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MULTIOBJECTIVE OPTIMIZATION OF MULTIPASS TURNING MACHINING PROCESS USING THE GENETIC ALGORITHMS SOLUTION

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Abstract: The study involves the development of multi-objective optimization model for turning machining process. This model was developed using a GA - based weighted-sum of minimum production cost and time criteria of multipass turning machining process subject to relevant technological/practical constraints. The results of the single-objective machining process optimization models for the multipass turning machining process when compared with those of multi-objective machining process model yielded the minimum production cost and minimum production time as $5.775 and 8.320 min respectively (and the corresponding production time and production cost as 12.996 min and $6.992, respectively), while those of the multi-objective machining process optimization model were $5.841and 9.097 min. Thus, the multi-objective machining process optimization model performed better than each of the single-objective model for the two criteria of minimum production cost and minimum production time respectively. The results also show that minimum production time model performs better than the minimum production cost model. For the example considered, the multi-objective model gave a lower production time of 30.0% than the corresponding production time obtained from the minimum production cost model, while it gave a lower production cost of 16.46% than the corresponding cost obtained by the minimum production time model.

Keywords: Turning process, Genetic Algorithms, minimum production cost, minimum production time, single-objective, multi-objective model

1. INTRODUCTION

The machining optimization problem being considered is a multi-objective problem.

The multi-objective methods provide two ways to solve multi- objective problems: combine them into a single objective using the weighted sum method or utility functions; and solve to obtain a set of non-dominated Pareto optimal solutions, each solution providing a different tradeoff between the objectives under consideration. However, these single objective approaches have a limited value to fix the optimal cutting conditions, due to the complex nature of the machining processes, where several different and contradictory objectives must be simultaneously optimized.

Ahmad [1] stated that an optimal cutting condition for a machining operation is a multi-objective problem hence requires Multi-Criteria Decision-Making (MCDM) approaches. He used goal programming approach for the multi-objective optimization of the single-pass turning process, to find the optimal machining speed and feed rate values subject to a number of practical constraints including horsepower, permissible cutting speed, and permissible feed rate; with the objective functions of tool life and metal removal rate.

Cus et al [2] presented a multi-objective optimization of the end milling process by using neural network modeling and particle swamp optimization. They used the neural network to predict cutting forces during the machining operation and the particle swamp optimization to obtain the cutting speed and feed rate.

Bouzakis et al [3] proposed, a multi-objective optimization procedure, based on Genetic Algorithms, to obtain the optimum cutting conditions (cutting depth, feed rate and cutting speed) in milling. Objective functions, like machining cost and machining time and several technological constrains were simultaneously taken into consideration. A Pareto ranking approach was used to determine the optimum cutting parameters. Milling simulation algorithms were taken into account in order to calculate chip thickness, cutting force, etc. An application example demonstrating the effectiveness of the proposed methodology was also presented.

Marler and Arora [4] surveyed the current continuous non-linear Multi-Objective Optimization (MOO) methods as well as the Genetic Algorithms. They also provided commentaries on the advantages and pitfalls of individual methods, the different classes of methods, and the field of MOO as a whole as well as the characteristics of the most significant methods. They found that no single approach was superior. Rather, the selection of a specific method depends on the type of information that is provided in the problem, the user's preferences, the solution requirements, and the availability of software.

Other multi-objective approaches have been reported in cutting parameters optimization [5, 6], but mainly use a priori techniques, where the decision maker combines the different objectives into a scalar cost function. This actually makes the multi-objective problem, single-objective prior to optimization [7].

Quiza-Sardinas et al [8], proposed a multi-objective optimization method, based on a posteriori techniques and using genetic algorithms, to obtain the optimal parameters in turning processes.

The widely used approach for solving multi-objective optimization problems is to transform a multiple objective (vector) problem into a single-objective (scalar) problem. Among decision methods, weighted-sum aggregation of preferences is by far the most common, as it is a direct specification of important weights [9]. The weighted sum method transforms multiple objectives into an aggregated scalar objective function by multiplying each objective function by a weighting coefficient and summing up all contributors to look for the Pareto solution [10].

But the minimum production cost objective and the minimum production time objective are quite different by nature and values and could therefore not be aggregated as comparable objectives. Thus a normalization scheme is needed for the two objectives to be comparable criteria and their weights correctly applied to represent their relative importance [11, 12, 13]. The normalization not only transforms data to have comparable values but also transforms the problem to a maximization problem [9]. The weighted sum method requires multiplying each of the normalized objective functions by some weighting coefficients and summarizing them into a single objective function.

This work presents a method that determines weights for the objective functions without the articulation of preferences among the many criteria by the decision maker and without arbitrary choice of weights. This method is based on Genetic Algorithms, which maintains a population of encoded feasible solutions and guides the population towards the optimum solutions [14]; then after each search interval (i.e. generation), ideas or information about the performance (or possible solution) found by each member of the Genetic Algorithms population (i.e. the search team) can be used to determine such weights. The contribution of each member of the Genetic Algorithms population is reflected in the weight assigned to each objective function in the multi-objective optimization problem. This work is also concerns with evaluation of cost and time functions involved in multipass turning machining process, development of single-objective cost and time model as well as evaluation of the related practical constraints in order to determine optimum machining cutting parameters [15]. The model developed is then implemented in a Microsoft Visual Basic.Net environment to obtain optimum cutting machining parameters.

2. METHODOLOGY

2.1. Development of the single-objective turning machining process optimization models

Mathematical models have been developed for the multipass turning machining process for the unit production cost and time.

