UDK 621.941:519.24:519.852

OPTIMIZACIJA TOKARENJA UPORABOM EVOLUCIJSKIH ALGORITAMA
OPTIMIZATION OF TURNING USING EVOLUTIONARY ALGORITHMS

Goran CUKOR – Zoran JURKOVIĆ

Sažetak: *Napredna proizvodnja zahtijeva snažne alate za pouzdano modeliranje i rješavanje složenih optimizacijskih problema u obradi odvajanjem čestica. U ovom se radu predlaže nekonvencionalni pristup koji koristi evolucijske algoritme nadahnute Darwinovim otkrićima o evoluciji bioloških vrsta i opstanku najprilagođenijih organizama (tj. prirodnoj selekciji). Pristup je ilustriran na pokusu gruboga uzdužnog tokarenja. Genetsko programiranje (GP) korišteno je za razvijanje modela postojanosti alata, tangencijalne komponente sile rezanja i hrapavosti površine razmatrajući brzinu rezanja, posmak i dubinu rezanja kao predodređene parametre rezanja. Konačno, za njihovu je optimizaciju primijenjen genetski algoritam (GA).*

Ključne riječi:
– tokarenje
– optimizacija
– evolucijski algoritmi

Abstract: *Advanced manufacturing requires a powerful tool for reliable modeling and solving complex machining optimization problems. A non-conventional approach using evolutionary algorithms inspired by Darwinian findings about the evolution of the biological species and the survival of the fittest organisms (i.e. natural selection) is proposed in this paper. It is illustrated with an experiment of rough longitudinal turning. Genetic programming (GP) is used to develop the models of the tool life, the tangential cutting force component and the surface roughness considering the cutting speed, and the feed and the depth of cut as predetermined cutting parameters. Finally, the genetic algorithm (GA) is applied for their optimization.*

Keywords:
– turning
– optimization
– evolutionary algorithms

1. UVOD

Za velik je broj proizvodnih poduzeća karakteristično da određuju parametre rezanja, tj. brzinu rezanja v_c, posmak f i dubinu rezanja a_p, na temelju iskustva operatora ili preporuka iz priručnika. S rastućom uporabom CNC alatnih strojeva, što uključuje velike kapitalna ulaganja, primjena ekonomske analize kombinirane s tehnološkim razmatranjima postaje imperativ. Globalizacija također potiče potrebu za proizvodima visoke kvalitete, koji su proizvedeni brzo te uz najniže moguće troškove. Stoga optimalni parametri rezanja imaju ključnu ulogu u kompetitivnosti na tržištu.

Dobro poznate metode za određivanje optimalnih parametara rezanja su: grafičke tehnike [1], linearno programiranje [2], sekvencijalno kvadratno programiranje [3], geometrijsko programiranje [4], dinamičko programiranje [5], numeričke tehnike i tehnike direktnog traženja [6], umjetne neuronske mreže [7], i

1. INTRODUCTION

Numerous manufacturing firms typically determine cutting parameters, namely cutting speed v_c, feed f and depth of cut a_p, based on the machinist's experience or handbook recommendations. With the increasing use of CNC machine tools, which involve large capital expenditures, the use of economic analysis combined with technological considerations becomes an imperative. Globalization also drives the need to manufacture a product of high quality, at the lowest possible cost and rapidly. Hence, optimum cutting parameters play a key role in market competitiveness.

Well known methods to determine the optimum cutting parameters are: graphical techniques [1], linear programming [2], sequential quadratic programming [3], geometric programming [4], dynamic programming [5], numerical and direct search techniques [6], artificial neural networks [7], and approaches based on traditional tehnike direktnog traženja [6], umjetne neuronske i tehnike direktnog traženja [6], umjetne neuronske mreže [7], te pristupi temeljeni na tradicionalnoj matematičkoj optimizaciji (gradijentna metoda itd.) [8]. Taj se zadatak određivanja optimalnih parametara rezanja pokazao iznenađujuće teškim. Naime, on zahtijeva složenu matematičku analizu i pomoć računala, a ovisi o pouzdanim kvantitativnim matematičkim modelima pokazatelja obradivosti (kao što su postojanost alata T, tangencijalna komponenta sile rezanja F_c, hrapavost površine Ra itd.) te detaljnim specifikacijama alatnih strojeva, reznih alata i komponenata, koje djeluju kao ograničenja na moguće parametre rezanja. Štoviše, za razvijanje modela obradivosti konvencionalni pristup koristi regresijsku analizu zasnovanu na metodi najmanjih kvadrata (OLS).

U zadnjem se desetljeću proširila uporaba evolucijskih računalnih metoda, također nazivanih i genetskima, temeljenih na imitiranju Darwinove prirodne selekcije. Razlog je u činjenici što su mnogi sustavi presloženi za uspješnu optimizaciju uporabom konvencionalnih determinističkih algoritama. Suprotno tome evolucijski algoritmi (EA) uključuju probabilističke operacije. Genetski algoritam (GA) je najuspješnije implementirana evolucijska računalna metoda u optimizaciji različitih procesa obrade odvajanjem čestica [9 -11]. S druge strane, među svim evolucijskim računalnim metodama genetsko programiranje (GP) je vjerojatno najopćenitiji evolucijski pristup [12].

