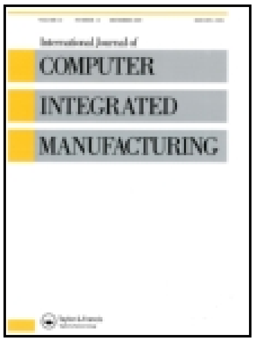

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An integrated evolutionary approach for modelling and optimisation of CNC end milling process

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In this research, a novel integrated evolutionary based approach is presented for the modelling and multi-objective optimisation of a machining process. Computer numerical control end milling process has been considered in the present work as it finds significant applications in diversified engineering industries. Firstly, genetic programming (GP) has been proposed for explicit formulation of non-linear relations between the machining parameters (spindle speed, feed and depth of cut) and the performance measures of interest (material removal rate and tool wear) using experimental data. Genetic programming approach optimises the complexity and size of the model during the evolutionary process itself and hence this technique has the potential to identify the true models avoiding the problems of conventional methods. Central composite second-order rotatable design had been utilised to plan the experiments and the effect of machining parameters on the performance measures is also reported. In the second part, as the chosen responses are conflicting in nature, a multi-objective optimisation problem has been formulated. A non-dominated sorting genetic algorithm-II (NSGA-II) has been used to simultaneously optimise the objective functions. The Pareto-optimal set generated is useful for process planning which is a critical link in computer-integrated manufacturing (CIM).

Keywords: end milling; modelling; genetic programming; multi-objective optimisation; NSGA-II

1. Introduction

Machining processes find extensive applications in most of the engineering industries such as aerospace, automotive, defence and tool and die industries. In this work, one of the most widely used machining processes, computer numerical control (CNC) end milling is considered for investigation. End milling is a complex and costly shape machining process used for obtaining profiles, slots, engraving, surface contouring and pockets on finished components. This machining process has become indispensable in industry and is continuously finding further applications with the developments of new cutting tool materials.

Computer numerical control machining being an expensive process (Tolouei-rad *et al*. 1997), there can be a big payoff from even small increase in performance. Hence, the selection of optimum process parameters is highly essential to reduce the machining cost and increase the production rate. Optimisation through full enumerations is not possible owing to the complex nature of the machining process and complicated interaction between the variables of machining. Moreover, the said procedures neither lead to optimal use of the machines nor the quality of surface generated. Though considerable number of researchers carried out various investigations for improving the process performance, proper selection of machining parameters for best process performance is nevertheless a challenging job. Owing to the highly complicated interactions between process parameters, current analytical models and analyses cannot provide accurate prediction for better quality control and higher throughput. Therefore, an efficient method is needed to determine the optimal machining parameters.

In case of CNC milling, material removal rate (MRR) and tool wear (TW) are the most important response parameters. Specifically in rough machining operations, these responses directly affect the economy of the process. While material removal rate indicates the productivity, tool wear is a measure of the quality of machined components. As CNC milling, is a complex process (Wang *et al*. 2006), it is very difficult to determine the optimal machining parameters for the best machining performance. Moreover, the performance measures, namely MRR and TW, are conflicting in nature as it is desirable to have higher MRR with lower value of TW.

The overall objective of this research is to apply a new methodology for modelling and optimisation of

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the non-linear and complex CNC end milling process. With this aim, accurate prediction models to estimate MRR and TW were developed from the experimental data using a potential evolutionary algorithm called genetic programming (GP). Subsequently, the developed models were used for optimisation of the process. As the chosen objectives, MRR and TW, are conflicting in nature, the problem was formulated as a multi-objective optimisation problem. A popular evolutionary algorithm, non-dominated sorting genetic algorithm II (NSGA-II), was then used to solve and thereby retrieve the multiple optimal sets of input variables.

2. Literature survey

Many approaches have been proposed for end milling to select the appropriate process parameters. A review of literature is presented here:

Machinability database systems were in use for long time for the selection of appropriate cutting conditions. Model building in machinability database systems was studied using regression based and artificial neural networks (ANNs) techniques (Choudhury and El-baradie 1996, Wong and Hamouda 2003).

Optimum cutting parameters for multi-pass milling utilising the two mathematical techniques dynamic programming and geometric programming were determined by İhsan Sönmeza *et al.* (1999). Shunmugam *et al.* (2000) used genetic algorithm to optimise the machining parameters for multi-pass milling operations. El-Mounayri *et al.* (2002) performed modelling and optimisation of flat end milling process using artificial neural networks (ANNs) and particle swarm optimisation (PSO) respectively. Linear regression models were developed for cutting force using ANNs, while a production cost objective function was used to optimise the variables, spindle speed and feed rate. Tandon *et al.* (2002) applied the evolutionary computation technique, PSO to optimise multiple machining parameters simultaneously for the case of pocket-milling on CNC milling machine. A hybrid approach based on genetic algorithm (GA) and simulated annealing (SA) was developed by Wang *et al.* (2004) to select the optimal machining parameters for plain milling process, the obtained results demonstrate that the hybrid method is superior to those using GA alone. Baskar *et al.* (2005) demonstrated the efficiency of several optimisation procedures such as GA, tabu search, ant colony algorithm and particle swarm optimisation for the optimisation of machining parameters for milling operation. Oktem *et al.* (2006) optimised the cutting parameters for minimum surface roughness in end milling mould surfaces of a component used in biomedical applications by coupling ANN and GA. Yih-fong (2007) applied Taguchi methods coupled with principal component analysis in the process optimisation of the high-speed CNC milling. Krain *et al.* (2007) experimentally optimised the tool life, tool wear and productivity when end milling Inconel 718. For optimisation they considered the effects of fed rate, radial depth of cut, tool material and geometry. They concluded that no single tool material or geometry gave the best overall performance. Palanisamy *et al.* (2008) used regression and ANN techniques for developing models to predict tool wear on AISI 1020 steel using a carbide cutter in a universal milling machine. In their work, flank wear was taken as the response variable measured during milling, while cutting speed, feed and depth of cut as input parameters. Bala Murugan *et al.* (2009) carried out experimental investigations for machinability study of hardened steel and obtained optimum process parameters by grey relational analysis. The machining process parameters considered were cutting speed, feed, depth of cut and width of cut and the multiple responses that were optimised were volume of material removed, surface finish, tool wear and tool life. Öktem (2009) used ANNs to model surface roughness and applied GA to optimise the cutting parameters when end milling of AISI 1040 steel material with TiAlN solid carbide tools under wet condition. Lu *et al.* (2009) applied grey relational analysis coupled with principal component analysis for optimisation of cutting parameters for rough cutting in high speed end milling on SKD61 tool steel. Modelling results for surface roughness in end milling of 6061 aluminium using combined adaptive neuro-fuzzy inference system and genetic algorithms were presented by Samanta (2009). Ding *et al.* (2011) investigated the main effects and interaction effects and optimised the cutting parameters for desirable surface roughness in end milling of hardened AISI H13 steel with PVD coated carbide insert. The best surface roughness was achieved with high cutting speed, small axial depth of cut, high feed and small radial depth of cut. Azlan *et al.* (2011) applied an integrated approach to search for optimal cutting conditions leading to the minimum value of surface roughness in end milling of Ti-6AL-4V alloy. Regression equations were developed for surface roughness which were then optimised by conventional GA and conventional simulated annealing (SA) algorithms separately and then by an integrated GA and SA technique.

3. Critique on literature survey

The literature survey reveals that specific efforts were devoted to determine the most accurate empirical models for process performances such as surface roughness, material removal rate and tool wear. These models were utilised as objective functions and optimised to obtain the machining conditions.

The other main findings of literature survey are:

(1) The predominant modelling technique for establishing the process models were regression based techniques and ANNs.
(2) Multi-objective optimisation for multi pass milling has been performed considering production time and production cost as objective functions.
(3) Efforts were mainly focused on optimisation of only single performance characteristic in CNC end milling.
(4) No published work available on multi-objective optimisation of the conflicting objectives, MRR and TW.