The unit production costs for the multi-pass turning Cut, is given by [16]:

$$\begin{aligned} C_{ut} = {} & k_O\left[\frac{\pi DL}{1000v_r f_r}N_{rp} + \frac{\pi DL}{1000v_s f_s}\right] + \\ & + k_o\left[t_c + (h_1 L + h_2)(N_{rp}+1)\right] + \\ & + k_o t_e\left\{\frac{1}{T_r}\left[\frac{\pi DL}{1000v_r f_r}N_{rp}\right] + \frac{1}{T_s}\left[\frac{\pi DL}{1000v_s f_s}\right]\right\} + \\ & + k_t\left\{\frac{1}{T_r}\left[\frac{\pi DL}{1000v_r f_r}N_{rp}\right] + \frac{1}{T_s}\left[\frac{\pi DL}{1000v_s f_s}\right]\right\}. \end{aligned} \tag{1}$$

The unit production time for the multi-pass turning T_{ut}, as given by [17] is given in eqn. (2) as:

$$\begin{aligned} T_{ut} = {} & \left[\frac{\pi DL}{1000v_r f_r}N_{rp} + \frac{\pi DL}{1000v_s f_s}\right] \\ & + \left[t_c + (h_1 L + h_2)(N_{rp}+1)\right] \\ & + t_e\left\{\frac{1}{T_r}\left[\frac{\pi DL}{1000v_r f_r}N_{rp}\right] + \frac{1}{T_s}\left[\frac{\pi DL}{1000v_s f_s}\right]\right\}. \end{aligned} \tag{2}$$

2.2. Development of the multi-objective machining process optimization model

The developed multi-objective machining process optimization model can be written as:

$$\max.\ \Phi(v, f, d) = (C_{ut}(v, f, d), T_{ut}(v, f, d))^T = \text{Max.}\left(w_1 C_{ut}^N + w_2 T_{ut}^N\right) = 1$$

subject to $g_j(v, f, d) \le 0$ j = 1, J

$h_k(v, f, d) = 0$ K = 1, K (3)

$$v_L \le v \le v_U$$
$$f_L \le f \le f_U$$
$$d_L \le d \le d_U$$
$$v, f, d \ge 0.$$

The normalized production cost and time for the turning machining operations are given by eqns. (4) and (5) as:

$$C_{u,j}^N = \frac{C_u^{max} - C_{u,j}}{C_u^{max} - C_u^{min}},\ j = 1, 2,..,n_p, \tag{4}$$

$$T_{u,j}^N = \frac{T_u^{max} - T_{u,j}}{T_u^{max} - T_u^{min}},\ j = 1, 2,..,n_p. \tag{5}$$

The corresponding weights, w_1 and w_2 as given by [18] are shown in eqns. (6) and (7) as:

$$w_1 = \frac{\sum_{j=1}^{n_p}\left(\frac{C_u^{max} - C_{uj}}{C_u^{max} - C_u^{min}}\right)}{\sum_{j=1}^{n_p}\left\{\left(\frac{C_u^{max} - C_{uj}}{C_u^{max} - C_u^{min}}\right) + \left(\frac{T_u^{max} - T_{uj}}{T_u^{max} - T_2^{min}}\right)\right\}} = \frac{\sum_{j=1}^{n_p} C_{u,j}^N}{\sum_{j=1}^{n_p}\left(C_{u,j}^N + T_{u,j}^N\right)}, \tag{6}$$

$$w_2 = \frac{\sum_{j=1}^{n_p}\left(\frac{T_u^{max} - T_{uj}}{T_u^{max} - T_u^{min}}\right)}{\sum_{j=1}^{n_p}\left\{\left(\frac{C_u^{max} - C_{uj}}{C_u^{max} - C_u^{min}}\right) + \left(\frac{T_u^{max} - T_{uj}}{T_u^{max} - T_2^{min}}\right)\right\}} = \frac{\sum_{j=1}^{n_p} T_{u,j}^N}{\sum_{j=1}^{n_p}\left(C_{u,j}^N + T_{u,j}^N\right)}. \tag{7}$$

These models are optimized subject to the constraints specified by eqns. (8) – (31):

– bounds on cuttings peed:

roughing: $$v_{rL} \le v_r = \frac{\pi D N_r}{1000} \le v_{rU}, \tag{8}$$

finishing: $$v_{sL} \le v_s = \frac{\pi D N_s}{1000} \le v_{sU}, \tag{9}$$

– bounds on feed rate:

roughing: $$f_{rL} \le f_r \le f_{rU}, \tag{10}$$

finishing: $$f_{sL} \le f_s \le f_{sU}, \tag{11}$$

– bounds on depth of cut:

roughing: $$d_{rL} \le d_r \le d_{rU}, \tag{12}$$

finishing: $$d_{sL} \le d_s \le d_{sU}, \tag{13}$$

– tool Life constraint:

roughing: $$T_L \le T_r = \frac{C_o}{v_r^{\alpha} f_r^{\beta} d_r^{\gamma}} \le T_U, \tag{14}$$

finishing: $$T_L \le T_s = \frac{c_o}{v_s^{\alpha} f_s^{\beta} d_s^{\gamma}} \le T_U, \tag{15}$$

– cutting force constraint:

roughing: $$F_r = k_f f_r^{\mu} d_r^{\nu} \le F_U, \tag{16}$$

finishing: $$F_s = k_f f_s^{\mu} d_s^{\nu} \le F_U, \tag{17}$$

– cutting power constraint:

roughing: $$P_r = \frac{k_f f_r^{\mu} d_r^{\nu} v_r}{60,000\,\eta} \le P_U, \tag{18}$$

finishing: $$P_s = \frac{k_f f_s^{\mu} d_s^{\nu} v_s}{60,000\,\eta} \le P_U, \tag{19}$$

– chip-tool interface temperature constraint:

roughing: $$Q_r = k_q v_r^{\tau} f_r^{\varphi} d_r^{\delta} \le Q_U, \tag{20}$$

finishing: $$Q_s = k_q v_s^{\tau} f_s^{\varphi} d_s^{\delta} \le Q_U, \tag{21}$$

– dimensional accuracy constraint:

roughing: $$DA_r = k_g v_r^{\chi} f_r^{\varsigma} d_r^{\psi} \le DA_U, \tag{22}$$

finishing: $$DA_s = k_g v_s^{\chi} f_s^{\varsigma} d_s^{\psi} \le DA_U, \tag{23}$$

– stable cutting region constraint:

roughing: $$SC_r = v_r^{\lambda} f_r d_r^{\upsilon} \ge SC, \tag{24}$$

finishing: $$SC_s = v_s^{\lambda} f_s d_s^{\upsilon} \ge SC, \tag{25}$$

– surface finish constraint:

finishing: $$SR_s = \frac{f_s^2}{8R} \le SR_U, \tag{26}$$

– miscellaneous constraints:

finishing cutting speed: $$v_s \ge 1.2 v_r, \tag{27}$$

finishing feed rate: $$f_s \le 0.6 f_r, \tag{28}$$

finishing depth of cut: $$d_s \le 0.5 d_r, \tag{29}$$

Total depth of cut constraint: $$d_s = d_t - n, \tag{30}$$

– bounds on number of rough cuts:

$$N_L = \frac{d_t - d_{sU}}{d_{rU}} \le n \le N_U = \frac{d_t - d_{sL}}{d_{rL}}. \tag{31}$$

2.3. Steps in the multi-objective Genetic Algorithm methodology

The multi-objective Genetic Algorithms methodology was implemented by applying the weighted method developed by [18], given as Figs 1-2.