U ovom je radu predložen izvorni, integrirani GP-GA koncept za modeliranje i optimizaciju tokarenja, slika 1. GP modul za modeliranje koji zamjenjuje standardnu OLS regresijsku analizu koristi se kada je model obradivosti nepoznat. Ulaz modula sastoji se od eksperimentalnih vrijednosti nezavisnih varijabli (parametara rezanja) i pridruženih vrijednosti zavisne varijable (pokazatelj obradivosti). Kako se evolucija odvija u virtualnom svijetu računala, moguće je analizirati velik broj različitih rješenja u relativno kratkom vremenu. Izlaz modula sastoji se od jednog (ili više ako je to zadano) slučajno generiranog modela obradivosti koji, što je najviše moguće, odgovara ulaznim podacima. GA modul za optimizaciju koristi se kada je optimizacijski model odnosnog procesa obrade tokarenjem već poznat. Izlaz modula sastoji se od slučajno generiranog skupa optimalnih parametara rezanja. Predloženi je koncept ilustriran na primjeru gruboga uzdužnog tokarenja.

mathematical optimization (gradient method, etc.) [8]. This task has proven to be surprisingly difficult. It requires intricate mathematical analysis and computer assistance, and depends on quantitatively reliable mathematical models for machinability performance measures (such as tool life T, tangential cutting force component F_c, surface roughness Ra, etc.) and detailed specifications of the machine tools, cutting tools and components, which act as constraints on the feasible cutting parameters. Furthermore, the conventional approach is to use an ordinary least squares (OLS) regression analysis for developing the machinability models.

In the last decade, the use of evolutionary computation methods, or also called the genetic methods, based on imitation of Darwinian natural selection has become widespread. This is due to the fact that many systems are too complex to be successfully optimized by the use of conventional deterministic algorithms. On the contrary, the evolutionary algorithms (EA) involve probabilistic operations. The genetic algorithm (GA) is the most successfully implemented evolutionary computation method for optimizing various machining processes [9 - 11]. On the other hand, out of the evolutionary computation methods, genetic programming (GP) is probably the most general evolutionary approach [12].

In this paper, the original, integrated GP-GA concept for modelling and optimization of turning is proposed, Figure 1. GP modeller replacing the standard OLS regression analysis is used if the machinability model is unknown. Modeller input consists of experimental values of the independent variables (cutting parameters) and associated values of the dependent variable (machinability performance). As evolution takes place in virtual computer space, it is possible to analyze a great number of different solutions within a relatively short time. Modeller output consists of one (or more if desired) randomly generated machinability model(s) corresponding as much as possible to the experimental data. GA optimizer is used if the optimization model of the respective turning process is already known. Optimizer output consists of a randomly generated set of optimized cutting parameters. The proposed concept is illustrated on a rough longitudinal turning example.

2. GP MODELIRANJE

U ovom se poglavlju istražuje GP za specifični problem: pronalaženje valjane regresijske funkcije za skup parova podataka (x_i, y_i) za i = 1, ..., N. Ako podaci "izgledaju" linearni, može se pokušati s OLS linearnom regresijom: naći a i b tako da je $y = ax + b$ najbolje prilagođena linija

2. MODELLING BY GP

In this section, GP is going to be explored for a specific problem: finding a good regression function for a set of data pairs (x_i, y_i) for i = 1, ..., N. If the data "look" linear, OLS linear regression might be tried: find a and b such that $y = ax + b$ is the best-fit line (in the sense of least podacima (u smislu najmanjih kvadrata). Međutim, što ako odnos nije linearan (to je obično slučaj kod procesa obrade odvajanjem čestica)? Tada treba pogađati oblik regresijske jednadžbe (npr. kvadratni, log-linearni itd.) te smisliti način za pronalaženje njezinih koeficijenata. To može biti teško ili, što je još gore, arbitrarno. Također, može biti više nezavisnih varijabli x_1, x_2, x_3 itd.

Što ako tko misli da najmanji kvadrati nisu najbolji kriterij za korištenje? Treba istaknuti: OLS regresija ima doduše neka dobra svojstva, no glavni je razlog njezine vrlo česte primjene upravo to što je jednostavna za računanje.

Nije teško zamisliti regresijsku jednadžbu kao svojevrsni "računalni program" koji proizvodi neki izlaz (y vrijednost) za neki zadani ulaz (skup x_i vrijednosti). Regresijska jednadžba može biti jednostavna ili vrlo komplicirana. To nije važno sve dotle dok predviđene vrijednosti y za sve x_i u području interesa imaju dovoljnu točnost.

Dakle, traži se program koji može naći oboje: funkcijski oblik i odgovarajuće koeficijente. GP to može napraviti.

Procesi koji čine čitav tijek GP-a mogu se podijeliti na sljedeće sekvencijalne korake:

1. Kreirati slučajnu populaciju programa (organizama ili kromosoma) različitih oblika i duljina koristeći gene na dispoziciji. Ti su geni simboli nezavisnih varijabli (x_1, x_2, x_3, ...), numeričke konstante i matematički operatori (+, -, *, / itd.).
2. Evaluirati svaki program dodjeljujući mu mjeru prikladnosti prema unaprijed određenoj funkciji prikladnosti koja mjeri sposobnost programa da riješi problem.
3. Osigurati opstanak bolje prilagođenih programa i njihovo napredovanje u nepromijenjenom obliku u sljedeću generaciju koristeći operator reprodukcije

squares) to the data. But what if the relationship is not linear (usually case when dealing with machining processes)? Then the form of the regression equation (e.g., quadratic, log-linear, etc.) must be guessed, and a way to find its coefficients must be figured. This may be hard, or worse, arbitrary. There may also be several independent variables, x_1, x_2, x_3, etc.