In statistical-based techniques like regression analysis, a prediction model has to be determined in advance and a set of coefficients have to be found. The pre-specified size and shape of the model means that these are not adequate to capture the complex relation between influencing variables and output parameters. Although ANNs have also been used in the literature for modelling, they have the drawback of not being able to quantify explicitly the relationships between inputs and outputs (Baykasoğlu 2008). Consequently, great care must be taken with the ANN approach to prevent over-fitting (Benyamin and Daniel 2002). However, the accuracy and possibility of determining the global optimum solution depends on the type of modelling technique used to express the objective function and constraints as functions of the decision variables (Jain *et al.* 2007). Therefore, effective, efficient and economic utilisation of the CNC milling process necessitates an accurate modelling and optimisation procedure.

4. Proposed methodology

In this paper, a novel approach using GP is presented for modelling of material removal rate and tool wear. Genetic programming is a technique pioneered by Koza (1992) and belongs to the class of genetic or evolutionary algorithms. Since its introduction in the early 1990's GP has a number of significant achievements in tackling industrial scale modelling, data analysis, search and optimisation problems (Riolo *et al.* 2007). The capabilities of GP in capturing the empirical relationship between input variables and output features are of primary significance for modelling machining processes. The distinctive aspect of GP as compared to traditional approaches is in the model structure definition which is not *apriori*. Therefore, an advantage of this approach is that fewer assumptions have to be made regarding the final form of the model as the algorithm can evolve the model structure from elementary building blocks. The generated model helps directly to obtain an interpretation of the parameters affecting the process. More details of this methodology are discussed in section 5. The models developed by GP were subsequently used for optimisation.

In the current study, the optimisation problem of CNC milling was explicitly formulated as a multi-objective optimisation problem, as the determination of the optimal machining conditions involves a conflict between maximising MRR and minimising the TW. It can be noted that the classical optimisation methods (gradient descent, weighted sum methods, goal programming, min–max methods, etc.) are not efficient for handling multi-objective optimisation problems. The aforesaid methods do not find multiple solutions in a single run, and therefore it is necessary for them to be applied as many times as the number of desired Pareto-optimal solutions (Sardiñas *et al.* 2006). In addition, classical methods fail when the objective function becomes discontinuous. The above-mentioned difficulties of classical optimisation methods are eliminated in evolutionary algorithms, as they can find the multiple solutions in a single run. As a result, one of the best evolutionary approaches, the NSGA-II is proposed in this paper for multi-objective optimisation of CNC milling. Genetic algorithm (GA) based multi-objective optimisation methodologies have been widely used in the literature to find Pareto-optimal solutions (Fonseca and Fleming 1993, Horn *et al.* 1994, Zitzler and Thiele 1998). In particular, NSGA-II has proven its effectiveness and efficiency in finding well-distributed and well-converged sets of near Pareto-optimal solutions (Deb 2002). The proposed methodology of integrating GP and NSGA-II is depicted in Figure 1.

5. Modelling using GP

The Evolutionary Algorithms (EAs) are stochastic search methods which combine important characteristics like robustness, versatility and simplicity. The ability of EAs to search for complete and global solutions for a given problem makes them powerful problem solving tools. EAs exploit not only the information contained in each individual, but also the information of the population as a whole. Genetic programming is one such EA to generate an optimum model structure with interaction terms or higher order terms. Genetic programming is a fairly recent EA method compared to other three variants of evolutionary computation viz., genetic algorithms,

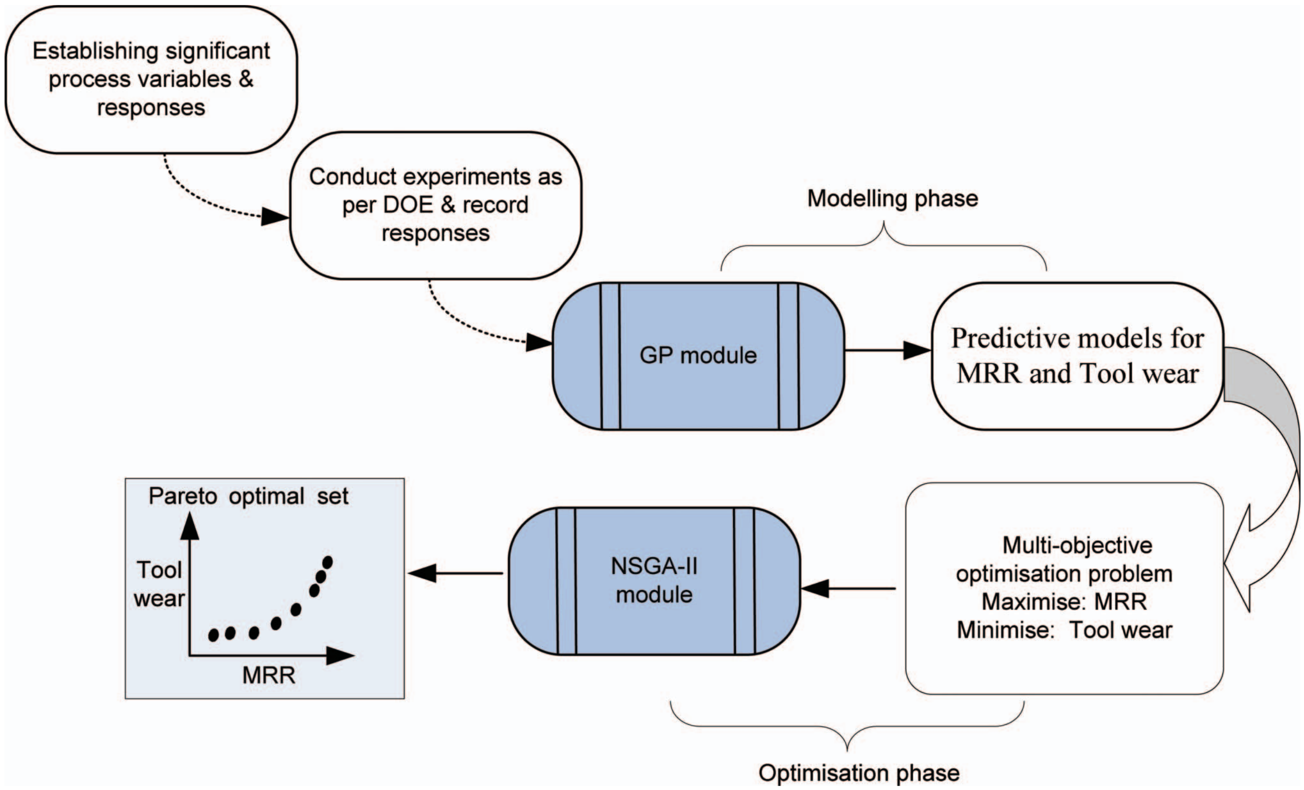

Figure 1. Proposed methodology.

evolutionary strategies and evolutionary programming (Angeline 1995).

The cardinal principles of GP were originally proposed by Koza (1992). Since then this technique has found widespread applications in diversified fields such as industrial robotics (Dolinsky *et al*. 2007), chemical process modelling (Greeff and Aldrich 1998), prediction of shear strength of beams (Ashour *et al*. 2003), etc. However, it is noteworthy that the potential of this tool has not been exploited in the field of manufacturing and few applications in the field of manufacturing can be found in the literature (Nastran and Balic 2002, Brezocnik *et al*. 2004, Kovacic *et al*. 2007). Therefore, in the present work, the proposed method is used to model the machining process.

Genetic Programming principles are primarily derived from GAs, and hence share most of GAs' properties. The main difference between GP and GAs lies in the individual representations. In GAs population of individuals is represented as strings whereas in GP individuals are represented as tree structures. The tree like structures of GP, which are in fact solutions to problems, have hierarchical compositions of *terminals* and *functions*. *Terminals* are input variables appropriate to a particular problem domain and user specifies a number of *functions* that manipulate *terminals*. The primitive functions typically include:

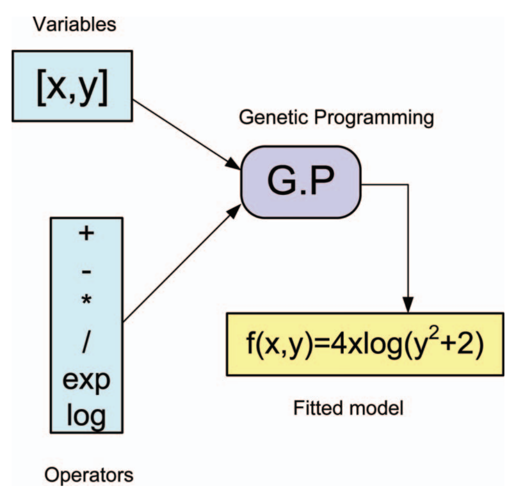

Figure 2. Example of GP procedure.

arithmetic operations (+, −, *, /), Boolean operations (AND, OR, NOT), logical operations (IF–THEN–ELSE), and non-linear functions (sin, cos, tan, exp, log). Compatibility between the functions and terminals must be ensured in order to pass information impeccably between each other (Sette and Boullart 2001). Figure 2 shows a typical example of GP procedure. Representation of an individual in GP is shown in Figure 3 which corresponds to the expression of $(x-2)+y/(z^2)$. The set of *functions* in the representation are {+, −, *, /} whereas the set of *terminals* are {*x, y, z*}.

