© Strojniški vestnik 50(2004)5,252-266
ISSN 0039-2480
UDK 621.9.01:621.941
Izvirni znanstveni članek (1.01)
© Journal of Mechanical Engineering 50(2004)5,252-266
ISSN 0039-2480
UDC 621.9.01:621.941
Original scientific paper (1.01)

Določevanje značilnih tehnoloških in gospodarskih parametrov med postopkom odrezovanja

A Determination of the Characteristic Technological and Economic Parameters during Metal Cutting

Uroš Župerl - Franci Čuš

V prispevku je predlagan nov nedeterministični optimizacijski postopek za zahtevno optimizacijo rezalnih parametrov pri odrezovanju. Ta postopek uporablja umetne nevronske mreže (ANN) za reševanje problema optimiranja rezalnih pogojev. Predlagan postopek temelji na kriteriju največje stopnje proizvodnje in vključuje štiri tehnološke omejitve. Z izbiro optimalnih rezalnih parametrov je mogoče doseči ugodno razmerje med nizkimi obdelovalnimi stroški in visoko produktivnostjo ob upoštevanju podanih omejitev postopka rezanja. Eksperimentalni rezultati kažejo, da je predlagani algoritem pri reševanju nelinearnih optimizacijskih problemov s postavljenimi omejitvami učinkovit in ga je mogoče vključiti v inteligentne obdelovalne sisteme. Najprej je oblikovan problem določitve optimalnih parametrov odrezovanja, kot večciljni optimizacijski problem. Nato so predlagane nevronske mreže za predstavitev proizvajalčevih prednostnih struktur. Za demonstracijo zmogljivosti predlaganega postopka je nadrobno obravnavan nazoren primer.

(Ključne besede: odrezovanje, pogoji rezanja, struženje, optimiranje, postopki nedeterministični)

A new non-deterministic optimization approach to the complex optimization of cutting parameters during machining is proposed. It uses artificial neural networks to solve the cutting-conditions optimization problem. The developed approach is based on the "maximum production rate criterion" and incorporates four technological constraints. By selecting the optimum cutting conditions it is possible to reach a favourable ratio between low machining costs and high productivity, taking into account the given limitation of the cutting process. First, the problem of determining the optimum machining parameters is formulated as a multiple-objective optimization problem. Then, neural networks are proposed to represent manufacturers' preference structures. The experimental results show that the proposed algorithm for solving the non-linear-constrained optimization problems is efficient and can be integrated into intelligent manufacturing systems. To demonstrate the performance of the proposed approach, an illustrative example is discussed in detail.

(Keywords: machining, cutting parameters, turning, nondeterministic optimization)

0 UVOD

Inteligentna proizvodnja dosega znatne denarne in časovne prihranke, če vključuje učinkovito avtomatično načrtovanje postopka. Načrtovanje postopka obsega določitev primernih strojev, odrezovalnih orodij in odrezovalnih parametrov pri določenih pogojih rezanja za vsako opravilo na danem obdelovancu. Optimalna izbira rezalnih pogojev pomembno prispeva k povečanju produktivnosti in zmanjšanju stroškov, zato je največji del pozornosti v tem prispevku posvečen prav temu problemu. Problem gospodarnosti

0 INTRODUCTION

Intelligent manufacturing achieves substantial savings in terms of money and time if it integrates an efficient automated process-planning. Process planning involves a determination of the appropriate machines, the tools for machining parts and the machining parameters under certain cutting conditions for each operation of a given machined part. The optimum selection of the cutting conditions contributes significantly to an increase in productivity and a reduction of costs. For this reason a lot of attention is paid to this problem in this contribution. The machining-economics problem obdelave vključuje določitev karakterističnih parametrov postopka, in sicer običajno hitrosti rezanja, stopnje podajanja in globine rezanja, z namenom optimirati ciljno funkcijo. Vključene ciljne funkcije, s katerimi merimo optimalnost rezalnih pogojev, so: (1) najmanjši stroški na enoto, (2) največja stopnja proizvodnje, (3) utežna kombinacija večciljnih funkcij. Rezalne omejitve, ki bi jih morali upoštevati pri gospodarnosti obdelave vključujejo: omejitev obstojnosti, rezalne sile, moči, temperature odrezka in omejitev hrapavosti površine.

Običajno so problem gospodarnosti obdelave reševali z uporabo optimizacijskih algoritmov, ki vsebujejo geometrično in stohastično programiranje [1], diferencialni račun [2], linearno programiranje [2] in računalniške simulacije [3]. Ti algoritmi so bili razviti ob upoštevanju samo enega cilja, to je npr. zmanjševanje stroškov, povečanje dobička, itn.

Medtem ko večina dosedanjih raziskav temelji na enovariantni optimizaciji, obstaja nekaj uspelih poskusov tudi pri večvariantni optimizaciji. Philipson in Ravidran [2] uporabita ciljno programiranje za optimiranje postopka obdelave, Ghiassi [4] uporabi več ciljne tehnike linearnega programiranja in interaktivne tehnike. Raznolikost izdelkov in negotovost na tržišču povzročata, da so interaktivne metode načrtovanja postopka obdelave neučinkovite zaradi močnih in pogostih interakcij z izdelovalci pri načrtovanju postopkov obdelave. Bolj zaželena je metoda na podlagi prednostnega modela, npr. večatributna vrednostna funkcija, ki predstavlja izdelovalčevo celovito prednost.

Optimiranje rezalnih parametrov je nelinearna optimizacija z omejitvami, zato je težko rešiti ta problem z nedeterminističnimi algoritmi. Zato so bile nedavno uporabljene nedeterministične tehnike reševanja različnih tipov optimizacijskih problemov pri odrezovanju. Lokalne iskalne tehnike vključujejo simulacijsko ohlajanje (SA) [5], genetske algoritme (GA) [6], algoritma UNM in PSO [7].