// Set i_{max} = Max. No. of generations
i = 1: //Initialize generations
For j = 1 To n_q: // n_q = 20 GA population size
For k = 1 To n_r: //
// Generate initial random population
// of n_q chromosomes (suitable solutions
// for the problem)
//Evaluate the fitness $f_{ijk}(x) = f(x)$ of each
// chromosome x in the population
Next k
Next j
1 For j = 1 To n_q
Sum = 0
For k = 1 To n_r

$$f_{ijk}^{norm} = \frac{\left(f_{ijk}^{max} - f_{ijk}\right)}{\left(f_{ijk}^{max} - f_{ijk}^{min}\right)}$$

$$Sum(ijk) = Sum + f_{ijk}^{norm}(x)$$

$$Sum = Sum(ijk)$$

Next k
Next j
SumTotal = 0
For k = 1 To n_r

$$SumTotal = SumTotal + Sum(ijk)$$

Next k
For k = 1 To n_r

$$w(ijk) = \frac{Sum(ijk)}{SumTotal}$$

Next k
For j = 1 To n_q
Cum = 0
For k = 1 To n_r

$$F_{ijk}^{N}(x) = w(ijk) * f_{ijk}^{norm}(x)$$

$$C_{ijk}^{N}(x) = Cum + F_{ijk}^{N}(x)$$

$$Cum = C_{ijk}^{N}(x)$$

If $C_{ijk}^{N}(x) = f_{ijk}^{norm}(x) = 1$ *Then GoTo 2*
Next k
Next j
//Carry out GA procedure of creation of new populations as thus:
//Create a new population by repeating following steps until the new population is complete

Fig. 1. Genetic Algorithm methodology 1/2

a. [Selection] Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected)
b. [Crossover] With a crossover probability cross over the parents to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents.
c. [Mutation] With a mutation probability mutate new offspring at each locus (position in chromosome).
d. [Accepting] Place new offspring in the new population

// Evaluate the new generated population for a further run of the algorithm
For j = 1 To n_q: // n_q = 20 GA population size
For k = 1 To n_r:
//Evaluate the fitness $f_{ijk}(x) = f(x)$ of
//each chromosome x in the population
Next k
Next j
i = i + 1
GoTo 1
2 /Display optimum results: Optimum decision variables; optimum objective functions
// values; Optimum multi-objective function value; and no. of GA generations
End

Fig. 2. Genetic Algorithm methodology 2/2

2.4. Implementation

The elements of the proposed models developed using Genetic Algorithm have been implemented in the software developed in Microsoft Visual Basic.Net environment and run on a Pentium 4 PC with 3.0 GHz Intel Processor and 2 GB of RAM. The values set for different parameters of the genetic algorithm are shown in Table 1.

Tab. 1. Genetic Algorithms parameters

Population size	20
Number of population generation	50
Length chromosomes	49
Selection operator	Roulette Wheel
Crossover operator	One-point operator
Crossover probability	0.80
Mutation probability	0.01
Fitness measure	Multi-objective model

2.5. Illustrative example

An illustrative example has been adopted from [15, 16] to demonstrate the performance of the proposed models. Table 2 shows the data of the illustrative example.

Tab. 2. Data of Chen and Tseng [19] and Onwubolu and Kumalu [16]

v_{rL} = 90 m/min	v_{rU} = 500 m/min	v_{sL} = 90 m/min
v_{sU} = 500 m/min	f_{rL} = 0.1 mm/rev	α = 5
τ = 0.40	f_{sL} = 0.1 mm/rev	f_{sU} = 1.0 mm/rev
d_{rL} = 1.0 mm	d_{rU} = 3.0 mm	d_{sL} = 1.0 mm
ν = 0.95	μ = 0.75	K_o = 0.5 \$/min
K_t = 2.5 \$/min	T_L = 25 min	T_U = 45 min
SR_U = 10 μm	ς = 0.9709	Q_U = 1000°C
h_2 = 0.3 min	F_U = 5.0 kgf	P_U = 200 kW
R = 1.2 mm	η = 0.85	C = 140
K_f = 108	K_q = 132	d_{sU} = 3.0 mm
Φ = 0.2	h_1 = 7x10^{-4} min/mm	T_e = 1.5 min/edge
δ = 0.105	f_{rU} = 1.0 mm/rev	β = 1.75
C_o = 6x10^{11}	k_r = 100.66	X = -0.2848
Tc = 0.75 min/piece	ψ = 0.4905	υ = -1
γ = 0.75	λ = 2	

2.6. Illustration of the multi-objective model using data of Amiolemhen and Ibhadode [15]

An illustrative example has been adopted from [15] to demonstrate the performance of the the multi-objective model for multi-pass turning operation.

The cutting parameters of cutting speed, feed rate and depth of cut are shown in columns 2, 3 and 4 of Table 3, while the objective functions values of the minimum production cost and minimum production time are shown in columns 5 and 6 of Table 3.

The normalized values of the minimum production cost, minimum production time and the multi-objective models are shown in columns 7, 8 and 9 of Table 3.

The normalized values of the Multiobjective model, shown in column 9; were obtained by summation of each normalized single objective model multiply by its respective estimated weight, w^*. And, these weights were determined from eqns. (6) and (7) as thus:

$$w_1 = \frac{\sum_{j=1}^{n_p}\left(\frac{C_u^{max} - C_{uj}}{C_u^{max} - C_u^{min}}\right)}{\sum_{j=1}^{n_p}\left\{\left(\frac{C_u^{max} - C_{uj}}{C_u^{max} - C_u^{min}}\right) + \left(\frac{T_u^{max} - T_{uj}}{T_u^{max} - T_2^{min}}\right)\right\}} = \frac{\sum_{j=1}^{n_p} C_{u,j}^N}{\sum_{j=1}^{n_p}\left(C_{u,j}^N + T_{u,j}^N\right)} = \frac{14.085}{14.085 + 14.682} = 0.490, \quad (32)$$

$$w_2 = \frac{\sum_{j=1}^{n_p}\left(\frac{T_u^{max} - T_{uj}}{T_u^{max} - T_u^{min}}\right)}{\sum_{j=1}^{n_p}\left\{\left(\frac{C_u^{max} - C_{uj}}{C_u^{max} - C_u^{min}}\right) + \left(\frac{T_u^{max} - T_{uj}}{T_u^{max} - T_2^{min}}\right)\right\}} = \frac{\sum_{j=1}^{n_p} T_{u,j}^N}{\sum_{j=1}^{n_p}\left(C_{u,j}^N + T_{u,j}^N\right)} = \frac{14.682}{14.085 + 14.682} = 0.510. \quad (33)$$