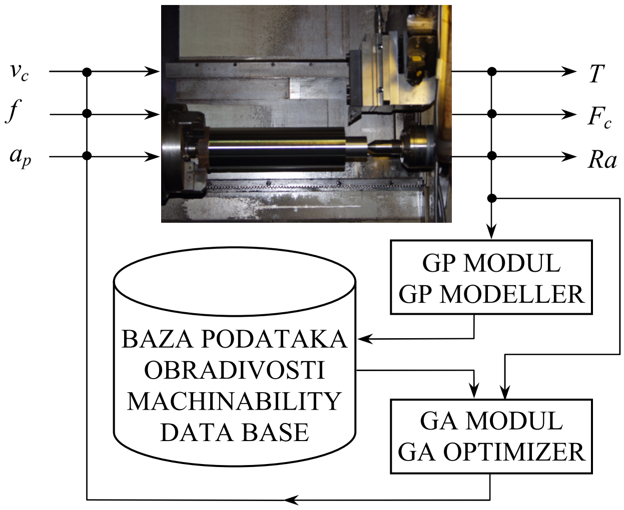
What if one thinks that smallest squares are not the best criteria to use? It should be pointed out, OLS regression has some nice properties, but it is commonly used just as much for the fact that it is easy to compute.

It's not hard to think of a regression equation as a "computer program" that produces some output (a y value) given some input (a set of x_i values). The regression equation can be simple or horribly complicated. It's not important so long as the predicted values of y for all the x_i in the domain of interest are pretty accurate.

Hence, a program that can figure out both the functional form and the appropriate coefficients is needed. GP can do this.

The processes that make up a complete run of GP can be divided into a number of sequential steps:

1. Create a random population of the programs (organisms or chromosomes) of various forms and lengths using the genes provided. These genes are independent variable symbols (x_1, x_2, x_3, ...), numerical constants and mathematical operators (+, -, *, /, etc.).
2. Evaluate each program assigning a fitness value according to a pre-specified fitness function that measures the ability of the program to solve the problem.
3. Assure survival of more fit programs and their advance in unchanged form into the next generation



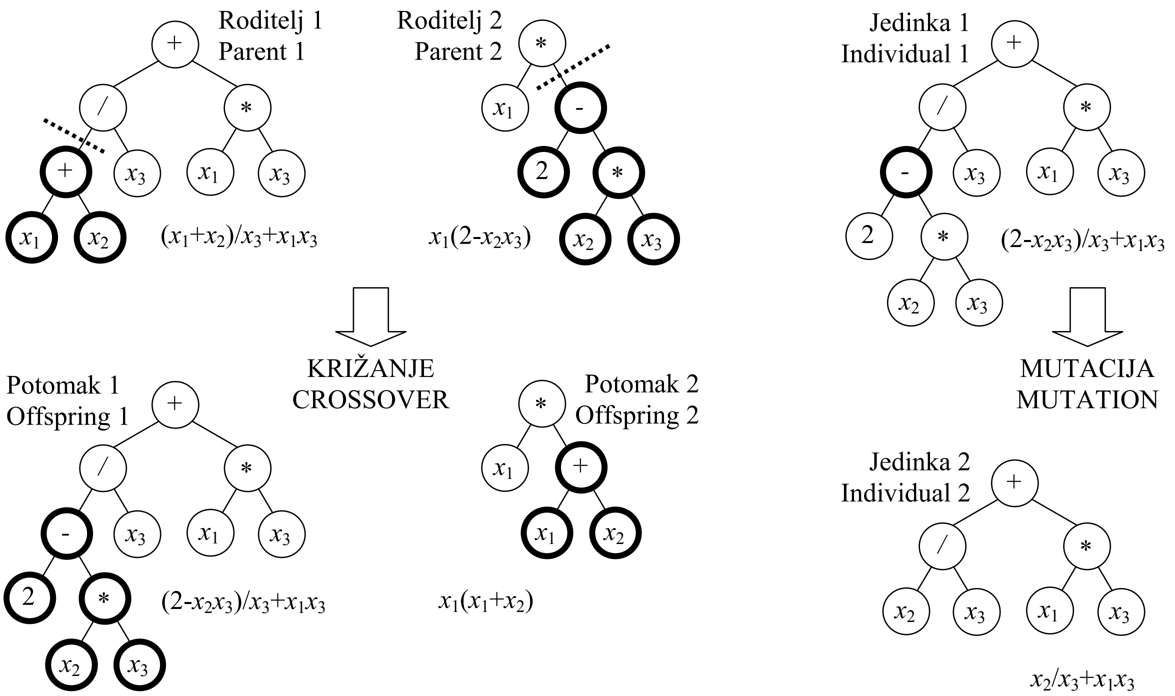
Slika 1. Integrirani GP-GA koncept za tokarenje
Figure 1. Integrated GP-GA concept for turning

(selekcije).

4. Iz slučajno odabranog skupa roditelja genetički rekombinirati novu populaciju pomoću operatora križanja, slika 2.

using the reproduction (selection) operator.

4. Genetically recombine the new population with the crossover operator from a randomly chosen set of parents, Figure 2.



Slika 2. Križanje i mutacija u GP
Figure 2. Crossover and mutation in GP

5. Uvesti manje slučajne promjene u genetsku strukturu razvijenih organizama koristeći operator mutacije, slika 2.
6. Ponavljati korake od 2. nadalje za nove populacije sve dok se ne zadovolji unaprijed određeni kriterij zaustavljanja ili ne završi fiksirani broj generacija.
7. Rješenje problema je najbolje prilagođeni genetski program unutar svih generacija.

5. Introduce the minor random changes in the gene structure of developed organisms using the mutation operator, Figure 2.
6. Repeat steps 2 onwards for new populations until a pre-specified termination criterion has been satisfied or a fixed number of generations has been completed.
7. The solution to the problem is the genetic program with the best fitness within all the generations.