Nov postopek, ki omogoča učinkovito in hitro izbiro optimalnih rezalnih pogojev brez kršenja postavljenih rezalnih omejitev so umetne nevronske mreže (UNM - ANN). Algoritem deluje na podlagi usmerjenih in žarkovnih mrež ob hkratni uporabi novih sodobnih algoritmov učenja, ki se avtomatično prilagajajo trenutnim razmeram med postopkom učenja.

Cilj raziskave je prikazati potencial nevronskih mrež pri optimiranju postopka odrezovanja. Gibalo študije je tudi predstaviti proizvajalčeve prednostne strukture z uporabo UNM. Glavni cilj prispevka je določiti takšne optimalne rezalne pogoje (rezalno hitrost, podajanje in globino reza), ki čim bolj povečajo obseg proizvodnje, zmanjšajo obdelovalne stroške in izboljšajo kakovost izdelka.

consists of determining the characteristic process parameters, usually the cutting speed, the feed rate and the depth of cut, in order to optimize an objective function. The included objective functions for measuring the optimality of the machining conditions are: (1) minimum unit-production cost, (2) maximum production rate, (3) maximum production rate and (4) a weighted combination of several objective functions. The cutting constraints that should be considered in machining economics include the following: tool-life constraint, cutting-force constraint, power, chip-tool interface-temperature constraint, surface-finish constraint.

Usually, the machining-economics problem has been solved using optimization algorithms, which include geometric and stochastic programming [1], differential calculus [2], linear programming [2], and computer simulating [3]. These algorithms were developed by considering only a single objective, such as minimization of cost or maximization of profit, etc.

While most of the research undertaken so far has been based on single-objective optimization, there have been some successful attempts at multi-objective optimization. Philipson and Ravidran [2] apply goal-programming techniques for machining-process optimizations, Ghiassi [4] applies multi-objective linear-programming techniques and interactive techniques. The diversity of product mix and the uncertainty of market value make interactive approaches to machining-process planning inefficient owing to the extensive and frequent interactions with manufacturers for planning the machining process. A global approach based on a preference model, such as a multi-attribute value function that represents a manufacturer's overall preference, is more desirable.

The optimization of machining parameters is a non-linear optimization with constraints, so it is difficult for non-deterministic optimization algorithms to solve this problem. Consequently, non-deterministic techniques have recently been applied to solve various types of optimization problems in machining. Local search techniques include the simulated annealing (SA) algorithm [5], the genetic algorithm (GA) approach [6], the ANN approach and the PSO algorithm [7].

The new approach, which ensures efficient and fast selection of the optimum cutting conditions, without violating any imposed cutting constraints, is the artificial neural network (ANN). The algorithm works on the basis of feedforward and radial basis networks with the simultaneous use of a new, advanced learning algorithm, which automatically adapts to current conditions during the training process.

The purpose of this study is to demonstrate the potential of neural networks for machining-process optimization. The motivation of this study is also to represent the manufacturer's preference structures using ANNs. The main objective of the paper is to determine the optimal machining parameters (cutting speed, feedrate, depth of cut) that maximize the extent of production, reduce the manufacturing costs and improve the product quality.

Prispevek je oblikovan takole. V poglavju 1 je oblikovano opravilo struženja kot večciljni optimizacijski problem s tremi neprimerljivimi in nasprotujočimi si cilji. V poglavju 1 je predlagana nevronska mreža, da pridemo do izdelovalčeve posredne večatributne vrednostne funkcije. Nato je opisan nevronski algoritem za optimiranje rezalnih parametrov. V poglavju 4 so obravnavani rezultati izračunov, ki kažejo razlike med različnimi metodami.

The paper is organised as follows. In section 2, a turning operation is formulated as a constrained multi-objective optimisation problem with three non-commensurate and conflicting objectives. In Section 3, a neural network is proposed for accessing a manufacturer's implicit multi-attribute value function. Then a neural algorithm for cutting-parameter optimization is described. In Section 5, computational results are discussed to show the differences between the various approaches.

1 TEORETIČNI POSTOPEK K REŠEVANJA PROBLEMA OPTIMIRANJA

Naloga optimizacije je določiti takšen niz rezalnih pogojev *v* (rezalna hitrost), *f* (podajanje), *a* (globina rezanja), ki zadosti omejitvenim enačbam in uravnoteži nasprotujoče si ciljne dejavnike. Opravilo struženja je oblikovano kot večvariantni optimizacijski problem z omejitvenimi neenačbami ter s tremi nasprotujočimi si cilji (stopnja proizvodnje, stroški opravila, kakovost obdelave). Rezalni parametri morajo biti tako izbrani, da je stroj čim bolj izkoriščen in obstojnost orodja čim daljša. V splošnem izbira lažjih delovnih razmer ni gospodarsko upravičena. Z zmanjševanjem rezalne hitrosti, podajanja in globine rezanja se zmanjša delovni učinek in podaljša obstojnost orodja. Tako se sicer prihrani pri orodjih in zmanjša stroške za menjavo orodij, vendar se povečajo stroški delovnega mesta. Nasprotno tudi velja, da ni vedno namen izdelati čim več v najkrajšem mogočem času. Pri izbiri optimalnih rezalnih pogojev za dano strojno opravilo naredimo kompromis med največjo stopnjo odvzemanja materiala in najmanjšo obrabo orodja.

1 THEORETICAL APPROACH TO SOLVING THE OPTIMIZATION PROBLEM

The purpose of the optimization is to determine such a set of cutting conditions – *v* (cutting speed), *f* (feedrate), *a* (depth of cut) – that satisfies the limitation equations and balances the conflicting objectives. The operation of turning is defined as a multiple-objective optimization problem with limitation non-equations and with three conflicting objectives (production rate, operation cost, quality of machining). The cutting parameters must be selected so that the machine is utilised to the maximum possible extent and that the tool-life is as long as possible. In general, the selection of the easier operating conditions is not economically justified. If the cutting speed, feeding and cutting depth are decreased, the work efficiency is reduced and the tool resistance to is wear prolonged. In this way the tools are saved and the cost of the tool replacement is reduced, but the labor costs are increased. Conversely, it is not always our aim to produce as much as possible within the shortest possible time. When selecting the optimum cutting conditions for some machine operation we make a compromise between the extent of removal of the material and the minimum tool wear.