The normalization processes were computed using eqns. (4) and (5) as follows:

$$C_{u,j}^N = \frac{C_u^{max} - C_{u,1}}{C_u^{max} - C_u^{min}} = \frac{83.75 - 20.13}{83.75 - 14.95} = 0.872$$
$$\ldots\ldots\ldots = \ldots\ldots\ldots = \ldots\ldots \quad (34)$$
$$C_{u,,20}^N = \frac{C_u^{max} - C_{u,20}}{C_u^{max} - C_u^{min}} = \frac{83.75 - 15.62}{83.75 - 14.95} = 0.998,$$

$$T_{u,1}^N = \frac{T_u^{max} - T_{u,1}}{T_u^{max} - T_u^{min}} = \frac{167.34 - 38.00}{167.34 - 19.01} = 0.923$$
$$\ldots\ldots\ldots = \ldots\ldots\ldots = \ldots\ldots \quad (35)$$
$$T_{u,,20}^N = \frac{T_u^{max} - T_{u,20}}{T_u^{max} - T_u^{min}} = \frac{167.34 - 19.33}{167.34 - 19.01} = 0.989.$$

The multi-objective model values were computed using eqn. (3) as follows:

$$\left(w_1 C_{u1}^N + w_2 T_{u1}^N\right) = 0.490 \times 0.872 + 0.510 \times 0.923 = 0.898 \quad (36)$$
$$\ldots\ldots\ldots\ldots\ldots\ldots$$
$$\left(w_1 C_{u20}^N + w_2 T_{u20}^N\right) = 0.490 \times 0.998 + 0.510 \times 0.989 = 0.993.$$

Tab. 3. Data of Amiolemhen and Ibhadode [15]

S/N	Cutting speed ,*v* (m/min)	Feed rate, *f* (mm/rev)	Depth of cut, *d*(mm)	Min. prod. time, *Tu* (min/piece)	Min. prod. cost, *Cu* ($/piece)	Norm. min. prod. time, *TuN*	Norm. min. prod. cost, *CuN*	Multi- obj.
1	157.770	0.249	1.331	38.000	20.13033	0.923	0.872	0.898
2	199.365	0.340	1.533	22.653	14.84944	1.000	0.975	0.988
3	209.031	0.361	1.581	20.945	14.89608	0.999	0.987	0.993
4	149.362	0.230	1.290	43.695	22.71106	0.886	0.834	0.860
5	158.331	0.250	1.333	37.668	19.98419	0.925	0.874	0.900
6	149.792	0.231	1.292	43.477	22.61254	0.887	0.835	0.862
7	93.737	0.108	1.018	167.343	83.75185	0.000	0.000	0.000
8	145.458	0.222	1.271	46.823	24.11693	0.865	0.813	0.839
9	154.471	0.242	1.314	40.083	21.06037	0.910	0.858	0.884
10	149.672	0.231	1.291	43.466	22.60522	0.887	0.835	0.862
11	106.529	0.136	1.081	112.542	56.42846	0.397	0.369	0.383
12	226.139	0.399	1.664	19.013	15.95387	0.984	1.000	0.992
13	119.894	0.166	1.145	79.664	40.12018	0.633	0.591	0.613
14	149.774	0.231	1.292	43.390	22.57031	0.888	0.836	0.862
15	218.626	0.382	1.627	19.705	15.33786	0.993	0.995	0.994
16	98.2160	0.118	1.040	144.239	72.22248	0.167	0.156	0.162
17	116.554	0.158	1.130	86.436	43.46744	0.585	0.545	0.565
18	104.948	0.133	1.073	117.760	59.02573	0.359	0.334	0.347
19	106.948	0.137	1.083	111.342	55.83138	0.405	0.378	0.392
20	222.380	0.391	1.646	19.330	15.61603	0.989	0.998	0.993

3. RESULTS AND DISCUSSION

3.1. Figures and Tables

Figures 3 and 4 show the plot of the fractional fitness superimposed on the plots for the minimum production time, Tu and minimum production cost, Cu. The figure also shows that there seems to be no immediate discernable pattern of variation of fractional fitness with number of generations. This is due to the complex operations that take place in the implementation of the GAs solution that give rise to the fractional fitness. However, the spikes appearing at the 2nd, 18th, 26th, 28th, 40th, 42nd and 50th generations may be due to the resetting of the GAs operators at those generations. However, changes observed between the 1st and 9th, 16th and 21st, 21st and 32nd GA generations are due to the setting of the Gas operators of crossover and mutation at those generations.

Figure 5 shows the plots of the normalized combined criteria superimposed on the plots for minimum production time Tu and minimum production cost Cu against number of generations. The figure shows that from the 1st to the 9th generations, there are sharp reductions in production time and production cost of 47.4% and 53.8% respectively along with instability in their variations within this region. From the 10th to the 33rd generations, further reductions are shown with some instability in variations observed more for the production cost curve. Thereafter, the curves converge to constant values of 9.1min/piece and $5.8/piece for the minimum production time and minimum production cost respectively.

The figure also shows that there are variations of the combined criteria curve at generations where the minimum production time and minimum production cost are varying. At generations where minimum production time and minimum production cost are constant, the combined criteria curve has constant value of 1. This is a consequence of the definition of the multi-objective model given by eqn. (3).

Figure 6 shows the variations of the normalized values of the minimum production time, Tu, minimum production cost, Cu and the combined criteria against number of generations. The figure shows that the combined criteria plot is a weighted mean of the normalized minimum production time and normalized minimum production cost as given by eqn. (3).