3. EKSPERIMENTALNI PODACI

Pokusi gruboga uzdužnog tokarenja izvedeni su na NC tokarilici "Georg Fisher NDM-16" na *Inštitutu za proizvodno strojništvo* Sveučilišta u Mariboru. Materijal obratka bio je opći konstrukcijski čelik oznake Ck45 (DIN) promjera ∅100 mm i duljine 380 mm. Pokusi su provedeni korištenjem tokarskog noža za vanjsko tokarenje oznake DDJNL 3225P15 s izmjenjivim pločicama oznake DNMG 150608-PM4025 i bez sredstva za hlađenje, ispiranje i podmazivanje. Geometrija alata: prednji kut 17°, stražnji kut 5°, kut namještanja glavne oštrice 93° i polumjer zaobljenja vrha alata 0,8 mm. Korišten je centralni kompozicijski plan pokusa s pet razina brzine rezanja v_c, posmaka f i dubine rezanja a_p, tablica 1 [13]. Rezna pločica mijenjana je prije svakog rezanja kako bi se eliminirao utjecaj trošenja

3. EXPERIMENTAL DETAILS

The rough longitudinal turning experiments were carried out on NC lathe machine "Georg Fisher NDM-16" at the Production Engineering Institute of the University of Maribor. Test samples were carbon steel bars DIN Ck45 100 mm in diameter and 380 mm in length. Experiments were carried out by the external machining turning tool with the holder mark DDJNL 3225P15 and coated inserts type DNMG 150608-PM4025 under dry cutting conditions. The tool geometry was: rake angle 17°, clearance angle 5°, and main cutting edge 93° with a nose radius of 0,8 mm. The experiments have been carried out by using the rotatable central composite design with five levels of the cutting speed v_c, the feed f and the depth of cut a_p, Table 1 [13]. Before each cut, the insert was changed to eliminate the effect of tool wear.

alata. Postojanost alata T određena je za kriterij istrošenosti alata V_B = 0,25 mm. Za mjerenje trošenja stražnje površine V_B korišten je alatni mikroskop *Carl Zeiss* s očitanjem od 0,0001 mm. Tangencijalna komponenta sile

The tool life T was defined for the tool wear criterion V_B = 0,25 mm. The flank wear land V_B was measured by using the tool microscope Carl Zeiss (0,0001 mm). The tangential cutting force component F_c was measured

Tablica 1. Rezultati pokusa grubog uzdužnog tokarenja [13]
Table 1 Results of the rough longitudinal turning experiments [13]

Pokus br. Test No.	Ulazni parametri Input parameters			Rezultati pokusa Experimental results		
	v_c (m/min)	f (mm)	a_p (mm)	$T^{(E)}$ (min)	$F_c^{(E)}$ (N)	$Ra^{(E)}$ (µm)
1	300	0,3	1,5	17,60	879,224	4,30
2	400	0,3	1,5	4,73	894,327	3,88
3	300	0,5	1,5	6,68	1436,299	11,11
4	400	0,5	1,5	1,88	1408,114	11,48
5	300	0,3	3,0	13,86	1754,215	4,21
6	400	0,3	3,0	3,80	1726,937	4,50
7	300	0,5	3,0	4,10	2896,122	14,29
8	400	0,5	3,0	1,16	2860,663	13,71
9	350	0,4	2,25	5,38	1677,149	8,10
10	350	0,4	2,25	5,10	1672,771	8,13
11	350	0,4	2,25	5,44	1679,359	8,12
12	350	0,4	2,25	5,28	1678,825	8,12
13	350	0,4	2,25	5,50	1675,829	8,11
14	350	0,4	2,25	5,22	1678,223	8,10
15	266	0,4	2,25	12,95	1697,504	7,82
16	434	0,4	2,25	1,81	1683,361	8,15
17	350	0,23	2,25	10,52	1002,763	2,46
18	350	0,57	2,25	0,75	2609,254	17,95
19	350	0,4	1,0	6,65	765,921	6,36
20	350	0,4	3,5	3,58	2746,389	9,07

rezanja F_c mjerena je dinamometrom KISTLER (Tip: 9257 A). Hrapavost površine *Ra* mjerena je uređajem Surftest Mitutoyo SJ-201P.

utilizing the dynamometer KISTLER (Type: 9257 A). Surface roughness *Ra* measurements were performed with Surftest Mitutoyo SJ-201P.

4. ANALIZA REZULTATA

Važno je znati da modeliranje postojanosti alata, tangencijalne komponente sile rezanja i hrapavosti površine pomoću GP-a uključuje oboje: pronalaženje oblika funkcije i pronalaženje numeričkih koeficijenata matematičkog modela. Treba istaknuti da pritom nisu unaprijed postavljene nikakve pretpostavke o veličini, obliku i složenosti krajnjih zadovoljavajućih rješenja. To čini ovu studiju potpuno različitom od konvencionalnog pristupa koji koristi OLS regresijsku analizu s ciljem pronalaženja jedino skupa numeričkih koeficijenata za funkciju čiji je oblik unaprijed specificiran.
OLS regresijskom analizom (RA) i genetskim programiranjem (GP) generirani su sljedeći prognostički modeli:

4. ANALYSIS OF RESULTS

It is very important to know that modelling of the tool life, the tangential cutting force component and the surface roughness using GP involves finding both the functional form and the numerical coefficients of the mathematical model. It should be noted that no assumptions are made here in advance about the size, shape and complexity of the eventual satisfactory solutions. These facts make this study completely different from the conventional approach of using OLS regression analysis where the goal is to discover merely a set of numerical coefficients for a function whose form has been pre-specified.
The prediction models generated by OLS regression analysis (RA) and genetically (GP) are as follows [13]:

$$T^{(\mathrm{RA})} = 170{,}239 - 0{,}529 \cdot v_c - 213{,}879 \cdot f - 12{,}572 \cdot a_p + 0{,}451 \cdot v_c \cdot f + 0{,}0282 \cdot v_c \cdot a_p + 13{,}363 \cdot f \cdot a_p - \\ - 0{,}0316 \cdot v_c \cdot f \cdot a_p + 0{,}000345 \cdot v_c^2 + 24{,}624 \cdot f^2 + 0{,}110 \cdot a_p^2, \quad (1)$$

$$F_c^{(\mathrm{RA})} = 187{,}937 + 1{,}847 \cdot v_c - 1970{,}77 \cdot f + 10{,}418 \cdot a_p - 3{,}918 \cdot v_c \cdot f - 0{,}633 \cdot v_c \cdot a_p + 1598 \cdot f \cdot a_p + \\ + 1{,}169 \cdot v_c \cdot f \cdot a_p - 0{,}00007676 \cdot v_c^2 + 4067{,}65 \cdot f^2 + 40{,}953 \cdot a_p^2, \quad (2)$$

$$Ra^{(\mathrm{RA})} = 16{,}783 - 0{,}0205 \cdot v_c - 72{,}619 \cdot f - 8{,}182 \cdot a_p + 0{,}124 \cdot v_c \cdot f + 0{,}021 \cdot v_c \cdot a_p + 27{,}493 \cdot f \cdot a_p - \\ - 0{,}055 \cdot v_c \cdot f \cdot a_p - 0{,}0000376 \cdot v_c^2 + 69 \cdot f^2 - 0{,}335 \cdot a_p^2, \quad (3)$$

$$T^{(\mathrm{GP})} = (-6{,}662 - a_p - (-5{,}110 + f + ((2{,}703 - (f + v_c + ((((((((((((2 \cdot f + 2 \cdot v_c)/(-5{,}110 \cdot f + f^2) + \\ + ((((15{,}228 + 4 \cdot f + e^{7{,}517})/(3 \cdot f - 2{,}758))/(2{,}703 - f + (e^{7{,}517}/(2 \cdot f - \\ - 2{,}758)) + e^{7{,}517})) + e^{7{,}517})) - v_c) - 2{,}758)/(v_c - 6{,}662 - a_p)) - \\ - 2{,}758)/((f + 7{,}614)/(e^{7{,}517}/2{,}703)))/f) + e^{7{,}517}) - \\ - v_c)/(-2{,}758 + v_c))/f))) + v_c))), \quad (4)$$

$$F_c^{(\mathrm{GP})} = ((6{,}570 + a_p + ((-8{,}799 \cdot (a_p + f - 3{,}471)) - (-8{,}799 \cdot (6{,}570 + a_p)))) + (a_p \cdot f \cdot ((6{,}570 + a_p - \\ - ((a_p - 4{,}371 + (-8{,}799 \cdot a_p \cdot (a_p - 4{,}371)) + v_c - (-4{,}542 + (a_p - (((3 \cdot f \cdot (6{,}570 + a_p) + \\ + a_p \cdot f^2) + a_p + (8{,}799 \cdot (6{,}570 + a_p))) \cdot (-8{,}799)))))) + ((a_p - ((a_p + \\ + ((-8{,}799 \cdot (a_p - 3{,}471)) + 2 \cdot (6{,}570 + a_p))) - 8{,}799)) + ((-4{,}542 + \\ + (a_p - ((-1{,}020 + f + ((a_p - 3{,}471 + (-8{,}799 \cdot (a_p + \\ + f - 3{,}471))) + a_p + (8{,}799 \cdot (6{,}570 + \\ + a_p)))) \cdot (-8{,}799)))) + v_c))))), \quad (5)$$

$$Ra^{(\mathrm{GP})} = ((((-3{,}784 + f) \cdot ((((-3{,}784 + f + 2 \cdot v_c) \cdot ((((((9{,}567 \cdot f - (a_p + v_c) \cdot (2 \cdot (9{,}567 \cdot f))) - \\ - (9{,}567 \cdot f) \cdot (((((9{,}567 \cdot f) + (9{,}567 \cdot f + f \cdot a_p)) \cdot f) + f \cdot a_p) - a_p)) + f) \cdot (a_p + \\ + f))) \cdot (a_p + f)) \cdot (a_p + f))) \cdot 19{,}134 \cdot f) + ((9{,}567 \cdot f + (((9{,}567 \cdot f + \\ + f \cdot a_p - a_p) \cdot a_p))) \cdot f) + (((19{,}134 \cdot f + f \cdot a_p) \cdot f) + f \cdot a_p))). \quad (6)$$

Prognostičke sposobnosti razvijenih modela testirane su izvođenjem dodatnih 26 pokusa, kao što je navedeno u tablici 2 [13]. Za ukupno 46 izvedenih pokusa odnosna srednja postotna odstupanja izračunata su prema sljedećem izrazu:

The predictive capabilities of developed models were tested with an additional set of 26 experiments as listed in Table 2 [13]. For a total of 46 experiments, the respective average percentage deviations were calculated according to the expression:

$$\bar{S} = \frac{1}{N} \cdot \sum_{j=1}^{N} \frac{\left| y_j^{(\mathrm{E})} - y_j^{(\mathrm{model})} \right|}{y_j^{(\mathrm{E})}} \cdot 100\,\%, \quad (7)$$

gdje su y_j rezultati pokusa (E) i modela u j-tom testiranju, a N je ukupni broj pokusa.