5.1. Initial population

Genetic programming algorithm begins with a set of randomly created individuals called initial population. Each individual is a potential solution represented as a tree. Each tree is constructed by random compositions of the sets of functions and terminals. The shape of a tree has an influence on its evolution and both sparse and bushy trees should be present in the initial population. To ensure this, a ramped half-and-half method, suggested by Koza (1992) is usually used in GP. In this method, half of the trees in the population are generated as full trees and other half as random trees. Once the population is generated, a suitable fitness function should be given for evaluating the fitness value of each individual. Then, a set of individuals with better fitness value will be selected and used to generate new population of next generation by the predefined genetic operators while the population size is kept constant.

5.2. Genetic operators

The purpose of genetic operators is to evolve individual trees. The main operators generally include reproduction, crossover and mutation. Reproduction involves copying of the selected individual into the next generation population. In general, about 10% of the population is selected for simple reproduction and 90% is selected through crossover. Crossover is usually the most important genetic operator in GP. Its application produces two children trees from two parent trees by exchanging randomly selected sub-trees of each parent. Both parents are selected using one of the stochastic selection methods such as fitness proportional selection or tournament selection.

The cross-over operator is illustrated in Figure 4. To avoid excessive growth of the branches of the program trees, a maximum depth value is usually established. If the crossover operation produces an offspring of impermissible depth, this offspring is disregarded and its parent is reproduced as it is. Koza (1992) uses the default maximum depth of 17. Similar to GAs, GP uses the mutation operator in order to avoid falling into the local optimal solution. Mutation is typically a replacement of a randomly selected single terminal of an individual with a new randomly generated terminal. While mutation plays an important role in maintaining genetic diversity in the population, most new individuals in a particular generation result from crossover. The mutation operator is illustrated in Figure 5.

5.3. Result designation and termination criteria

Execution of the aforementioned three genetic operators constitutes one generation and the procedure is repeated until a termination criterion is met. The single individual with the best value of fitness over all the generations is designated as the result of a run. The termination criterion can be either a fixed number of generations or specified quality of the solution. The number of runs required for a satisfactory solution depends on the complexity of the problem under consideration.

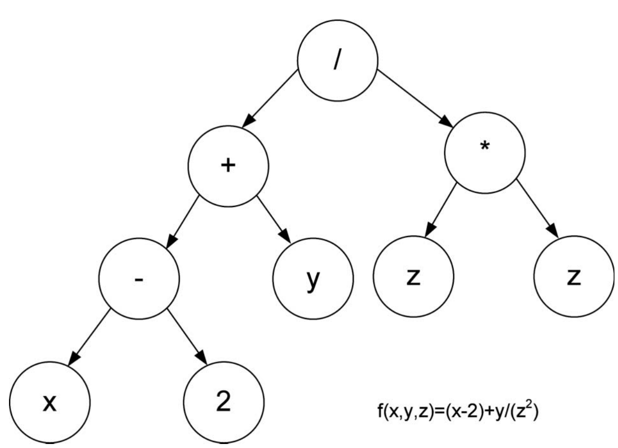

Figure 3. Representation of an individual in GP.

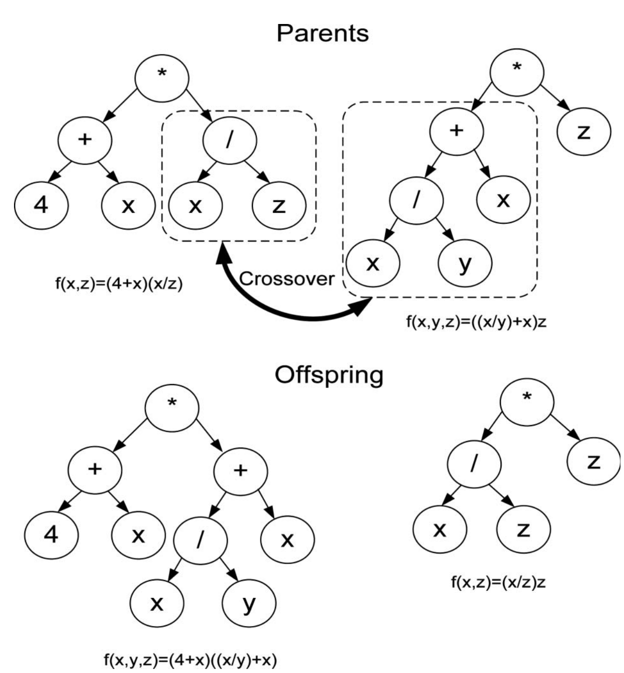

Figure 4. Illustration of cross-over operator.

6. Optimisation using NSGA-II

Multi-objective evolutionary algorithms (MOEAs) are optimisation methods that make the best use of the features of multipoint search of EAs, and can obtain Pareto approximation set at the same time. Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) proposed by Deb *et al.* (2002) is a well known and an excellent implementation of MOEA.

NSGA-II improves upon the original version by incorporating the following main features:

(1) At each generation, the best solutions found are preserved and included in the following generation using an elite-preserving operator.
(2) A fast algorithm is used to sort the non-dominated fronts.
(3) A two level ranking method is used to assign the effective fitness of solutions during the selection process.

6.1. Principle of NSGA-II

Initially, a random parent population P_{gt} (the subscript t indicates the generation) of size N is created. The population is sorted based on the non-domination principle. Each solution is assigned a fitness (i.e. rank) equal to its non domination level (1 is the best level, 2 is the next-best level, and so on). Thus, maximisation of fitness is assumed. At first, the usual binary tournament selection, recombination, and mutation operators are used to create an offspring population Q_{gt} of size N. Since elitism is introduced by comparing current population with the previously best found non-dominated solutions, the procedure is different after the initial generation. The procedural steps are illustrated in Figure 6. First, a combined population $R_{gt} = P_{gt} \cup Q_{gt}$ is formed. The population R_{gt} is of size $2N$. Then, a fast non-domination sorting algorithm is used to rank the solutions according to their dominance rank and organise fronts of equal rank.

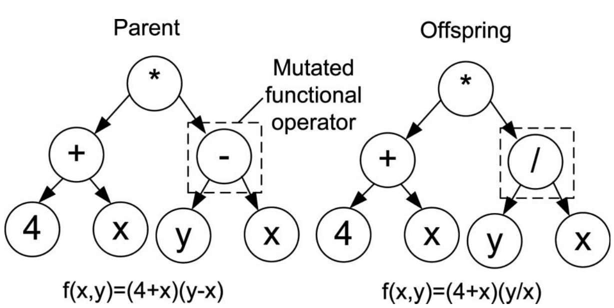

Figure 5. Illustration of mutation operator.

In this ranking method, an individual, k, is randomly chosen from the population R_{gt} and inserted in an intermediate set named *F1*. Then, another solution k' is drawn from R_{gt} and compared to all individuals from *F1*. If k' dominates k, k' enters *F1* and k is deleted, but if k dominates k', then k' is deleted and k stays in *F1*. Continuing this comparison for all individuals, *F1* will consist of all non-dominated individuals of R_{gt}, the Pareto front by definition. Now the first Pareto front is removed from the original population and the same procedure is iteratively continued to identify other layers of Pareto fronts $\{F_i\ i = 1,2,3\ldots\}$. Subsequently, individual solutions within each front are ranked according to a density measure using the *crowding operator*. This operator, as pictured in Figure 7, measures the diversity of each individual by measuring half of the perimeter of the rectangle that encloses a solution in the objective function space and assigning infinite distance to the extreme points of the Pareto-front. The next generation, P_{gt+1}, which has the same size as the first generation is filled with consecutive Pareto fronts $\{F_i\ i = 1,2,3\ldots\}$ until no full Pareto front can be fully accommodated anymore.

