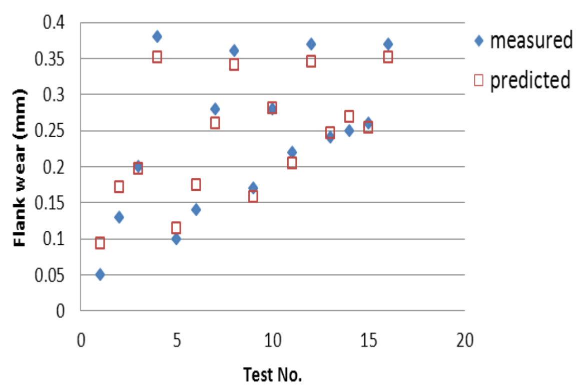

Fig. 8 Comparison of Measured and predicted results for AISI8620 testing data set

5 DISCUSSION

In this paper it is tried to predict the drill flank wear by genetically developed Eqs. (5) and (6) for AISI1020 and AISI8620. Considering the experimental results and genetically developed models, it can be concluded that any increase in feed rate and drill diameter leads to increase in wear values. But in the case of spindle speed and cutting speed, in other words, the problem slightly differs. As acknowledged, the cutting forces acting on flank-workpiece interface play an important role in the physical phenomena occurring in shear zone. The normal force in cutting processes is in fact the force needed to overcome the work material resistance against tool penetration into workpiece. This force depends on some geometrical features of cutting tool such as the curvature of the flank edges and work material properties such as yield strength of the work surface layer. So it can be concluded that the work material properties can influence the normal force or stresses applied in cutting. In other words, an increase in the yield strength of the surface layer of the workpiece leads to an increase in the force required to perform cutting process, thereby, wear rate will rise. On the other hand, in drilling process, extremely high and localized strains, strain rates and temperatures are encountered. Therefore, the amount of introduced stress into tool's faces and produced temperature in the shear zone are crucial factors in development of wear phenomena.

Therefore it is undeniable that the mechanical properties of work material are of great importance in flank wear during drilling operation. As such, the cutting speed has extremely great effect [7], since it can change stresses and temperature drastically during cutting process.

By considering the results shown in Fig. 5, it can be said that the minimum tool wear for AISI1020 occurs at an optimum cutting speed, v_{opt}. A similar trend was reported by Astakhov for turning W5 steel and by C.Y.H. Lim et al. for turning AISI1045 and AISI4340. However this result is in contradiction with Taylor's tool life equation. In fact, it seems that Taylor's equation has only a phenomenological nature and cannot consider behaviour of wear physically. To explain the variant behaviour of flank wear by increasing cutting speed, two crucially important factors must be considered.

The first factor is cutting temperature which will rise with any increase in cutting speed or strain rate. This increase can originate from two other important aspects; friction on the tool's flank surface and stresses as a result of cutting forces. In other words, any increase in cutting speed will result higher amount of friction and stresses on the tool's flank which both of them contribute to rise the temperature and intensify the wear rate in flank face.

The second important factor is plastic behaviour of material during deformation. It is believed that at specific temperatures, 0.5-0.6 melting point of material, ductility starts to increase because of some changes in microstructure and mechanical properties [7]. This increase in ductility leads to a drop in stresses on the flank contact area. As it can be realized, the two important factors which contribute in wearing process, temperature and stresses, in some cases work against each other. From obtained results it can be concluded that in cutting speeds below v_{opt}, although temperature is not high, plastic deformation occurs in high stresses which results specific wear on the drill flank area.

As cutting speed rises, temperature of shear zone increases which leads to a reduction in stress distribution, hence the rate of wear drops gradually. In higher cutting speeds than v_{opt}, temperature rises drastically and increasing in ductility and reduction in stresses cannot be an overwhelming factor any more. Therefore the rate of wear will increase rapidly. The effect of these parameters is obvious from Fig. 5 during drilling process of AISI1020. But referring to Fig. 6, it can be seen that such behaviour cannot be observed in AISI8620, so it is not an optimum cutting speed in drilling process of AISI8620.

In the case of flank wear in drilling operation of AISI8620, two distinct trends are distinguishable compared to AISI1020. First, it is realized that wear rate in AISI8620 is consistently higher under similar machining conditions. Such an observation was reported by other researchers [8]. It seems that the microstructure and elemental composition of work material is of great importance in this case.

According to table 3, yield strength of AISI8620 is greater than AISI1020. Moreover it must be added that although both AISI86220 and AISI1020 steels contain same content of C, Si and Mn, AISI8620 is more alloyed with some alloying elements such as Cr, Mo, and Ni and combining with C, Cr and Mo form stably hard carbides which can raise the hardness of the steel at higher temperatures [8]. These mentioned reasons lead to elevated wear in drilling of AISI8620 compared to AISI1020. The latter difference between the two materials is that no optimum cutting speed, in which wear rate is minimum, can be realized in drilling operation of AISI8620.

The main reason of this behaviour is Ni which by dissolving in the ferritic matrix, increases the strain hardening of AISI8620 steel. Increase in strain hardening changes the condition of plastic deformation and tends to increase the stresses on the tool flank, therefore, the effect of ductility will decrease against normal stress and no decrease in wear neither optimum cutting speed will appear. Therefore, it can be concluded that greater strength and toughness of AISI8620 results in higher stresses on the tool's flank and elevated temperature, leading to more severe flank wear compared to AISI1020.

6 CONCLUSION

In this paper, the genetic programming method was proposed to predict tool flank wear in drilling operation by developing the genetic equation between input cutting parameters, spindle speed, feed rate, and drill diameter, and output parameter, flank wear.

In order to develop the genetic equation, some experiments were performed. The results of experiments showed that properties of work material can affect drill bit flank wear drastically. It was concluded that greater toughness and strength of AISI8620, compared to AISI1020, lead to higher cutting stresses and temperatures, resulting more flank wear. In addition, some other properties of material such as strain hardening and thermal softening can influence the pattern of wear rate.

Prediction accuracy of flank wear model developed by genetic programming is acceptable for both AISI1020 and AISI8620 steels. The results obtained from GP method was an indicator of its efficiency in the modelling field of metal forming processes. This type of modelling method is preferable to other traditional models such that it present a mathematical relationship between input and output parameters and it does not assume any predefined functional form of the given equation.

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