1.1 Izoblikovanje ciljnih funkcij

1. Stopnja proizvodnje
   Stopnjo proizvodnje običajno merimo s celotnim časom, ki je potreben za izdelavo enega izdelka (T_p). Je funkcija stopnje odvzemanja kovine (*SOK - MRR*) in obstojnosti orodja;

1.1 Formulation of objective functions

1. Production rate
   The production rate is usually measured as the entire time necessary for the manufacture of a product (T_p). It is a function of the metal removal rate (*MRR*) and the the tool-life;

$$T_p = T_s + V \times \frac{(1+\frac{T_c}{T})}{MRR} + T_i \qquad (1),$$

kjer so = T_s, T_c, T_i in V pripravljalni čas orodja, čas menjave orodja, čas ko orodje ne reže in prostornina odvzetega materiala. V določenih opravilih so T_s, T_c, T_i in V stalnice, od koder izhaja, da je T_p funkcija *SOK* in *T*.

- Stopnja odvzemanja kovin (*SOK*). *SOK* lahko z analitično izpeljavo izrazimo kot zmnožek rezalne hitrosti, podajanja in globine reza:

where T_s, T_c, T_i and V are the tool set-up time, the tool change time, the time during which the tool does not cut and the volume of the removed metal. In some operations the T_s, T_c, T_i and V are constants, so that T_p is a function of *MRR* and *T*.

- The metal removal rate (*MRR*). *MRR* can be expressed by analytical derivation as the product of the cutting speed, the feeding rate and the cutting depth:

$$MRR = 1000 \cdot v \cdot f \cdot a \qquad (2)$$

- Obstojnost orodja (T). Obstojnost orodja je merjena kot povprečen čas med menjavami ali ostrenjem orodja. Zveza med dobo trajanja orodja in parametri je podana z dobro znanim Taylorjevim obrazcem:

- Tool-life (T). The tool-life is measured as the average time between tool changes or tool sharpenings. The relation between the tool life and the parameters is expressed with the well-known Taylor's formula:

$$T = \frac{k_T}{v^{\alpha_1} \cdot f^{\alpha_2} \cdot a^{\alpha_3}} \quad (3),$$

kjer so k_T, α_1, α_2 *in* α_3, vedno pozitivni stalni parametri, določeni statistično [8].

where k_T, α_1, α_2 and α_3, which are always positive constant parameters, are determined statistically [8].

2. Stroški opravila
Stroške obdelave lahko izrazimo kot stroške na izdelek (C_p). Pri stroških opravila ločimo dve veličini, povezani z rezalnimi parametri (T, T_p) [5]:

2. Operation cost
The operation cost can be expressed as the cost per product (C_p). In the cost of the operation two values connected with the cutting parameters (T, T_p) [5] are distinguished:

$$C_p = T_p \cdot \left(\frac{C_t}{T} + C_l + C_0 \right) \quad (4),$$

kjer so C_t, C_l in C_0 orodni stroški, stroški dela in režijski stroški. V določenih operacijah so C_t, C_l *in* C_0 neodvisni od rezalnih parametrov.

where C_t, C_l and C_0 are the tool cost, the labour cost and the overhead cost respectively. In some operations C_t, C_l and C_0 are independent of the cutting parameters.

3. Kakovost obdelave
Najpomembnejše merilo za oceno kakovosti površine je hrapavost, izračunana po:

3. Cutting quality
The most important criterion for the assessment of the surface quality is roughness, which is calculated according to:

$$R_a = k \cdot v^{x_1} \cdot f^{x_2} \cdot a^{x_3} \quad (5),$$

kjer so x_1, x_2, x_3 in k stalnice, ki pripadajo specifični kombinaciji orodje – obdelovanec.

where x_1, x_2, x_3 and k are the constants relevant to a specific tool-workpiece combination.

Na sliki 1 je na temelju zgornje razprave prikazana hierarhična struktura ciljev, prilastkov in rezalnih parametrov.

Da bi lahko ovrednotili medsebojne vplive in učinke med dejavniki ter dobili celostni pregled nad vrednostnim sistemom podjetja, je priporočljivo določiti večprilastno funkcijo proizvajalca (y) [5], ki pomeni zmožnost podjetja – proizvajalca. Večprilastna vrednostna funkcija je definirana kot funkcija z dejanskimi vrednostmi, ki priredi dejansko vrednost vsaki večprilastni alternativi, tako da je bolj zaželena alternativa povezana z večjo vrednostjo indeksa kakor manj zaželena alternativa. Izbrana je naslednja večprilastna vrednostna funkcija proizvajalca [5].

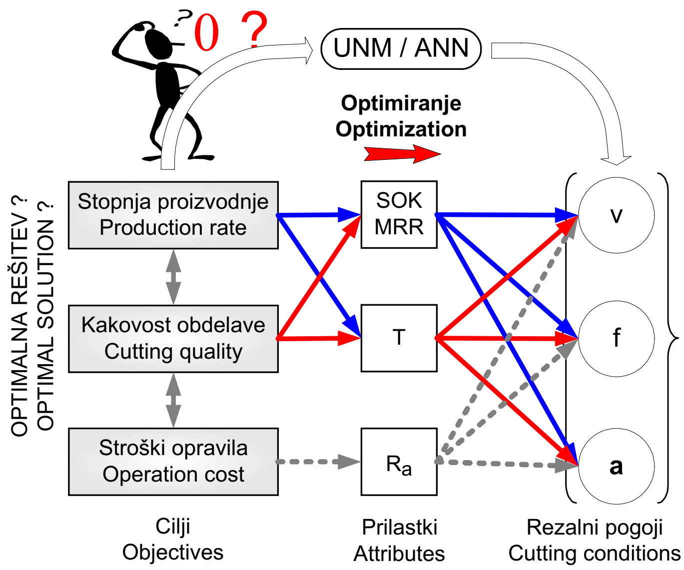
Based on the above discussion, a hierarchical structure of the objectives, attributes and cutting parameters is depicted in Figure 1.