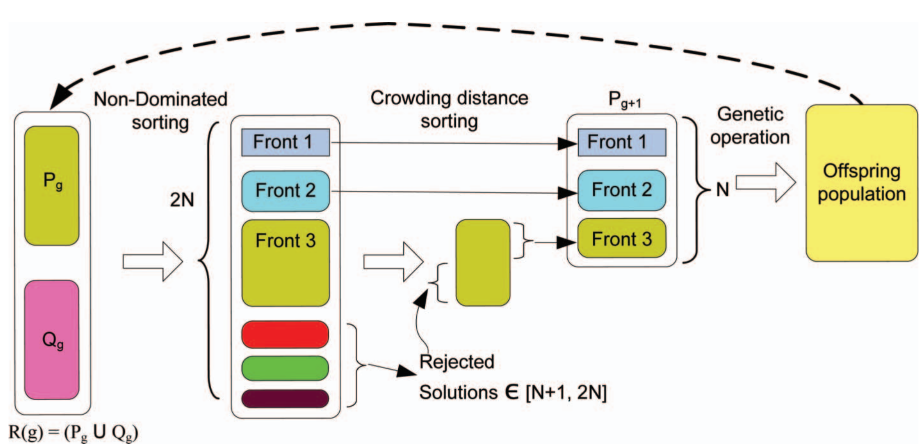

Figure 6. Procedural steps of NSGA-II.

Then, the solutions in the next Pareto layer are sorted in descending order according to their distance assignment and the empty spaces in the proceeding generation are filled with higher ranked solutions.

The next offspring population, Q_{gt+1}, is created by using the crowded tournament selection operator. Two attributes can be considered for each individual solution: First, a non-domination rank (equal to the Pareto layer rank) and second, a crowding distance. In the tournament selection, competitions are set up between individuals. The tournament is 'won' by that individual having a better non-dominated rank (lies on an outer Pareto front). If both individuals are on the same Pareto front, ties are broken by the crowded distance and the tournament is 'won' by the one which is least crowded. The procedure outlined in Figure 7 is repeated until the termination criterion is met and the best-known Pareto front is saved in an archive. The solutions in this archive are the Pareto optimal solutions of the problem under consideration.

7. Experimental details

The machining experiments were conducted on a powerful and precise 3-axis CNC vertical machining centre (model: AGNI BMV45 made by Bharat Fritz Werner Ltd.) employing a continuously variable spindle speed up to a maximum of 6000 rpm and with a maximum spindle power of 5.5 kW. The feed rates can be set up to a maximum of 10m/min. Workpieces of AISI 52100 steel of size 200 mm × 300 mm × 25 mm with hardness 50 HRC after heat treatment were prepared and utilised. All of the experiments were performed under dry conditions along the 300 mm length in conventional milling mode, as recommended by the tool supplier for the specific work material. Coated carbide inserts (ISO: APKT11T308-PM) were used to machine the tool steel. The inserts have rake angle of 0° and clearance angle of 11°. End milling inserts with this geometry are suited for semi-dry and dry machining operations of steels. A commercially available double end mill insert holder of type EMP01-020-G20-AP11–02 of 20 mm diameter and overall length 100 mm was utilised for experiments. Figures 8 and 9 show the CNC set-up of the experiment and view of the machining zone.

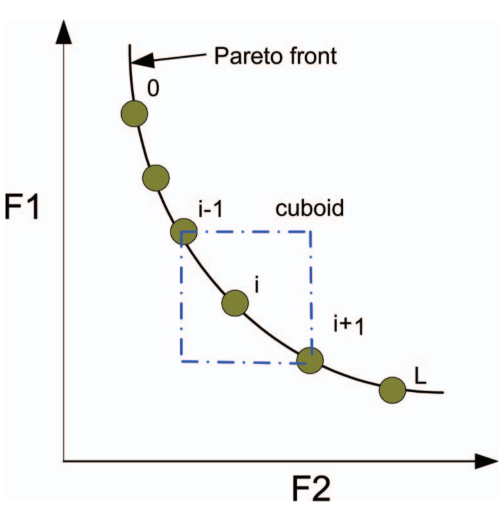

Figure 7. Illustration of Crowded comparision operator.

CNC end milling involves several control variables such as surface cutting speed, spindle speed, axial depth of cut, radial depth of cut, feed and radial engagement of tool. The workpiece and cutting tool material also influence the performance of the process. However, based on the literature survey and the trial experiments, the variables, namely, spindle speed ($x1$), feed ($x2$), and axial depth of cut ($x3$) were considered as the decision (control) variables and the MRR and the tool wear were considered as the output responses. Characterisation of wear on cutting tool insert is specified primarily by flank wear and its progressive growth (Urbanski *et al.* 2000). Flank wear evaluation of insert was made off line by a tool maker's microscope (make: Mitutoyo TM500) with 30X magnification and 1 μm resolution. The admissible wear was ascertained in accordance with ISO 8688:1989 standard and measured by taking the average flank wear for two inserts for each experiment. Each experiment was repeated twice and a new insert with same specification was used every time and machining was stopped after five passes for tool wear measurement. Machining time is noted at the end of each pass and the material removal rate is calculated by loss of weight method. The weight of work piece is measured accurately by digital balance with 0.001 mm accuracy and the material removal rate is expressed in g/min.

Experimental designs constitute powerful methodology for accumulating and analysing information about a given process rapidly and efficiently from a small number of experiments, thereby minimising the experimental costs. The GP models for material removal rate and tool wear were trained by a dataset constructed using design of experiment based rotatable central composite design (CCD). The 27 runs CCD method is chosen since the method provides a wider covering region of parameter space and good consideration of variables interaction in the model. The ranges of machining parameters used were as follows: spindle speed (x_1) of 900, 1200 and 1500 RPM, feed rates (x_2) of 30, 45, 60 mm/min and axial depth of cut (x_3) of 0.4, 0.5, 0.6mm. The radial depth of cut was maintained constant at half of the cutter diameter. The measured values of tool wear and material removal

Figure 8. CNC set-up of the experiment.

rate for 27 experiments conducted as per CCD are shown in Table 1. This constitutes the training dataset for the GP algorithm. In addition, the developed model is validated to ensure the generalisation capability of the predicted model for unseen cases and the data set used for validation is presented in Table 2.

8. Implementation issues

GP, being a stochastic search technique, makes no prior assumptions about the actual model form. The structure and complexity of the model evolve automatically. The populations of models of initial tree generation for MRR and tool wear are first initialised using the 'ramped half-and-half' method. The terminal set T and the function set F were defined as: $T=(x_1, x_2, x_3, \Re)$ and $F=(+, -, *, /)$. The terminal set consists of all input variables of the CNC end mill process and a random ephemeral constant $\Re \in (-200, 200)$. The function set contains addition, subtraction, multiplication and protected division. The genetic programming run is controlled by many parameters of which the two major numerical parameters are the population size and the maximum number of evolutionary generations. These two parameters depend on the difficulty of the problem involved. Other minor numerical parameters include the probability of crossover, reproduction and mutation (Koza 1992). Therefore, some preliminary experiments were carried out to obtain some estimates of workable parameters. These preliminary test runs in the GP system were executed for the output parameters independently. Based on these experiments, the final parameters used to generate the models are given in Table 3.

Evolutionary algorithms are generally robust to variations of control parameters and some guidelines are provided (Koza 1992) for choosing the control parameters of standard GP. Population size and number of generations were optimally set to 500 and 40 respectively as low population size did not show better results while still large population size appeared to yield little advantage in terms of the improvement of fitness. Also there was increase in computation times with large population size and higher number of generations. GP being probabilistic in application, it is important to study the problem by carrying out multiple runs of the algorithm, and analyse the results before arriving at conclusions, thus, multiple runs of the algorithm were conducted. After the investigation of various alternative models, the following expressions for MRR and TW were found to have the best fitness value.

$$\begin{aligned}\mathrm{MRR} = 0.9896x_3\big(\big(\big(\big(\big(x_2x_3^2\big) + \big(22.46/x_1\big)\big)/\big(0.24x_2x_3\big)\big) \\ + \big(x_2x_3\big(1-x_3\big)\big)\big)\big)\end{aligned} \tag{1}$$

$$\begin{aligned}\mathrm{TW} = \big(x_2x_3\big)/\big(\big(\big(x_2\big) - \big(24/\big(\big(x_3^2\big) - \big(0.997x_2\big) + 64.85 \\ - \big(160\big(x_1+36\big)/x_3\big)\big)\big) + 89\big)\big).\end{aligned} \tag{2}$$

Figure 9. View of machining zone.