Figure 7 shows the plot of minimum production cost and minimum production time against the number of GA generations for the turning machining operation. The figure shows that the production cost drops rapidly from $15.338/piece from the 1st generation to 9.328/piece at the 2nd generation, giving a cost slope of $6.010/generation. From the 2nd generation to the 3rd generation the production cost drops from $9.328/piece to $8.615/piece giving a cost slope decrease of $0.0.713/generation. From the 3rd generation to the 4th generation the production cost remains constant. From the 4th generation to the 5th generation the production cost increases from $8.615/piece to $10.081/piece giving a cost slope rise of $1.466/generation. From the 5th generation to the 6th generation the production cost remains constant. From the 6th generation to the 7th generation the production cost drops from $10.081/piece to $7.630/piece, giving a cost slope of $2.451/generation. From the 7th generation to the 8th generation the production cost drops from $7.630/piece to $7.483/piece, giving a cost slope of $0.147/generation. From the 8th generation to the 9th generation the production cost drops from $7.483/piece to $7.093/piece, giving a cost slope of $0.370/generation. From the 9th generation to the 16th generation the production time remains constant. From the 16th generation to the 17th generation, the production time increase from $7.093/piece to $8.013/piece, giving a time slope rise of $0.920/generation. From the 17th generation to the 20th generation the production time remains constant. From the 20th generation to the 21st generation the production cost drops from $8.013/piece to $7.062/piece, giving a cost slope of $0.951/generation. From the 21st generation to the 22nd generation the production time remains constant. From the 22nd generation to the 23rd generation the production cost increases from $7.062/piece to $7.136/piece, giving a cost slope of $0.074/generation. From the 23rd generation to the 32nd generation the production time remains constant. From the 32nd generation to the 33rd generation the production cost drops from $7.136/piece to $5.841/piece, giving a cost slope of $1.265/generation. Thereafter, the production cost remains constant till the 50th generation. This is a cost slope of about 190 times less than that between the 1st and the 7th generations. This goes to show how effective the GAs solution technique is in converging quickly to the optimum value.

The figure also shows that the production time drops rapidly from 19.705 min/piece from the 1st generation to 14.916 min/piece at the 2nd generation, giving a time slope of 4.789 min/generation. From the 2nd generation to the 3rd generation the production time increases from 14.916 min/piece to 15.893 min/piece giving a time slope increase of 0.977 min/generation. From the 3rd generation to the 4th generation the production time remains constant. From the 4th generation to the 5th generation the production time drops from 15.893 min/piece to 14.338 min/piece giving a time slope drop of 1.555 min/generation. From the 5th generation to the 6th generation the production time remains constant. From the 6th generation to the 8th generation the production time had average drops of 1.68 min/generation. From the 8th generation to the 16th generation the production time remains constant. From the 16th generation to the 17th generation the production time drops from 10.369 min/piece to 9.780 min/piece giving a time slope drop of 0.589 min/generation. From the 17th generation to the 20th generation the production time remains constant. From the 20th generation to the 33rd generation the production time drops from 9.780 min/piece to 9.097 min/piece giving a time slope drop of 0.683 min/generation. Thereafter, the production time remains constant till the 50th generation giving a time slope of 0.04/generation. This is a time slope of about 180 times less than that between the 1st and the 7th generations. This goes to show how effective the GAs solution technique is in converging quickly to the optimum value.

Figure 8 shows the variation of the weights of the normalized criteria over the 50 population generations. The figure shows that the values of weights are mirror images of each other about the mean weight of 0.5.

Figure 9 shows the optimum results obtained from the three models for the turning machining operation. The figure shows that using the minimum production cost model while giving an optimum production cost of $5.775 predicts a much higher production time of 12.996 min over the optimum production time of 8.320 min predicted by the minimum production time model; that is 56.20% greater. On the other hand, the minimum production time model giving an optimum production time of 8.32 min predicts a slightly more production cost of $6.992 over the optimum production cost of $5.775 predicted by the minimum production cost model, that is, 21.07% greater. These results suggest that the minimum production time model seems to perform better than the minimum production cost model. This may be true for most cases in the real world of work. Hence, we find that the minimum production time model is adopted when productive efficiency is desired. Whereas, the minimum production cost model is adopted when there is ample time for production. However, in high-performing organizations which all organizations strive to be, time is of utmost importance; and it will be counter-productive to spend more time on a job which can be done in less time for the same quality.

The multi-objective model gave the production cost of $5.841/piece and the production time of 9.097 min/piece. The multi-objective model gives a higher production cost of 1.14% than the minimum production cost model while it also gives a higher production time of 9.34% than the minimum production time model. These higher results from the multi-objective model than the single-objective models are expected because the multi-objective model is a combination of the two conflicting single-objective models and therefore gives compromise results (or tradeoff results). However, the figure shows that the multi-objective model gives a lower production time of 43.9% than the corresponding production time obtained from the minimum production cost model while it also gives a lower production cost of 19.7% than the corresponding production cost obtained by the minimum production time model.

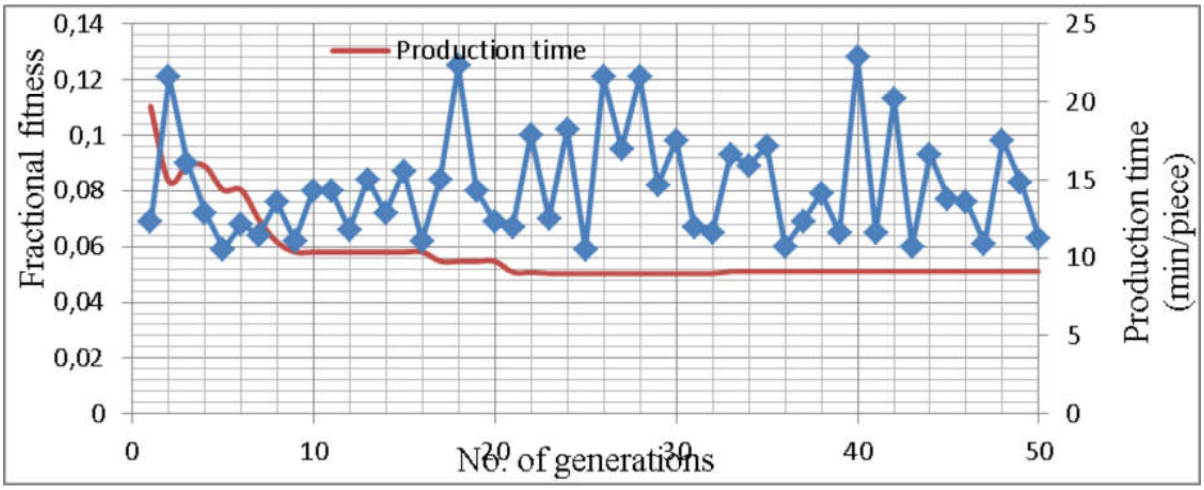

Fig. 3. Plots of fractional fitness and minimum production time against number of generations