In order to ensure an evaluation of the mutual influences and the effects between the objectives, and to be able to obtain an overall survey of the manufacturer's value system it is recommendable to determine the multi-attribute function of the manufacturer (y) [5] representing the company's (or manufacturer's) overall preference. A multi-attribute value function is defined as a real-valued function that assigns a real value to each multi-attribute alternative, in such a way that a more preferable alternative is associated with a larger value index than a less preferable alternative. The following manufacturer's implicit value function [5] is selected:

$$y = 0,42 \cdot e^{(-0,22Tp)} + 0,36 \cdot e^{(-0,32Cp)} + 0,17 \cdot e^{(-0,26Ra)} + \frac{0,05}{\left(1 + 1,22 \cdot T_p \cdot C_p \cdot R_a\right)} \quad (6).$$

Celostni postopek določevanja najprimernejših rezalnih parametrov je postopek z največjo večprilastne posredne funkcije proizvajalca. Natančneje, zanima nas modeliranje večprilastnih vrednostnih funkcij z nevronskimi mrežami. Vsak proizvajalec ima svojo obliko funkcije (y); to pomeni, da ima tudi svoje drugačne optimalne rezalne pogoje.

One global approach to determining the most desirable cutting parameters is by maximising the manufacturer's implicit multi-atttribute function. Specifically, we are interested in modelling a manufacturer's implicit multi-attribute value functions by neural networks. Every manufacturer has its own form of the function (y); it means that it also has its own different optimum cutting conditions.



Sl. 1. *Prikaz hierarhične strukture dejavnikov, prialstkov in rezalnih parametrov*
Fig. 1. *A hierarchical structure of the objectives, attributes and cutting parameters*

1. 2 Določitev omejitev

Obstaja več dejavnikov, ki omejujejo rezalne parametre. Ti dejavniki običajno izvirajo iz tehnoloških in organizacijskih specifikacij. Upoštevane so naslednje omejitve:

1. Dovoljeno območje rezalnih pogojev
   Zaradi omejitev na stroju in rezalnem orodju ter varnosti pri obdelavi so rezalni parametri omejeni z spodnjo in zgornjo dopustno mejo:

1.2 Definition of constraints

There are several factors limiting the cutting parameters. Those factors usually originate from technical specifications and organisational considerations. The following constraints are taken into account:

1. Permissible range of cutting conditions.
Due to the limitations of the machine and the cutting tool and due to the safety of the machining the cutting parameters are limited by upper and lower limits:

$$v_{min} \le v \le v_{max}\, , f_{min} \le f \le f_{max},\ a_{min} \le a \le a_{max} \qquad (7).$$

2. Posredne omejitve, ki izhajajo iz karakteristik orodja in zmogljivosti stroja.
   Za izbrano orodje poda omejitve rezalnih pogojev proizvajalec orodja. Omejitev na stroju pa sta rezalna moč, rezalna sila. Podobno so s fizikalnimi lastnostmi določene obdelovalne karakteristike materiala obdelovanca.
   - Rezalna moč in sila
     Potrebna rezalna moč za opravilo odrezovanja, ne sme prekoračiti dejanske moči stroja:

2. Implied limitations issuing from the tool characteristics and the machine capacity.
   For the selected tool the tool maker specifies the limitations of the cutting conditions. The limitation on the machine is the cutting power and the cutting force. Similarly, the machining characteristics of the workpiece material are determined by the physical properties.
   – Cutting power and force
     The cutting power required for the cutting operation should not exceed the effective power of the machine tool:

$$P = \frac{F \cdot v}{6122{,}45 \cdot \eta} \qquad (8),$$

kjer je η mehanski izkoristek stroja in je F podana z naslednjim obrazcem:

where η is the mechanical efficiency of the machine and F is given by the following formula:

$$F = k_F \cdot f^{\beta_2} \cdot a^{\beta_3} \qquad (9).$$

Pri vpeljavi enačbe (9) v enačbo (8) dobimo naslednje:

When Equation (9) is introduced into Equation (8) the following is obtained:

$$P = k_n \cdot v \cdot f^{\beta_2} \cdot a^{\beta_3} \quad \text{kjer je/where} \quad k_n = \frac{k_F}{(6122{,}45 \cdot \eta)} \qquad (10).$$

Omejitve moči in rezalne sil so enake:

The limitations of the power and cutting force are equal to:

$$P(v,f,a) \leq P_{max}\ ,\ F(v,f,a) \leq F_{max} \tag{11}$$

Problem optimizacije rezalnih parametrov je moč zapisati kot naslednji večciljni optimizacijski problem: min $T_p\ (v, f, a)$, min $C_p\ (v, f, a)$, min $R_a\ (v, f, a)$ podrejen omejitvam (7) do (11).

The problem of the optimization of the cutting parameters can be formulated as the following multi-objective optimization problem: min $T_p\ (v, f, a)$, min $C_p\ (v, f, a)$, min $R_a\ (v, f, a)$ subject to constraints (7) to (11).