The fitness measure while developing the above models is considered as the correlation coefficient, R^2 as this produces an accurate solutions in fewer generations. The algorithm run was continued until a value as close as possible to the maximum value of R^2 was obtained. The correlation coefficient value lies in the range [0, 1] and measures the way in which the predicted values and actual values vary together. Therefore credit is given to the solutions that are close to the correct form. Figures 10 and 11 show the convergence graphs of the models predicted by the proposed algorithm. The fitness measures for MRR and TW have gradually improved with the number of generations and finally converged to 0.9980 and 0.8950, respectively. On the basis of the high values of R^2 it can be said that the models are adequate in representing the process. The normal probability plots of the residuals for the output responses are also shown in Figures 12 and 13. A check on these plots reveals that the residuals are located on a straight line, which means that the errors are distributed normally and the obtained models are fairly well fitted with the observed values.

Table 1. Training dataset.

S. no.	Speed (x_1) (RPM)	Feed (x_2) (mm/min)	Depth of cut (x_3) (mm)	MRR (g/min)	TW (mm)
1	1500	30	0.6	5.587	0.163
2	900	30	0.4	3.487	0.09
3	1500	60	0.5	8.494	0.209
4	1200	45	0.6	7.87	0.199
5	1200	30	0.5	4.888	0.13
6	900	30	0.6	5.587	0.139
7	1500	30	0.4	3.492	0.115
8	1200	60	0.4	5.924	0.145
9	900	45	0.4	4.744	0.151
10	1200	45	0.5	6.641	0.174
11	900	45	0.5	6.741	0.149
12	1200	30	0.4	3.497	0.115
13	1200	45	0.4	4.744	0.148
14	1500	45	0.6	7.645	0.207
15	1500	60	0.6	9.479	0.225
16	900	45	0.6	7.59	0.175
17	1500	45	0.4	4.844	0.11
18	900	60	0.6	9.479	0.225
19	900	30	0.5	4.888	0.13
20	1500	30	0.5	4.988	0.116
21	900	60	0.5	8.376	0.189
22	1500	60	0.4	5.925	0.175
23	1200	60	0.5	8.294	0.202
24	1500	45	0.5	6.654	0.188
25	1200	60	0.6	9.579	0.235
26	900	60	0.4	5.624	0.173
27	1200	30	0.6	5.594	0.143

Table 2. Validation dataset.

S. no.	Speed (x_1) (RPM)	Feed (x_2) (mm/min)	Depth of cut (x_3) (mm)	MRR (g/min)	TW (mm)
1	1300	35	0.55	6.1	0.159
2	1000	35	0.42	4.429	0.123
3	1100	50	0.55	7.988	0.19
4	1300	40	0.45	5.68	0.146
5	1100	35	0.45	4.89	0.123
6	1300	35	0.32	2.832	0.097
7	1000	35	0.55	5.99	0.158
8	1000	50	0.45	6.461	0.167
9	1000	40	0.32	3.221	0.098
10	1100	40	0.45	5.34	0.143

Table 3. GP control parameters.

Terminal set:	$\{x_1, x_2, x_3\}$
Function set:	$\{+, -, *, /\}$
Population size:	500
Number of generations (max.):	55
Number of independent runs:	10
Crossover probability (%):	85
Mutation probability (%):	5
Reproduction probability (%):	10
Selection method:	Tournament
Fitness measure:	R^2

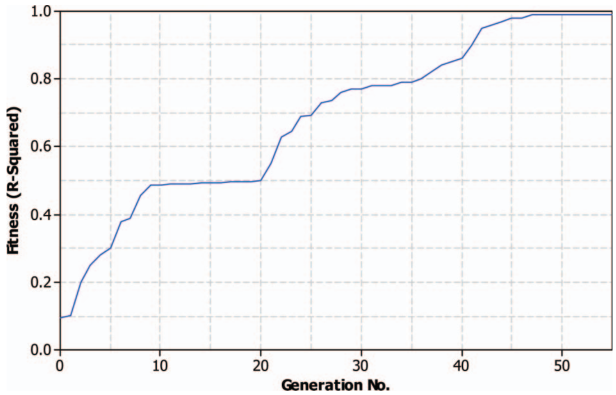

Figure 10. Convergence graph of MRR model.

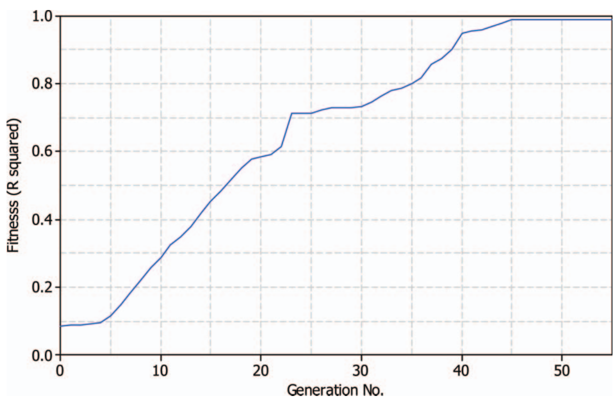

Figure 11. Convergence graph of Tool wear model.

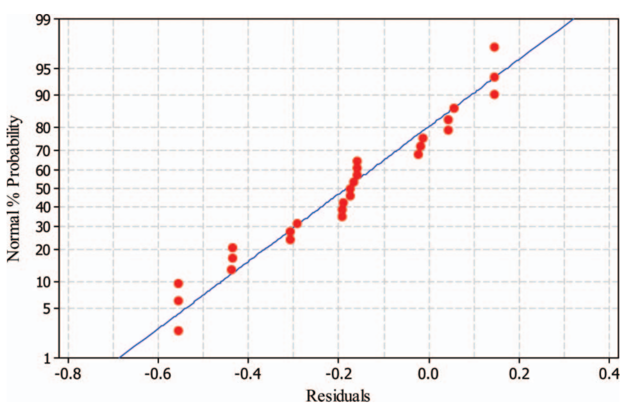

Figure 12. Probability plot of the residuals for the output response MRR.

A comparison of the predicted models and the experimental values for the validation datasets of MRR and TW are shown in Figures 14 and 15 respectively. Very high values of R^2 for MRR and TW of validation sets are obtained and found to be 0.9989 and 0.9988 respectively. These indicate that the developed models satisfactorily represent the outputs.

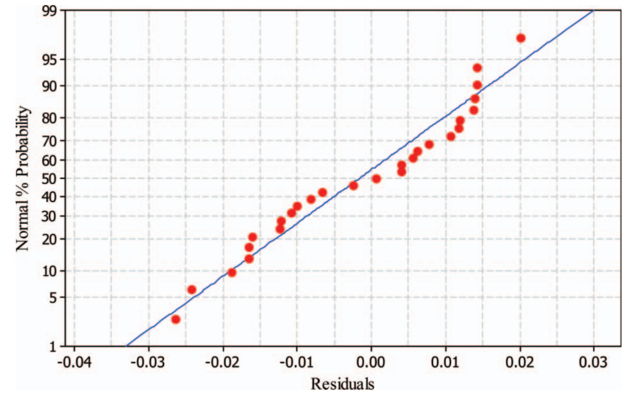

Figure 13. Probability plot of the residuals for the output response Tool wear.

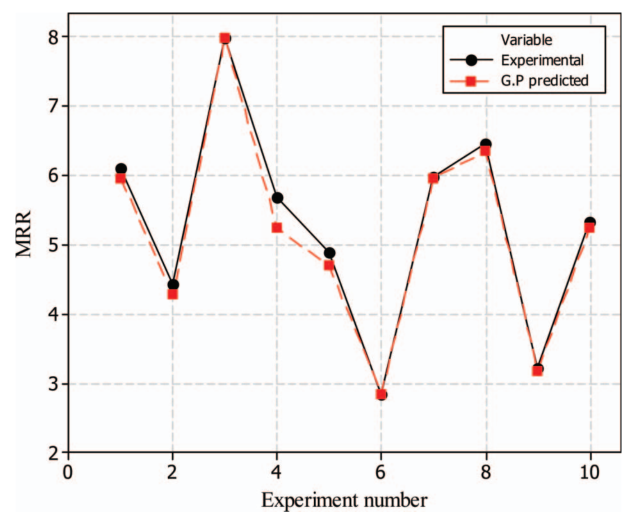

Figure 14. Comparison of the predicted model and the experimental value for the validation datasets of MRR.