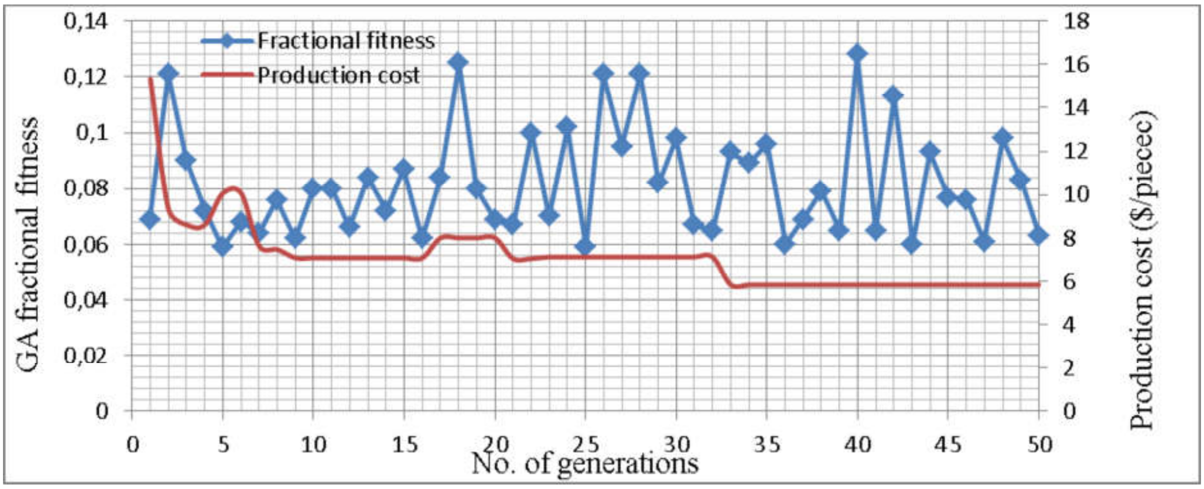

Fig. 4. Plots of fractional fitness and minimum production cost against number of generations

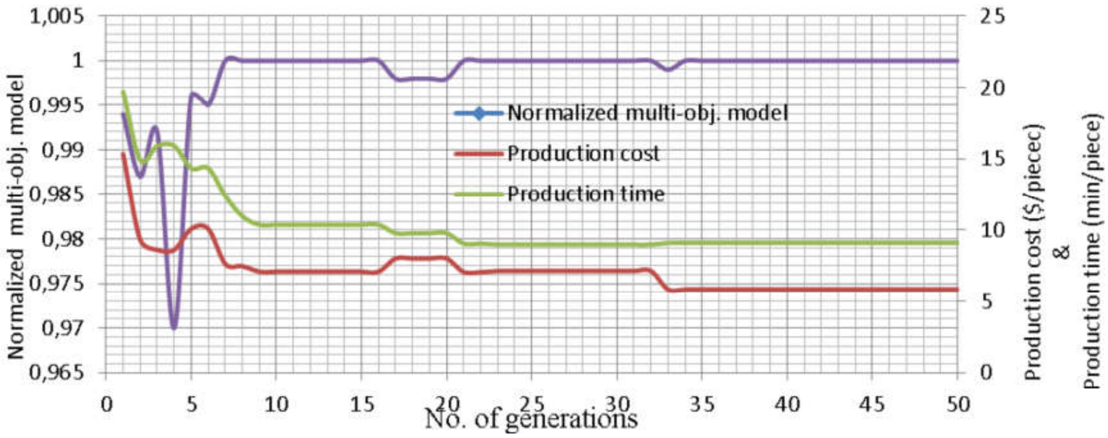

Fig. 5. Plots of normalized combined criteria, minimum production time and minimum production cost against number of generations

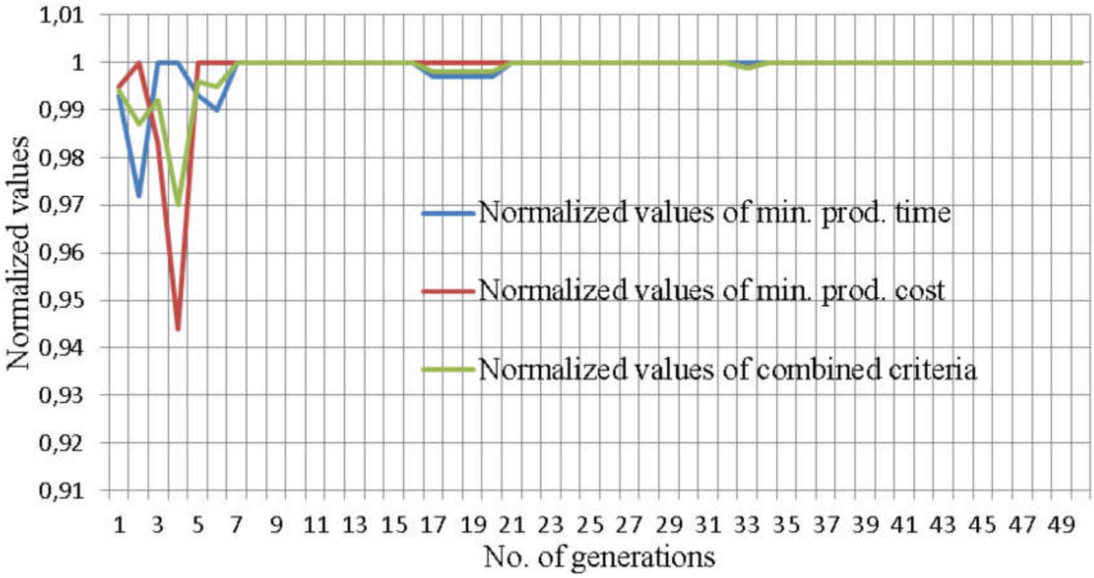

Fig. 6. Plots of normalized values of minimum production time, minimum production cost and the combined criteria against number of generations