2 PRILAGODITEV TOPOLOGIJE UNM K PROBLEMU OPTIMIRANJA

2 THE ANN TOPOLOGY ADAPTATION TO THE OPTIMIZATION PROBLEM

Za določitev večprilastne vrednostne funkcije lahko uporabimo popularne večnivojske usmerjene nevronske mreže ali žarkovne nevronske mreže. Večnivojska usmerjena nevronska mreža se je izkazala kot odličen splošni približek nelinearnih funkcij. Če je zmožna približati poljubno funkcijo, potem je z njo mogoče predstaviti poljubno večprilastno posredno funkcijo proizvajalca. UNM potrebuje tri vhodne nevrone za tri parametre: *v, f* in *a*. Če vrednosti *v, f, a* in *y* niso v enakem merilu, je treba vse podatke normalizirati. Izhod iz nevronske mreže je ocenjena večprilastna dejanska vrednost funkcije (*y*), zato je potreben le en izhodni nevron (sl. 2).

Pri postopku optimiranja so uporabljene usmerjene nevronske mreže z dvema ravnema. Vsebovale so 3 nevrone v vhodni ravni in 3, (6) nevronov v skritih ravneh. UNM so bile naučene z naslednjimi parametri: rezalni pogoji (*v, f, a*) in vrednost večprilastne funkcije proizvajalca (*y*). Učenje UNM je bilo izvedeno s podatki, ki vsebujejo 20 učnih vzorcev. Za testiranje naučene mreže je bilo uporabljenih še dodatnih 20 vzorcev. Učenje mreže je takšen postopek vzajemnega nastavljanja uteži na povezavah, da so napake napovedi na učnem nizu najmanjše. Ker je postopek učenja iterativen, je treba celotni učni niz predstavljati mreži tako dolgo, dokler celotna napaka ne doseže najmanjšo sprejemljivo vrednost. Poglavitni cilj pri učenju poljubne nevronske mreže je zmanjšati skupno napako mreže. Srednja absolutna napaka (*SAN - MAE*) je določena z:

For assessing the multi-ttribute value function we can use the popular multilayer feed-forward neural networks or radial basis networks. The multilayer feed-forward neural network has proved to be an excellent universal approximator of non-linear functions. If it is capable of approximating any nonlinear function, then it is possible to represent with it any manufacturer's implicit multi-attribute function. The ANN needs three input neurons for three parameters: *v, f* and *a*. If the values *v, f, a* and *y* are not ON the same scale, all the data must be normalized. The output from the neural network is a real valued multi-attribute value function (*y*), therefore only one output neuron is necessary (Figure 2).

For the optimization process, two-layer feed-forward neural networks were used. They contain three neurons in the input layer, and three, six in hidden layers. The ANN were trained with the following parameters: cutting conditions (*v, f, a*) and the value of the multi-attribute function of the manufacturer (*y*). The training of the ANN was made with the data of 20 training examples. An additional 20 examples were used to test the trained network. Network training is the process of interactively adjusting the interconnection weights in such a way that the prediction errors on the training set are minimized. Since the learning process is iterative, the entire training set will have to be presented to the network over and over again, until the global error reaches a minimum acceptable value. The basic goal when training any neural network is to minimize the overall error of the network. The Mean Absolute Error (MAE) is defined by:

$$(\,|\,y_1 - g(x_1, W)| + |\,y_1 - g(x_1, W))\,| + \ldots + |\,y_m - g(x_m, W)|\,)\,/\,m \tag{12}$$

kjer je $z_m = (x_i, y_i)$, $i = 1,...,m$, zaporednje *m* učnih primerov. *W* je utežna matrika mreže in $g(X,W)$ je rezultirajoča funkcija mreže.

Med postopkom učenja in testiranja nevronska mreža izračunava vso naslednjo statistiko:

- Napaka učenja (*NU - ETrn*). Celotna napaka za učni niz, izračunana po enačbi (12).
- Največja napaka učenja (*NNU - ETrnMax*). Določena je kot največja absolutna razlika med napovedanim in želenim izhodom mreže v učnem nizu.
- Napaka Testiranja (*NT - ETst*). Celotna napaka za

where $z_m = (x_i, y_i)$, $i = 1,...,m$, is a sequence of m training examples, *W* is the network weight matrix and $g(X,W)$ is the resulting network function.

In the course of training and testing, the neural network computes all of the following statistics:

- Training error (*ETrn*). The overall error for the Training Set calculated by Equation 12.
- Max Training error (*ETrnMax*). The largest absolute difference between an actual output and its desired output in the Training Set.
- Test error (*ETst*). The overall error for the Test Set

testni niz, izračunana po enačbi (12).

- Največja napaka testiranja (*NNT - ETstMax*). Določena je kot največja absolutna razlika med napovedanim in želenim izhodom mreže v testnem nizu.

Ko je večprilastna vrednostna funkcija ocenjena, bo uporabljena nevronska mreža, da razbere proizvajalčeve celotne prednosti in tako omeji večciljni optimizacijski problem na naslednji enociljni problem iskanja največje vrednosti:

calculated by Equation (12).

- Max Test error (*ETstMax*). The largest absolute difference between an actual output and its desired output in the Test Set.

Once a multi-attribute value function is validated the neural network will be used to decipher the manufacturer's overall preference and the multi-objective optimization problem will be reduced to a single objective maximization problem as follows:

$$\max_{v,f,a} y\left[T_p(v, f, a),\ C_p(v, f, a), R_a(v, f, a)\right]$$

Za ocenitev posameznih učinkov učnih parametrov na performance nevronske mreže je bilo testirano okrog sto mrež. Na podlagi rezultatov lahko podamo naslednje sklepe:

- Stopnje učenja manjše od 0,3 dajo sprejemljive napake napovedi, če pa hočemo čim bolj zmanjšati število ponovitev učenja in doseči majhne napake napovedi, mora biti stopnja učenja med 0,01 in 0.2.
- Za čim večje zmanjšanje napak napovedi je primerna vztrajnost učenja med 0,001 in 0,005. Toda vrednost vztrajnosti učenja ne sme presegati 0,004, če je treba čim bolj zmanjšati število ponovitev učenja.
- Optimalno število nevronov v skritih ravneh je od 3 do 6.
- Naučene mreže s sigmoidno prenosno funkcijo v vseh svojih nevronih dajo najmanjše napake napovedi, medtem ko mreže s hiperbolično in sinusno funkcijo dajo največjo in skoraj največjo napako napovedi.
- Mreže, ki uporabljajo sinusno funkcijo, terjajo najmanjše število ponovitev učenja, nakar sledi arctg, medtem ko mreže, ki uporabljajo hiperbolično, terjajo največje število ponovitev učenja.