Tablica 3 pokazuje srednja postotna odstupanja razvijenih modela od svih rezultata pokusa. GP je dao bolja rješenja za tangencijalnu komponentu sile rezanja i hrapavost površine, dok je OLS regresijska analiza dala bolje rješenje za postojanost alata.

where y_j are results of both experiment (E) and the model for j test, and N is the size of sample data.

Table 3 shows the average percentage deviations of developed models from all experimental results. GP gave better solutions for the tangential cutting force component and the surface roughness while OLS regression analysis gave a better solution for tool life.

5. GA OPTIMIZACIJA

Za uzdužno tokarenje agregatna funkcija cilja (s težinskim koeficijentima) kojoj treba naći minimum je:

5. GA OPTIMIZATION

When considering a longitudinal turning operation, the weighted objective function to be minimized is:

Tablica 2. Rezultati dodatnih pokusa grubog uzdužnog tokarenja [13]
Table 2. Results of the additional rough longitudinal turning experiments [13]

Pokus br. Test No.	Ulazni parametri Input parameters			Rezultati pokusa Experimental results		
	v_c (m/min)	f (mm)	a_p (mm)	$T^{(E)}$ (min)	$F_c^{(E)}$ (N)	$Ra^{(E)}$ (µm)
21	350	0,3	1,50	9,36	848,586	3,780
22	300	0,4	1,50	11,03	1119,517	7,630
23	350	0,4	1,50	6,28	1111,016	7,090
24	400	0,4	1,50	2,83	1177,007	7,140
25	350	0,5	1,50	3,13	1415,452	11,570
26	300	0,3	2,25	15,42	1289,769	4,080
27	350	0,3	2,25	8,37	1260,859	4,070
28	400	0,3	2,25	3,92	1333,207	3,840
29	300	0,4	2,25	9,21	1706,310	7,760
30	400	0,4	2,25	2,26	1711,773	7,950
31	300	0,5	2,25	4,68	2113,549	13,000
32	350	0,5	2,25	2,37	2210,386	14,620
33	400	0,5	2,25	1,42	2177,104	14,260
34	350	0,3	3,00	7,02	1745,217	4,730
35	300	0,4	3,00	7,92	2248,647	8,200
36	350	0,4	3,00	4,17	2370,946	8,130
37	400	0,4	3,00	2,06	2260,277	9,090
38	350	0,5	3,00	2,02	2886,451	14,250
39	325	0,35	2,00	9,26	1279,093	5,980
40	375	0,35	2,00	4,87	1303,333	5,690
41	325	0,45	2,00	5,56	1787,773	9,560
42	375	0,45	2,00	2,74	1722,324	10,090
43	325	0,35	2,50	8,54	1676,456	6,020
44	375	0,35	2,50	4,37	1648,966	6,220
45	325	0,45	2,50	4,69	2097,975	10,860
46	375	0,45	2,50	2,31	2119,506	11,300

Tablica 3. Srednja postotna odstupanja razvijenih modela od svih rezultata pokusa
Table 3. The average percentage deviations of developed models from all experimental results

Razvijeni modeli Developed models		$\bar{S}$, %		
		$T^{(E)}$	$F_c^{(E)}$	$Ra^{(E)}$
Regresijska analiza Regression analysis	$T^{(RA)}$ (1)	5,93		
	$F_c^{(RA)}$ (2)		1,76	
	$Ra^{(RA)}$ (3)			5,28
Genetsko programiranje Genetic Programming	$T^{(GP)}$ (4)	8,59		
	$F_c^{(GP)}$ (5)		1,68	
	$Ra^{(GP)}$ (6)			3,46

$$\varphi\left(v_c, f, a_p\right) = w_1 \cdot \frac{C_1}{C_1^*} + w_2 \cdot \frac{t_1}{t_1^*} + w_3 \cdot \frac{F_c^{(\text{model})}}{F_c^*} + w_4 \cdot \frac{Ra^{(\text{model})}}{Ra^*}, \tag{8}$$

$$C_1 = x \cdot t_1 + y \cdot \sum_{j=1}^{i} \frac{\pi \cdot D_j \cdot l}{10^3 \cdot v_{cj} \cdot f_j \cdot T_j^{(\text{model})}}, \tag{9}$$

$$t_1 = \sum_{j=1}^{i} \frac{\pi \cdot D_j \cdot l}{10^3 \cdot v_{cj} \cdot f_j} + t_2 \cdot \sum_{j=1}^{i} \frac{\pi \cdot D_j \cdot l}{10^3 \cdot v_{cj} \cdot f_j \cdot T_j^{(\text{model})}}, \tag{10}$$

podvrgnuta ograničenjima $v_{c\min} \le v_c \le v_{c\max}$, $f_{\min} \le f \le f_{\max}$, $a_{p\min} \le a_p \le a_{p\max}$, $F_c \le F_c^*$ i $Ra \le Ra^*$, gdje su w_k težinski koeficijenti ($0 < w_k < 1$, $w_1 + w_2 + w_3 + w_4 = 1$), C_1^* je očekivani limit jediničnoga troška obrade (EUR), t_1^* je očekivani limit jediničnoga vremena obrade (min), F_c^* je limit tangencijalne komponente sile rezanja (N), Ra^* je limit hrapavosti površine (μm), x normirana cijena rada tokarilice (EUR/min), y cijena rezne pločice svedena na jednu oštricu (EUR), t_2 je vrijeme potrebno za zamjenu alata (min), D je promjer rezanja (mm), l je dužina prolaza (mm), i je broj prolaza.