8.1. *Effects of cutting parmeters on the responses*

Surface plots have been drawn using MINITAB for the convenience of understanding the surface effects and selecting the best combinations of cutting parameters. The MRR and tool wear variation for different combinations of cutting parameters are shown in Figures 16 and 17.

8.1.1. *MRR*

Figure 16a shows how the material removal rate depends on the feed (x_2) and depth of cut (x_3) in the case when the spindle speed (x_1) of 1200 RPM is kept constant. It can be seen that even though both factors have influence on MRR the feed is a more dominant factor. The combination of high value of work piece feed and the depth of cut provide the highest material removal rate. The influence of the spindle speed and

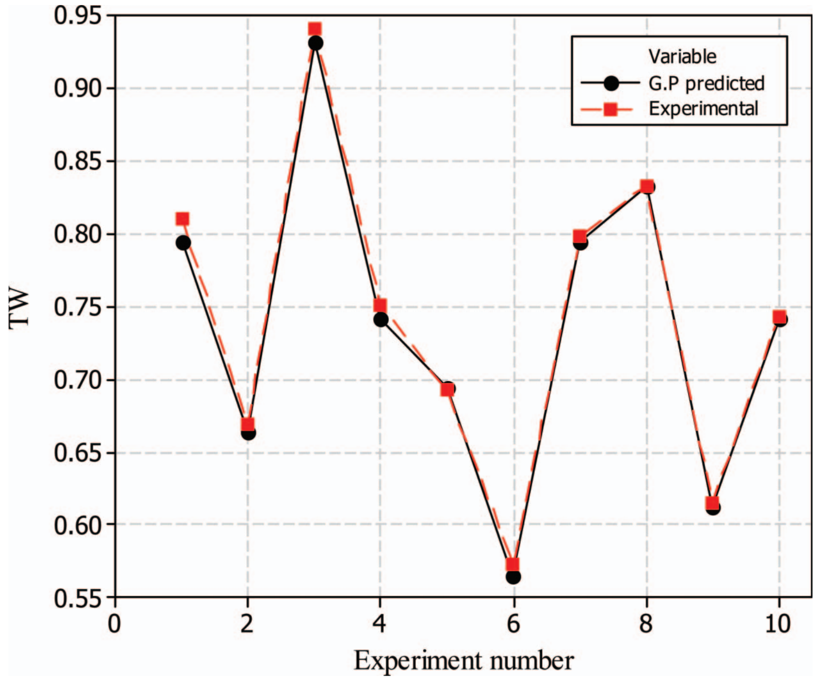

Figure 15. Comparison of the predicted model and the experimental value for the validation datasets of TW.

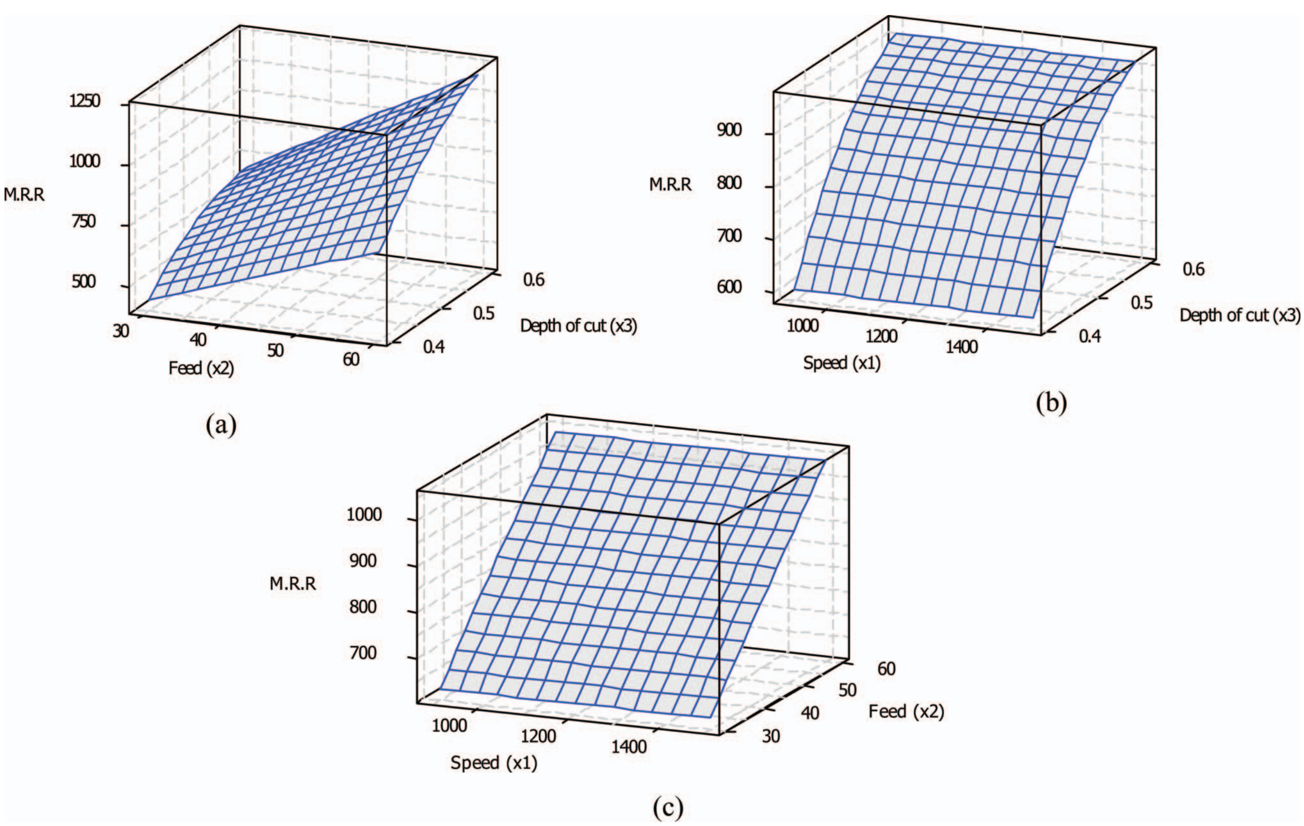

Figure 16. Surface plots of speed, feed and depth of cut on MRR.

depth of cut on the MRR for the constant feed of 45 (mm/min) is shown in Figure 16b. Both the factors show similar intensity of influence on MRR. The MRR decreases if the cutting speed increases. The depth of cut has the opposite effect, that is, MRR decreases when depth of cut decreases. Figure 16c shows the influence of the spindle speed and feed on the MRR for the constant depth of cut of 0.5mm. Inherent to milling machines is the cutting speed which is independent of table feed. Thus the MRR cannot be increased by increasing the cutting speed (Kopac and Krajnik 2007). It is obvious from the figure that MRR increases only marginally when the speed increases. The feed is again, by far, a more influential factor.

8.1.2. Tool wear

Figure 17a shows the distribution of tool wear with input parameters feed and depth of cut. It is evident from the contour surface that tool wear is maximum (about 0.24 mm) when x_2 and x_3 are at their higher limits and is minimum (about 0.10 mm) when x_2 and x_3 are at their lower limits. At lower values of depth of cut, fewer work piece material holds to the flank than at larger depth of cut. As the forces and heat generated during the machining process are higher at larger depth of cut, it is inferred that the higher temperature and the higher force are the major reasons that cause the adhesion of work piece material onto the tool flank face, thus hastening the tool wear. From Figure 17b it is clear from the contour surface that, wear is maximum (about 0.20 mm) when x_1 and x_2 are at their higher limits and is minimum (about 0.136 mm) when x_1 and x_2 are at their lower limits. The Figure 17c shows the disposition of tool wear with input parameters. In this figure, it could be generally inferred that as the spindle speed, feed, and depth-of-cut increase, the tool wear increases. These parameters clearly affect the tool wear. It is evident from the contour surface that wear is maximum (about 0.20 mm) when x_2 and x_1 are at their higher limits and is minimum (about 0.14 mm) when x_2 and x_1 are at the lower limit.