To evaluate the individual effects of training parameters on the performance of a neural network about one hundred networks were tested. From the results the following conclusions can be drawn:

- Learning rates below 0.3 give acceptable prediction errors, while learning rates must be between 0.01 and 0.2 to minimize the number of training cycles and obtain low predictions errors;
- To minimize the estimation errors, momentum rates between 0.001 and 0.005 are good. However, the momentum rate should not exceed 0.004 if the number of training cycles is also to be minimized;
- The optimum number of hidden layer nodes is from 2 to 6;
- Networks trained with the sigmoid transfer function in all their neurons give the smallest prediction errors, while those employing the hyperbolic tangent and sine give the highest and next-highest prediction errors, respectively;
- Networks that employ the sine function require the lowest number of training cycles, followed by the arctan, while those that employ the hyperbolic function require the highest number of training cycles;

2.1 Metodologija optimiranja opravila struženja

Za določitev optimalnih rezalnih pogojev je treba izvesti naslednje korake:

1. Vnos vhodnih podatkov
   - tehnološke in pripravljalno zaključne čase (nastavitveni čas, čas menjave orodja, neproduktivni čas orodja),
   - stroške (stroške orodja, stroške dela, režijske stroške),
   - omejitve (dovoljeno območje rezalnih pogojev, F_{max}, P_{max}).
2. Generiranje naključnih rezalnih pogojev.
3. Izračun preostalih veličin ($P, F, SOK, C_p, T, R_a, T_p, y$).
4. Priprava podatkov za učenje in testiranje UNM. Združitev rezalnih pogojev in preostalih izračunanih veličin v podatkovno matriko. Sledi normalizacija podatkov v matriki. Razčlenitev podatkovne matrike na vhodni in izhodni vektor. Razdelitev vhodno – izhodnega vektorja na niza podatkov za učenje in testiranje.
5. Uporaba UNM. Cilj nevronske mre□e je napovedati

2.1 Optimization methodology of the turning operation

To determine the optimal working conditions the following steps must be accomplished:

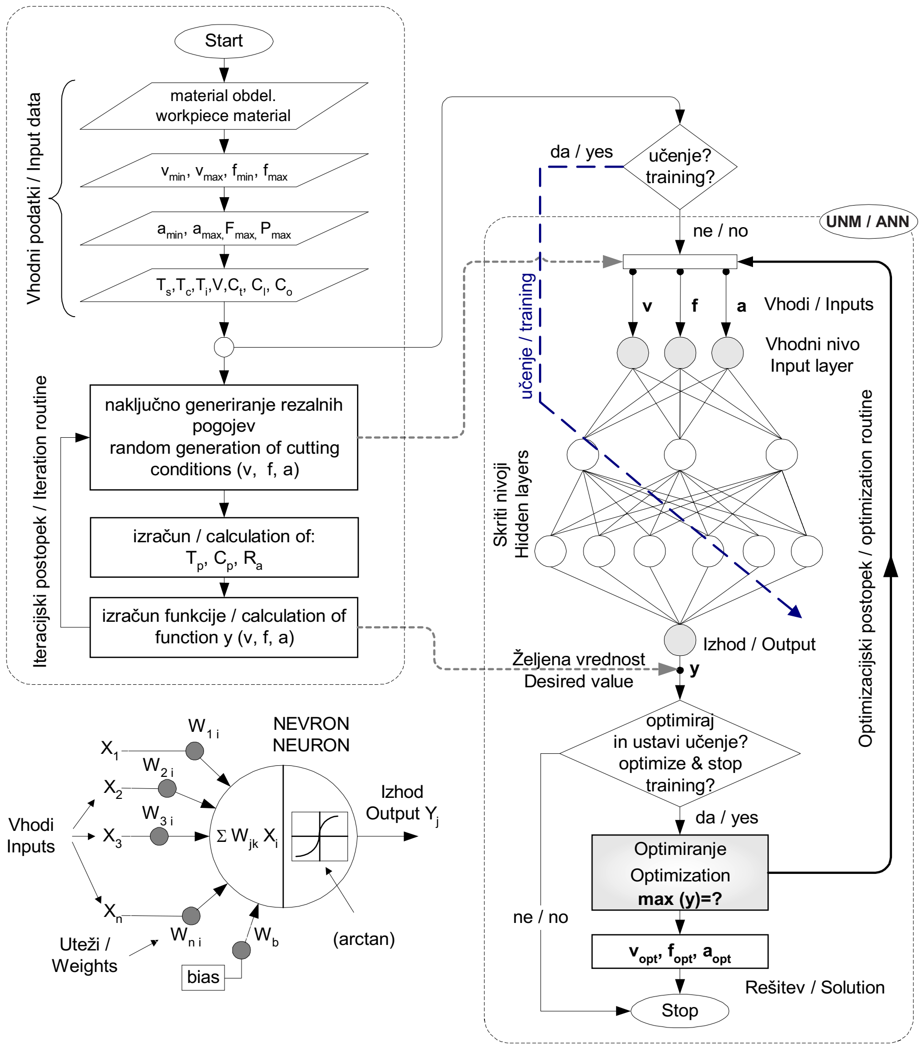
1. Entering of the input data:
   - technological and preparing/finishing times (set-up time, tool-change time, tool-idle time)
   - costs (tool cost, labour cost, overheads)
   - constraints (permissible range of cutting conditions, F_{max}, P_{max}).
2. Generation of random cutting conditions.
3. Calculation of other values ($P, F, MRR, C_p, T, R_a, T_p, y$)
4. Preparation of data for training and testing of ANN. Uniting of cutting conditions and other calculated values into a data matrix. Normalization of the data in the matrix follows. Breakdown of the data matrix into the input and output vector. Distribution of the input / output vector into the two sets for training and testing.
5. Use of the ANN. The purpose of the neural network is to predict the manufacturer´s value func-