Važan problem u implementiranju GA za optimizaciju procesa tokarenja je konstruiranje funkcije prikladnosti. U ovoj je studiji funkcija prikladnosti određena tako da je funkciji cilja dodana kaznena funkcija koja korespondira s ograničenjima. Kaznena se funkcija aktivira samo u slučaju ako su ograničenja narušena. Prema tome, funkcija prikladnosti je:

subjected to the constraints $v_{c\min} \le v_c \le v_{c\max}$, $f_{\min} \le f \le f_{\max}$, $a_{p\min} \le a_p \le a_{p\max}$, $F_c \le F_c^*$ and $Ra \le Ra^*$, where w_k is the weighting coefficients ($0 < w_k < 1$, $w_1 + w_2 + w_3 + w_4 = 1$), C_1^* is the expected machining cost limitation per piece (EUR), t_1^* is the expected machining time limitation per piece (min), F_c^* is the tangential cutting force component limitation (N), Ra^* is the surface roughness limitation (μm), x is the operating cost of the lathe (EUR/min), y is the cost of the cutting edge (EUR), t_2 is the tool change time (min), D is the cutting diameter (mm), l is the length of pass (mm) and i is the number of passes.

An important problem in the implementation of GA for turning process optimization is the construction of a fitness function. In this study, penalty terms corresponding to the constraint violation are added to the objective function and fitness is obtained. Penalty terms are added only if the constraints are violated. Hence, the fitness function is:

$$\Phi\left(v_c, f, a_p\right) = \varphi\left(v_c, f, a_p\right) + \left[\min\left\{0, g_j\left(v_c, f, a_p, F_c, Ra\right)\right\}\right]^2, \tag{11}$$

Tablica 4. Rezultati optimizacije
Table 4. The results of optimization

Funkcije cilja Objective functions	Optimalni ulazni parametri Optimal input parameters				Rezultati izlaznih parametara Results of output parameters	
	v_c (m/min)	f (mm)	a_p (mm)	i br. prolaza No. of passes		
C_1 (EUR)	300	0,37	2,4	4	4,41	$w_1 = 1$ $w_2 = w_3 = w_4 = 0$
t_1 (min)	372,5	0,38	2,4	4	3,53	$w_2 = 1$ $w_1 = w_3 = w_4 = 0$
Φ – dvokriterijska Φ – two-criterion	300	0,37	2,4	4	10,776	$w_1 = 0,25$ $w_2 = 0,75$ $w_3 = w_4 = 0$

gdje su g_j nejednakostna ograničenja optimizacijskog problema. Treba napomenuti da su u prikladnom području rješenja doprinosi kaznene funkcije = 0 (nula).

Ulazni podaci u GA modul bili su sljedeći: D = 80 mm, l = 300 mm, t_2 = 1 min, x = 1 EUR/min, y = 2,5 EUR,

where g_j are the inequality constraints to the optimization problem. Note that in the feasible space of solutions, the contributions from the penalty terms = 0 (zero).

Input data for the GA optimizer were as follows: D = 80 mm, l = 300 mm, t_2 = 1 min, x = 1 EUR/min, y = 2,5 broj generacija = 150, populacija = 200, vjerojatnost križanja = 0,75 i vjerojatnost mutacije = 0,01. Dobiveni optimalni parametri rezanja za kriterij minimalnoga jediničnog troška, kriterij minimalnoga jediničnog vremena te kompromisni kriterij (dvokriterijska optimizacija) navedeni su u tablici 4.

EUR, number of generations = 150, population = 200, crossover probability = 0.75 and mutation probability = 0.01. The founded optimal cutting parameters for the minimum unit machining cost criterion, the minimum unit machining time criterion and the compromise criterion (two-criterion optimization) are listed in Table 4.

6. ZAKLJUČAK

U ovom su radu primijenjeni evolucijski algoritmi za modeliranje i optimizaciju procesa uzdužnoga tokarenja pri čemu je korišten izvorno razvijeni integrirani GP-GA koncept. Taj koncept oponaša prirodnu evoluciju živih organizama, gdje u svakodnevnoj borbi za prirodnim resursima uspješne jedinke postupno postaju sve dominantnije i prilagođenije okolišu u kojem žive, dok su manje uspješne jedinke rijetko prisutne u sljedećoj generaciji.

U predloženom GP pristupu programi, tj. matematički modeli prolaze kroz adaptiranje. Evolucija spontano nalazi tajnu skrivene informacije unutar eksperimentalnih podataka i razvija matematički model. Predstavljeno istraživanje pokazuje da prosječno postotno odstupanje u slučaju modela hrapavosti površine dobiveno standardnom OLS regresijskom analizom iznosi 5,28 % te 3,46 % u slučaju simulirane evolucije. Prema tome, model razvijen bez utjecaja ljudske inteligencije približno je 1,5 puta precizniji od onoga čiji je oblik bio unaprijed specificiran.

Također, primjena GA pristupa za određivanje optimalnih parametara rezanja dokazala se kao učinkovita i robusna. To će biti od koristi pri računalom podržanom planiranju procesa (CAPP) u proizvodnji visokokvalitetnih proizvoda operacijama obrade odvajanjem čestica te pri adaptivnom upravljanju inteligentnim alatnim strojevima.

6. CONCLUSION

In this study, the evolutionary algorithms were applied for modelling and optimization of the longitudinal turning process using the original integrated GP-GA concept. It imitates the natural evolution of living organisms, where in the struggle for natural resources the successful individuals gradually become more and more dominant, and adaptable to the environment in which they live, whereas the less successful ones are present in the next generation rarely.