9. Formulation of multi-objective optimisation

The two objective functions considered in this study are:

(1) maximisation of material removal rate and
(2) minimisation of tool wear

which are given by Equations (1) and (2), respectively.

The two objective functions are optimised subject to the feasible bounds of input variables. The optimisation problem is defined as follows:

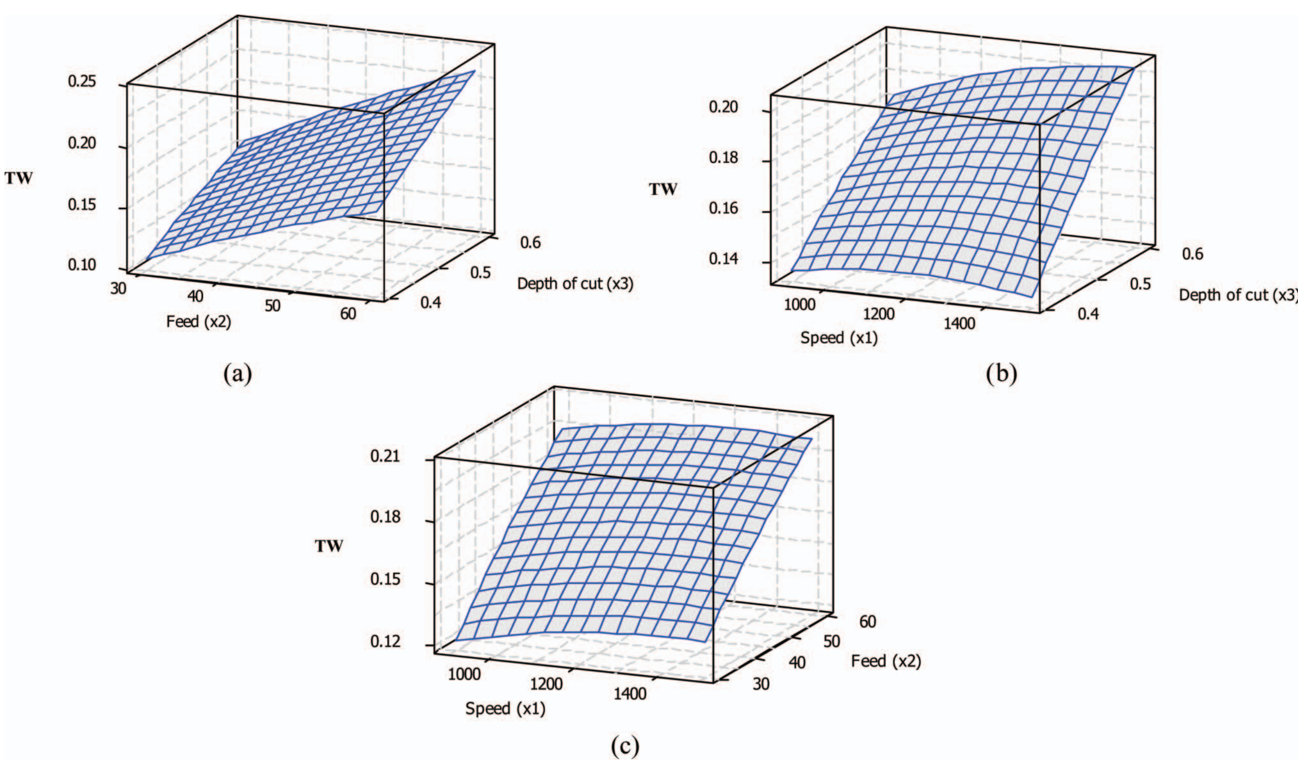

Figure 17. Surface plots of speed, feed and depth of cut on Tool wear.

Maximise

$$\mathrm{MRR} = 0.9896x_3\left(\left(\left(\left(x_2x_3^2\right)+\left(22.46/x_1\right)\right)/\left(0.24x_2x_3\right)\right) + \left(x_2x_3\left(1-x_3\right)\right)\right) \tag{3}$$

Minimise

$$\mathrm{TW} = \left(x_2x_3\right)/\left(\left(\left(x_2\right) - \left(24/\left(\left(x_3^2\right) - \left(0.997x_2\right) + 64.85 - \left(160\left(x_1+36\right)/x_3\right)\right)\right) + 89\right)\right). \tag{4}$$

Subject to

$900 \le x1 \le 1500$

$30 \le x2 \le 60$

$0.4 \le x3 \le 0.6$

10. Results and discussions

The source code of the proposed optimisation algorithm is based on the description provided by Deb *et al.* (2002). For the current work, the code was run on a Pentium IV processor using Microsoft VC++ programming language on a Windows XP platform. Tournament selection, Simulated Binary Crossover (SBX) and polynomial mutation operators were selected as the genetic operators of the real-coded NSGA-II algorithm. NSGA-II starts with a random generated population. To limit the effect of randomness on the results, the algorithm had to be run a number of times. Analysing the results of various simulations on number of test cases revealed that, after running the algorithm for about 15 times, no significant improvement could be obtained for the Pareto solutions. The control parameters required for implementation of the algorithm are listed in Table 4. For achieving better convergence, 350 generations were used in the study. The algorithm found the Pareto optimal front of conflicting objective functions with good diversity of solutions, as shown in Figure 18.

Table 4. NSGA-II Control parameters.

Population size (N):	100
Number of generations (n_{gen}):	350
Selection strategy:	Tournament
Crossover probability (p_c):	0.85
Mutation probability (p_m):	0.15
Distribution index for crossover operator: (n_c)	20
Distribution index for mutation operator: (n_m)	20
Population size (N):	50

The optimal input variables and their corresponding objective function values are presented in Table 5. Since none of the solutions in the non-dominated set is absolutely better than any other, any one of them is an acceptable solution. The choice of one solution over the other depends on the requirement of the process engineer. By analysing the Pareto front, some decisions could be taken, depending upon specific requirements of the process. Analysing point 1 which is at the extreme of the front, the highest value of material removal rate (maximum productivity) is achieved but the highest value of tool wear (worst surface quality) is achieved at this point too. On the lower side of the front at point 1 a component can be machined with low tool wear (best surface quality) but with minimum MRR (minimum productivity). All the other points are intermediate cases. They must be employed when a certain response factor is established beforehand. For example, to maintain accuracy of product, if the machining condition can allow a tool wear of 1.6 mm, the process engineer can choose the parameter setting to obtain maximum MRR at the specified value of tool wear. As can be observed from the graph, no solution in the front is better than any other as all of them are non-dominated solutions. The choice of a solution has to be made purely based on production requirements. To further illustrate the advantage of the proposed methodology, some examples are explained as follows.

From the experimental results of Table 1, the parameters listed in the ninth experiment lead to the TW value of 0.151 mm and the MRR of 4.744 g/min. After optimisation, it can be noted that the MRR is increased to 5.831 g/min for the same surface finish (S. no. 42, Table 5), with a 23% increase in MRR. In another instance, from Table 1, first experiment, the set of input variables leads to the MRR of 5.587 g/min and the TW value of 0.163 mm. After optimisation, the TW value is reduced to 0.1487 (Sl No. 13, Table 5)

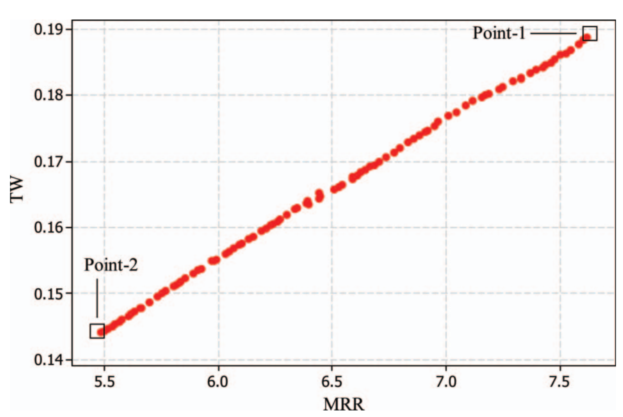

Figure 18. Pareto optimal front.