vrednostno funkcije proizvajalca (y) pri poljubno izbranih rezalnih pogojih:
- izbira zgradbe UNM ter iskanje optimalnih parametrov učenja,
- postopek učenja UNM z uporabo niza za učenje,
- testiranje naučene UNM. Testni niz je treba uporabiti za potrditev nevronske mreže, ki je rezultat nadzorovanega učenja. Izkustveni model je izdelan in pripravljen za uporabo, če je testiranje uspešno in je napaka napovedi (*NN - ETst*) v dovoljenih mejah.

6. **Postopek optimizacije**. Rezalni pogoji, pri katerih ima funkcija (y) največjo vrednost, so optimalni rezalni pogoji. Iščemo ekstrem funkcije (y) ob upoštevanju omejitvenih enačb. Ker pa je funkcija (y) podana z ANN, to pomeni, da iščemo ekstrem nevronske mreže. Z omejitvenimi enačbami je podano območje, na katerem iščemo ekstrem. Izpis optimalnih rezalnih pogojev in njim pripadajočih spremenljivk.

tion (y) in the case of randomly selected cutting conditions:
- Selection of the architecture of the ANN and searching for the optimum training parameters.
- Procedure of training the ANN by using the training set.
- Testing of the trained ANN. The testing set is to be used to verify the resultant neural network from supervised learning. If the testing is successful and the error of the prediction of *ETst* is within the permissible limits, the empirical model is finished and ready for use.

6. **Optimization process**; The cutting conditions where the function (y) has the maximum are the optimum cutting conditions. The extreme of the function (y), with consideration of the limitation equations, is searched for. Since the function (y) is expressed with the ANN, it means that the extreme of the neural network is searched for. The area in which the extreme is searched for is defined with the limitation equations. Survey of the optimum cutting conditions and the variables relevant to them.



Sl. 2. *Algoritem predlaganega postopka za optimiranje rezalnih parametrov z matematičnim načelom delovanja nevrona*

Fig. 2. *Algorithm of the proposed approach to cutting-parameter optimization with the mathematical principle of the functioning of the neuron*

7. Grafični prikaz rezultatov in statistike optimiranja. Slika 2 prikazuje algoritem opisanega postopka.

3 PRIMER UPORABE

Za demonstracijo predlaganega postopka za optimiranje postopka obdelave je v nadaljevanju obravnavan nazoren primer. Zadana naloga je poiskati optimalne rezalne pogoje za postopek struženja. Na RNK stroju želimo obdelati surovec iz medenine (Cu Zn 39 Pb 2.00; trdota po Brinellu HB =105; natezna trdnost-440 MPa) z orodjem iz hitroreznega jekla. Naloga je poiskati optimalne rezalne pogoje za postopek struženja. Vrednosti koeficientov so statistično določene na podlagi izkustveno izmerjenih podatkov (obstojnost, hrapavost, čas obdelave, rezalna sila).

Vrednosti koeficientov:

7. Graphical representation of the results and the optimization statistic. Figure 2 shows the algorithm of the described procedure.

3 AN APPLICATION EXAMPLE

To demonstrate the proposed approach to machining-process optimization an illustrative example is discussed, as follows. On the CNC lathe we want to machine a brass workpiece (Cu Zn 39 Pb 2.00; Brinell hardness number *HB* =105; Tensile strength-440 MPa) by means of a tool made from HSS. The task is to find the optimum cutting conditions for the process of turning. The values of the coefficients are statistically determined on the basis of the data measured experimentally (tool life, roughness, time of manufacture, cutting force).

Values of coefficients:

T_s = 0,12 min,	T_c = 0,26 min,	T_i = 0,04 min	V = 231376 mm
C_t = 13,55 \$	C_1 = 0,31 \$/min,	C_0 = 0,08 \$/min	η = 36 %
k = 1,001	x_1 = 0,0088	x_2 = 0,3232	x_3 =0,3144
k_T = 1575134.21	α_1 = 1,70	α_2 = 1,55	α_3 = 1,22
k_F = 1,38	β_1 = 0	β_2 = 1,18	β_3 = 1,26

Ciljne funkcije:

The objective functions:

$$\min T_p = 0{,}16 + 231276\,(1 + 0{,}26/T)/MRR$$

$$\min C_p = (13{,}55/T + 0{,}39) \cdot T_p$$

$$\min\ R_a\ =\ 0{,}0088 \cdot v + 0{,}3232 \cdot f + 0{,}3144 \cdot a$$

$$T = 1575134{,}21 \cdot v^{-1{,}70} \cdot f^{1.55} \cdot a^{-1.22};\ MRR = 1000 \cdot 9{,}81 \cdot v \cdot f \cdot a,\ F = 1{,}38 \cdot f^{1{,}18} \cdot a^{1{,}26},$$

$$P = 0{,}000626 \cdot v \cdot f^{0{,}24} \cdot a^{0{,}11}$$

Omejitve:

The constraints:

$$v_{min} \le v \le v_{max}, f_{min} \le f \le f_{max}, a_{min} \le a \le a_{max}, F \le F_{max}, P \le P_{max},$$

$$v_{min} = 70\ \mathrm{m/min}, v_{max} = 100\ \mathrm{m/min}, f_{min} = 0{,}1\ \mathrm{mm/rev}, f_{max} = 1{,}8\ \mathrm{mm/rev},$$

$$a_{min} = 0{,}1\ \mathrm{mm}, a_{max} = 4{,}0\ \mathrm{mm}, F_{max} = 250\ \mathrm{N}, P_{max} = 2\ \mathrm{kW}$$