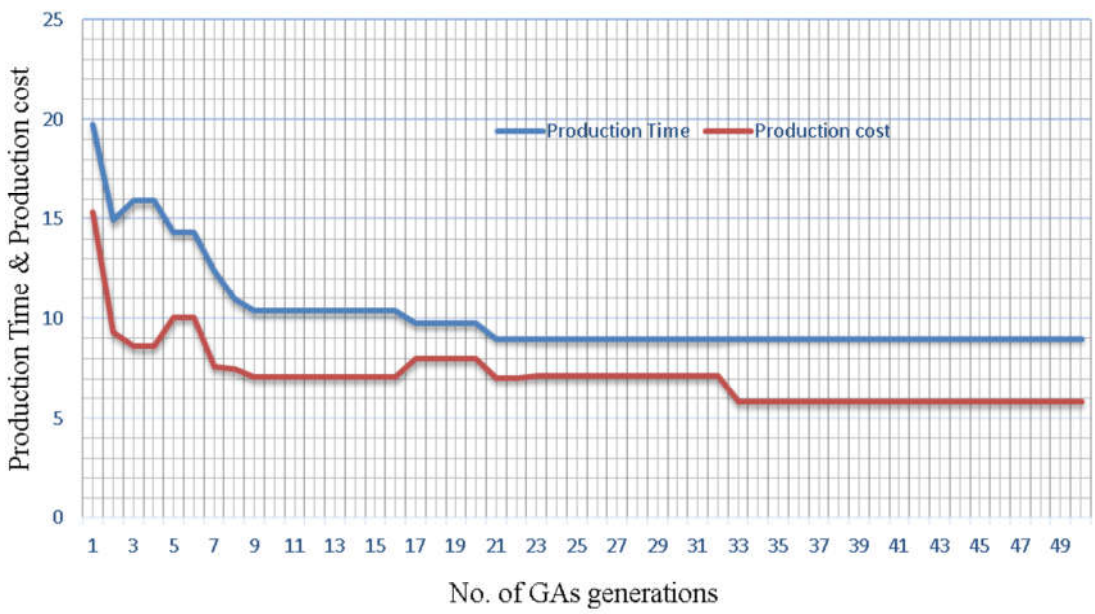

Fig. 7. Plots of minimum production time and minimum production cost against number of generations

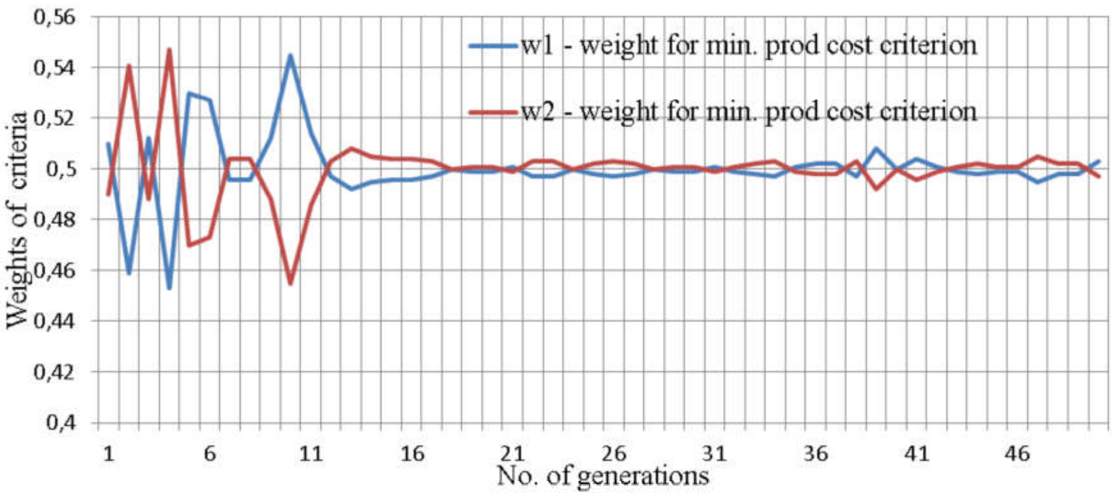

Fig. 8. Plots of weights of minimum production time and minimum production cost against number of generations

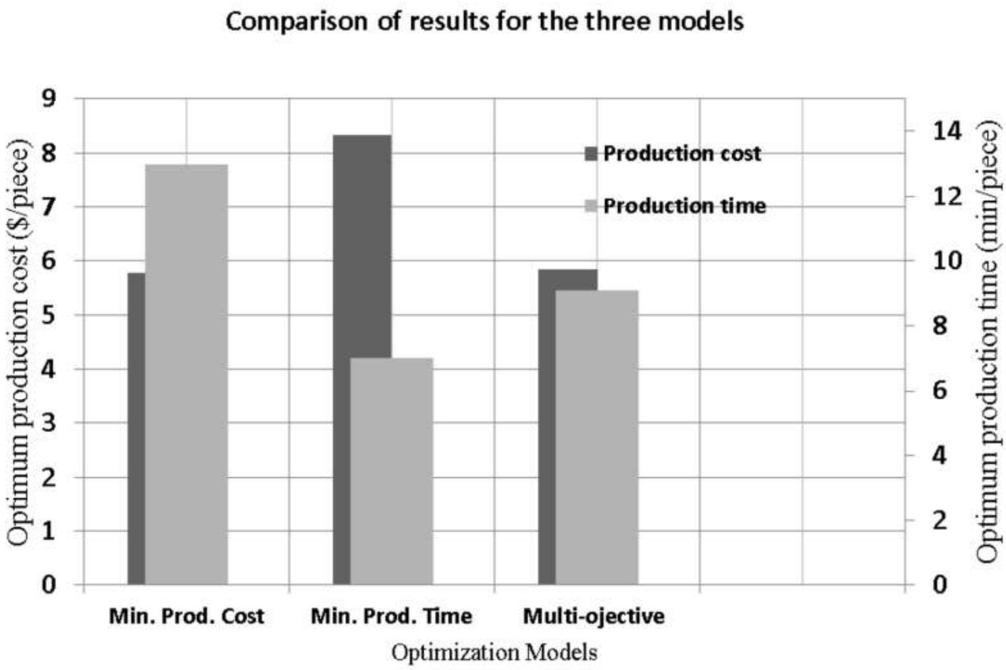

Fig. 9. Comparison of results of the three models

4. CONCLUSIONS

The results of the single-objective machining process optimization models for the multipass turning machining process when compared with those of multi-objective machining process model yielded the minimum production cost and minimum production time as $5.775 and 8.320 min respectively (and the corresponding production time and production cost as 12.996 min and $6.992, respectively), while those of the multi-objective machining process optimization model were $5.841 and 9.097 min. Thus, the multi-objective machining process optimization model performed better than each of the single-objective model for the two criteria of minimum production cost and minimum production time respectively. From the analysis of results, it appears that the minimum production time model performs better than the minimum production cost model. Thus, for real shop floor conditions in which time is of essence, it is recommended that the minimum production time model be used. Moreover, the analysis of results further shows that the machining process optimization problem is actually a multi-objective optimization problem with several constraints and two conflicting objective functions of minimum production cost and minimum production time models. Due to the ability of the multi-objective criteria model to combine the effects of two conflicting objectives, the model is able to predict better performance indices than the single-objective models of cost and time. Thus, for the example considered, the multi-objective model gave a lower production time of 30.0% than the corresponding production time obtained from the minim,um production cost model, while it gave a lower production cost of 16.46% than the corresponding cost obtained by the minimum production time model.