Table 5. Final optimal solutions.

S. no	Spindle Speed (RPM)	Feed (mm/min)	Depth of cut (mm)	MRR (g/min)	Tool wear (mm)
1	931.433	50.734	0.5012	7.629	0.1887
2	906.919	50.541	0.5146	7.524	0.1864
3	933.998	36.642	0.5224	5.855	0.1524
4	922.752	41.747	0.5008	6.209	0.1599
5	903.403	50.566	0.5159	7.547	0.1869
6	905.414	45.905	0.4892	6.543	0.1665
7	900.798	45.538	0.4854	6.438	0.1643
8	928.707	41.783	0.5025	6.238	0.1606
9	906.845	37.079	0.4898	5.483	0.1441
10	929.41	36.783	0.5141	5.768	0.1504
11	904.941	41.357	0.4989	6.133	0.1583
12	910.858	41.663	0.5104	6.336	0.1628
13	906.549	36.899	0.5072	5.593	0.1487
14	933.277	37.107	0.5218	5.907	0.1536
15	907.317	50.912	0.4897	7.157	0.1797
16	905.422	45.630	0.5099	6.829	0.1729
17	935.146	51.310	0.5025	7.422	0.1843
18	901.12	45.752	0.4893	6.526	0.1662
19	933.709	50.277	0.5226	7.616	0.1887
20	929.195	45.836	0.5043	6.769	0.1714
21	938.027	46.394	0.5225	7.113	0.1791
22	935.205	51.082	0.5025	7.394	0.1838
23	904.108	37.362	0.4968	5.613	0.1469
24	900.148	50.660	0.5096	7.458	0.1849
25	901.683	51.343	0.4884	7.187	0.1802
26	931.34	41.747	0.4994	6.189	0.1595
27	911.594	50.480	0.5096	7.435	0.1845
28	907.317	51.122	0.4892	7.173	0.1800
29	932.903	37.572	0.5219	5.968	0.1549
30	904.71	37.189	0.5147	5.826	0.1517
31	900.261	45.735	0.5029	6.735	0.1707
32	928.964	45.978	0.5149	6.948	0.1754
33	933.998	41.293	0.5216	6.443	0.1653
34	920.798	50.221	0.5157	7.501	0.1861
35	935.205	50.541	0.4976	7.246	0.1813
36	907.586	37.420	0.5105	5.801	0.1511
37	936.665	45.741	0.5212	7.010	0.1770
38	904.03	43.960	0.4984	6.447	0.1648
39	905.456	42.002	0.4889	6.066	0.1568
40	933.709	50.177	0.5226	7.602	0.1884
41	901.143	50.386	0.5129	7.477	0.1854
42	900.309	37.190	0.5150	5.831	0.1518
43	905.451	42.131	0.5096	6.383	0.1637
44	900.014	41.233	0.4893	5.979	0.1549
45	903.628	41.266	0.4972	6.099	0.1575
46	934.749	50.605	0.5178	7.582	0.1877
47	902.692	45.769	0.5006	6.705	0.1700
48	930.785	50.846	0.5026	7.366	0.1833
49	931.433	50.734	0.5012	7.328	0.1824
50	935.714	36.642	0.5223	5.485	0.1423

with almost the same value of MRR. Experiment number 11 of Table 1 leads to MRR of 6.741 g/min and TW of 0.149 mm for speed of 900 RPM, feed of 45 mm/min of and depth cut of 0.5 mm. In the optimal set for S. no. 7, Table 5 for speed of 900.798 RPM, feed of 45.5389 mm/min and depth of cut of 0.4854 mm the MRR is 6.438 g/min and TW is 0.1643mm. The above discussion signifies that there is conformity between values obtained from the optimisation technique with the experimental values for relatively same parameter settings.

The scanning electron microscopy (SEM) photographs of the tool inserts that correspond to the best values of MRR and TW are shown in Figures 19 and 20. Those values of MRR and TW correspond to the extreme positions (point 1 and point 2) of the Pareto optimal set shown in Figure 18. As can be observed from the photographs, the variation of tool wear and resultant effect on tool edge is apparent with respect to the different optimal sets of input variables.

11. Conclusions and future work

Material removal rate and tool wear are important machining performance measures which directly influence the productivity and accuracy of the process. In this paper, for the first time evolutionary based approaches were used to both model and optimise the CNC end milling process. Experimental data based on CCD were used to develop empirical models for MRR and TW in terms of prominent machining parameters such as spindle speed, feed and depth of cut, with an efficient evolutionary algorithm namely, GP. Genetic programming is a domain independent methodology which does not assume any *a priori* functional form of the solution and hence it can accurately model the complex relationships of the process. The high R^2 value of the models and the normal probability plots prove the effectiveness of the GP approach to establish substantially valid models. NSGA-II has been used to simultaneously optimise the conflicting objectives of material removal rate and tool wear. Accordingly the Pareto-optimal solution set is generated and presented. This enables the manufacturing engineer to select a particular optimal set of input variables according to production requirements. The optimum values are essential for the automation of the process and implementation of a computer integrated manufacturing system.

While the present study is sufficient to demonstrate the potential of the approach, for extending its capability towards real industrial implementation, future studies may also concentrate to include other responses such as surface finish, cutting forces and chatter for multi-objective optimisation. Furthermore, the models developed may include additional input parameters as encountered in industrial processes such as radial depth cut, geometry of cutting edge, diameter of tool etc. In such a case, the major problem is often one of determining the relevant input variables from a highly correlated data set. Also, it would be interesting to extend the proposed approach to other cutting conditions and workpiece/tool combinations as the

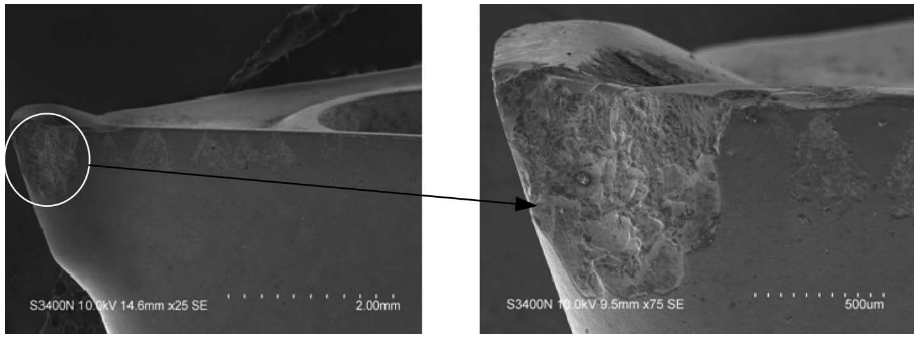

Figure 19. SEM photograph of cutting tool insert corresponding to point 1 of Pareto-optimal front. Machining conditions: $x_1 = 931.433$ RPM, $x_2 = 50.734$ mm/min, $x_3 = 0.5012$ mm, MRR = 7.629 g/min, TW = 0.1887 mm.

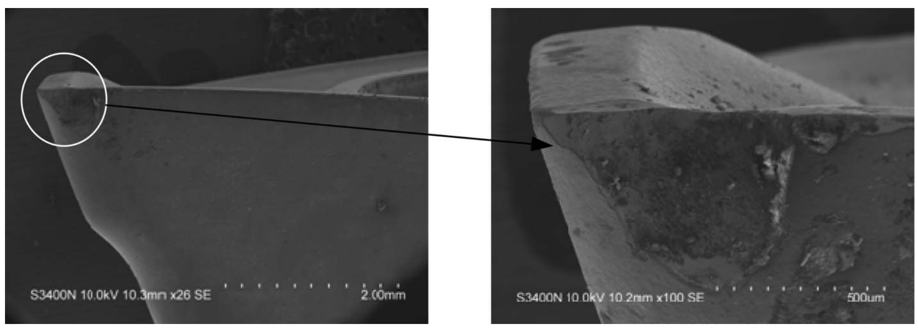

Figure 20. SEM photograph of cutting tool insert corresponding to point 2 of Pareto-optimal front. Machining conditions: $x_1 = 935.714$ RPM, $x_2 = 36.642$ mm/min, $x_3 = 0.5223$ mm, MRR = 5.485 g/min, TW = 0.1423 mm.

modelling and optimisation algorithms are of generic type and the approach is systematic.

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