In the proposed GP approach the programs, i.e. mathematical models, undergo adaptation. The evolution spontaneously finds the secret of hidden information within the experimental data and develops a mathematical model. The presented research shows that the average percentage deviation in the case of the surface roughness model obtained by standard OLS regression analysis is 5,28 %, and 3,46 % in the case of simulated evolution. Therefore, the model developed without the influence of human intelligence is about 1,5 times more precise than one whose form has been pre-specified.

Also, the application of the GA approach to obtain optimal cutting parameters has proven to be efficient and robust. It will be quite useful in the computer-aided process planning (CAPP) stages in the manufacturing of high quality goods by a variety of machining operations, and in adaptive control of intelligent machine tools.

7. POPIS OZNAKA

7. LIST OF SYMBOLS

dubina rezanja	a_p,	mm	depth of cut
jedinični trošak izrade	C_1,	EUR	machining cost per piece
početni promjer obratka	D,	mm	starting workpiece diameter
tangencijalna komponenta sile rezanja	F_c,	N	tangential cutting force component
posmak po okretaju obratka	f,	mm	feed per revolution
broj prolaza	i,	-	number of passes
dužina prolaza	l,	mm	length of pass
hrapavost površine	Ra,	µm	surface roughness
srednje postotno odstupanje	$\bar{S}$,	%	average percentage deviation
postojanost alata	T,	min	tool life
jedinično vrijeme izrade	t_1,	min	machining time per piece
vrijeme za jednokratnu zamjenu alata	t_2,	min	tool change time
brzina rezanja	v_c,	m/min	cutting speed
težinski koeficijenti	w_j,	-	weighting coefficients
normirana cijena rada tokarilice	x,	EUR/min	operating cost of lathe
nabavna cijena alata po jednoj oštrici	y,	EUR	purchase cost of tool per single cutting edge

LITERATURA
REFERENCES

[1] Kiliç, S. E., Cogun, C., Sen, D. T.: *A Computer-Aided Graphical Technique for the Optimisation of Machining Conditions*, Comp. Ind., Vol. 20 (1992), pp. 319-326.

[2] Ermer, D. S., Patel, D. C.: *Maximization of the Production Rate with Constraints by Linear Programming and Sensitivity Analysis*, Proc. 2nd NAMRC, Madison, 1974, pp. 436-443.

[3] Chua, M. S., Loh, H. T., Wong, Y. S., Rahman, M.: *Optimisation of Cutting Conditions for Multi-Pass Turning Operations Using Sequential Quadratic Programming*, J. Mater. Proc. Technol., Vol. 28 (1991), pp. 253-262.

[4] Eskicioglu, H., Nisli, M. S., Kiliç, S. E.: *An Application of Geometric Programming to Single-Pass Turning Operations*, Proc. 25th Int. Mach. Tool Des. Res. Conf., Birmingham, 1985, pp. 149-157.

[5] Shin, Y. C., Joo, Y. S.: *Optimisation of Machining Conditions with Practical Constraints*, Int. J. Prod. Res., Vol. 30 (1992), No. 12, pp. 2907-2919.

[6] Cukor, G., Kuljanic, E.: *CAPP Software for Tool Selection, Optimisation and Tool Life Data Base Adaptation in Turning*, AMST, CISM Courses and Lectures No. 406, Springer Verlag, Wien New York, 1999, pp. 241-248.

[7] Wang, J.: *Multiple-Objective Optimisation of Machining Operations Based on Neural Networks*, Int. J. Advanced Manufacturing Technol., Vol. 8 (1993), pp. 235-243.

[8] Abuelnaga, A. M., El-Dardiry, M.: *Optimisation Methods for Metal Cutting*, Int. J. Mach. Tool Des. Res., Vol. 24 (1984), No. 1, pp. 11-18.

[9] Tandon, V., El-Mounayri, H., Kishawy, H.: *NC End Milling Optimisation Using Evolutionary Computation*, Int. J. Mach. Tools Manuf., Vol. 42 (2002), pp. 595-605.

[10] Saravanan, R., Asokan, P., Sachidanandam, M.: *A Multi-Objective Genetic Algorithm (GA) Approach for Optimisation of Surface Grinding Operations*, Int. J. Mach. Tools Manuf., Vol. 42 (2002), pp. 1327-1334.

[11] Cukor, G., Kuljanic, E., Barisic, B.: O*ptimisation of Machining Process Using Evolutionary Algorithms*, AMST, CISM Courses and Lectures No. 406, Springer Verlag, Wien New York, 2005, pp. 135-142.

[12] Brezocnik, M., Kovacic, M.: *Integrated Evolutionary Computation Environment for Optimising and Modelling of Manufacturing Processes*, Proc. 6th TMT, Neum, 2002, pp. 107-110.

[13] Jurkovic, Z.: *Modeliranje i optimizacija parametara obrade primjenom evolucijskih algoritama kod inteligentnih obradnih sustava / Modeling and Optimization of the Cutting Parameters Using Evolutionary Algorithms at the Intelligent Machining Systems*, PhD Thesis, Faculty of Engineering of the University of Rijeka, 2007.

Primljeno / Received: 14.06.2010.

Prihvaćeno / Accepted: 14.10.2010

Izvornoznanstveni članak

Original scientific paper

Adresa autora / Authors' address
Goran Cukor
Zoran Jurković
Tehnički fakultet Sveučilišta u Rijeci
Vukovarska 58
51000 Rijeka
HRVATSKA
goranc@riteh.hr
Zoran.Jurkovic@riteh.hr