Nomenclature

Symbols

C	conservative tool-life constant, dependent on cutting tool material/work-piece combination
Cf_i	cumulative fitness of a population
C_{it}	machine idle cost due to loading and unloading operations and tool idle motion
C_{mt}	cutting cost by actual time in cut for turning ($/piece)
C_u^{Norm}	normalized minimum production cost
C_o	tool-life constant, dependent on cutting tool material/work-piece combination
C_{rt}	tool replacement cost for turning ($/piece)
C_{tt}	tool cost for turning ($/piece)
C_{ut}	unit production cost except material cost for ($/piece)
D	diameter of work-piece (mm)
DA_r	dimensional accuracy in roughing machining operation (mm)
DA_U	limit of dimensional accuracy (mm)
F	$\{F_r, F_s\}$, cutting forces during rough and finishing machining (kgf)
F_U	maximum allowable cutting force (kgf)
K_o	direct labour cost + overhead ($/min)
K_t	cutting edge cost ($/edge)
L	length of work-piece (mm)
N	$\{N_r, N_s\}$, spindle speeds for roughing and finishing machining (rpm)
N_j	length of chromosome (binary string) of each design variable
N_{rp}	number of rough passes
P	$\{P_r, P_s\}$, cutting powers during roughing and finishing machining (kW)
Pf_i	% fitness of each chromosome
P_U	maximum allowable cutting power (kW)
Q	$\{Q_r, Q_s\}$, chip-tool interface temperature constraints for roughing and finishing machining (°C)
Q_U	maximum allowable chip-tool interface temperature °C)
R	nose radius of cutting tool (mm)
SC_r	stable cutting region for roughing machining
SC_s	stable cutting region for finishing machining
SC_U	limit of stable cutting region
SR_U	maximum allowable surface roughness (μm)
T	$\{T_r, T_s\}$, expected tool-lives for roughing and finishing machining (min)
T_u^{Norm}	normalized minimum production time
T_L, T_U	lower and upper bounds for tool life for roughing and finishing machining (min)
T_i	machine idling time (min)
T_m	actual machining time (min)
T_p	tool life of weighted combination of T_r and T_s (min)
Tu_u^{max}	undesired production time estimate (min)
Tu_u^{min}	desired production time estimate (min)
T_{Ut}^N	normalized production time for turning
b_i	$\{ b_{i-1}, b_{i-2}, \dots\dots b_0 \}$ binary string comprising genes
d	$\{d_r, d_s\}$, depth of cut in rough and finish machining operations (mm)
d_r	$\{d_{rL}, d_{rU}\}$, lower and upper bound of depth of cut in roughing machining (mm)
d_{rt}	depth of cut in roughing for straight turning (mm)
d_s	$\{d_{sL}, d_{sU}\}$, lower and upper bound of depth of cut in finish machining (mm)
d_t	depth of material to be removed (mm)
f	$\{f_r, f_s\}$, feed rates in roughing and finishing machining operations (rev/mm)
f_{ij}	the i^{th} objective function value in the j^{th} position of the current population
f_i^{min}	the minimum ith objective function value
f_i^{max}	the maximum ith objective function value
f^N	$\{f_i^N, f_j^N, f_n^N\}$, the i, j and n normalized objective function values
f_r	$\{f_{rL}, f_{rU}\}$, lower and upper bound of feed rate in roughing machining (rev/mm)
f_s	$\{f_{sL}, f_{sU}\}$, lower and upper bound of feed rate in finishing machining (rev/mm)
g_i	{i = 1, 2, …., J}, J numbers of inequality constraints
h_1	constant relating to tool travel and approach/departure time (min/mm)
h_2	constant relating to tool travel and approach/departure time (min)
h_k	{k = 1, 2, …., K}, K numbers of equality constraints
k_f	constant pertaining to a specific tool-workpiece combination for cutting force and cutting power
k_q	constant pertaining to the constraint of chip-tool interface temperature
k_r	constant pertaining to the constraint of dimensional accuracy
l	$\{ l_v, l_d, l_f \}$lengths of range of the variables of cutting speed, depth of cut and feed rate
l_r	run back length (mm)
m	number of objective functions
n	number of rough cuts (an integer)
n_t	an exponent that depends on cutting conditions
n_p	population size
n_{pt}	number of passes in roughing turning
q	$\{q_v, q_d, q_f\}$ levels of precision of the variables of cutting speed, depth of cut and feed rate
r	$r \in (0,1)$ random number
t_c	constant term(due to loading and unloading operations) (min)
t_e	tool exchange time (min)
v	$\{v_r, v_s\}$, cutting speeds in rough and finish machining operations (m/min)
v_r	$\{v_{rL}, v_{rU}\}$, lower and upper bound of cutting speed in rough machining (m/min)
v_s	$\{v_{sL}, v_{sU}\}$, lower and upper bound of cutting speed in finish machining (rev/mm)
w_1	weight coefficient representing the relative importance of production cost criterion
w_2	weight coefficient representing the relative importance of production time criterion
w_1^*	estimated value of w_1
w_2^*	estimated value of w2
x	$\{x_1, x_2\}$ lower and upper values of the variables
x'	integer value of the corresponding random binary string
z	$\{z_v, z_d, z_f\}$binary string lengths of the variables

Greek letters

Φ_t	utility function of turning multi-objective model
α, β, δ	constants in the modified Taylor's tool life equation relating to cutting speed, feed rate and depth of cut
μ, ν	constants relating to expression of cutting force and cutting power constraints
η	machine efficiency
θ	a weight for T_p [0,1]

λ, υ constants relating to expression of stable cutting region constraint
τ, φ, δ constants relating to expression of chip-tool interface temperature constraint
χ, ς, ψ constants relating to the dimensional accuracy constraint

Acronyms

CNC Computer Numerical Control
GAs Genetic Algorithms

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