V preglednicah 1 in 2 je seznam dvajsetih vadbenih in dvajsetih testnih primerov. Rezalni pogoji so generirani naključno znotraj predpisanih mej. Druge vrednosti so izračunane po enačbah (1) do (5) pri izbranih rezalnih pogojih. Izbrana je naslednja implicitna vrednostna funkcija proizvajalca [5]:

The Table 1 and Table 2 contain a list of 20 training and 20 testing examples. The cutting conditions are generated at random inside the specified limits. The other values are calculated according to Equations (1-5) with selected cutting conditions. The following manufacturer's implicit value function [5] is selected:

$$z\left(T_p, C_p, R_a\right) = 0{,}42 \cdot e^{(-0{,}22Tp)} + 0{,}36 \cdot e^{(-0{,}32Cp)} + 0{,}17 \cdot e^{(-0{,}26Ra)} + 0{,}05 / \left(1 + 1{,}22 \cdot T_p \cdot C_p \cdot R_a\right) \qquad (13).$$

Naučena nevronska mreža je testirana na podlagi vhodno-izhodnih vzorcev 21-40. Celotna napaka *MAE* je 1,5x10^{-4}. Naučena mreža pri poljubnih rezalnih pogojih približa funkcijo (z) z zadovoljivo natančnostjo, zato jo uporabimo za

The trained neural network is tested based on the input-output samples 21–40. The overall *MAE* error is 1.5x10^{-4}. With any cutting conditions the trained network approximates the function (z) with satisfactory accuracy; therefore, it is used for the

Preglednica 1. *Naključni podatki za učenje UNM*
Table 1. *Random data for training of the ANN*

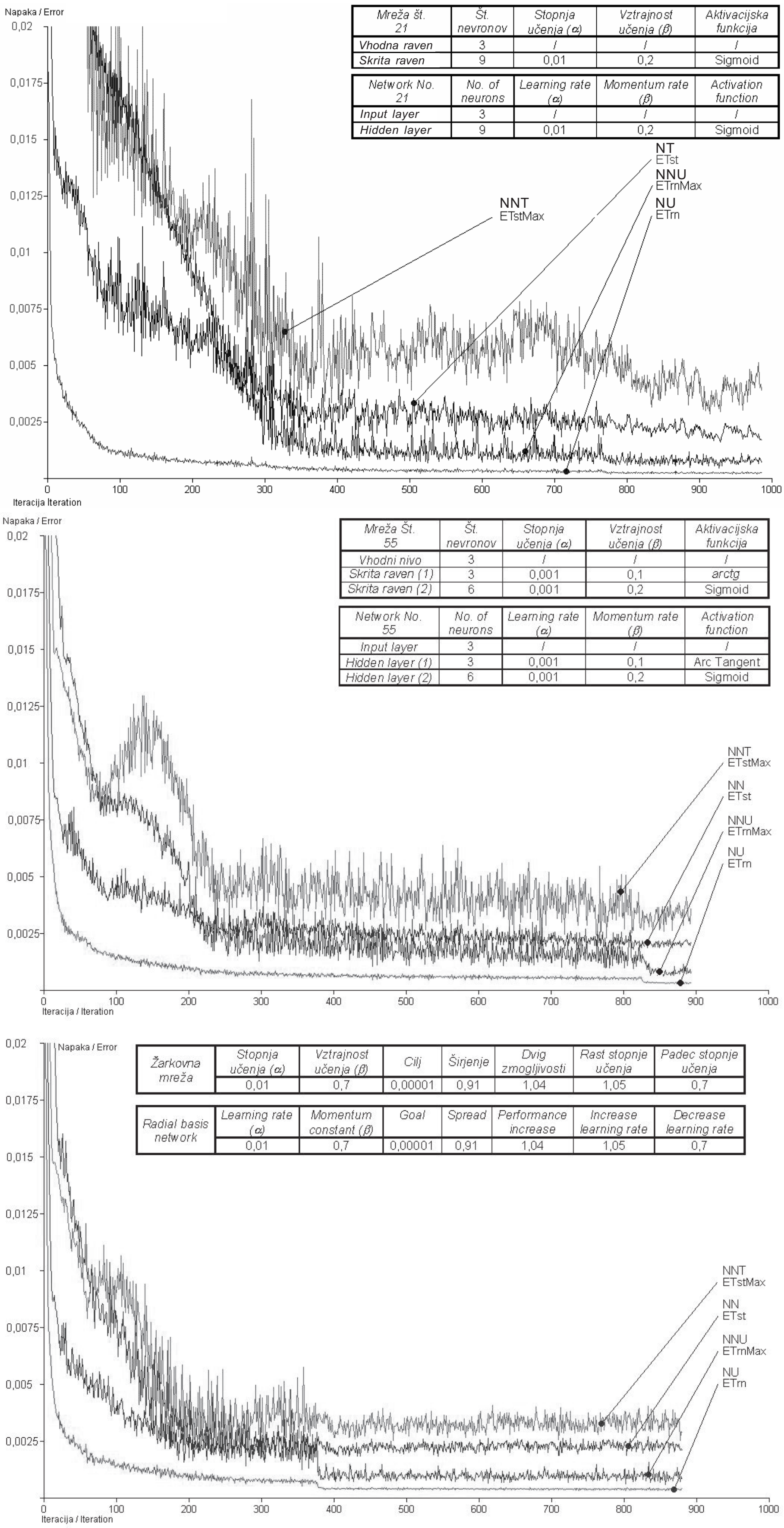
	v m/min	*f* mm/rev	*a* mm	T_p min	C_p \$	R_a µm
1.	70,3844	1,6234	3,2082	0,7925	0,3919	2,1527
2.	75,302	0,5613	3,2745	1,8324	0,7571	1,8736
3.	81,0487	0,9458	3,5282	1,0166	0,4621	2,1282
4.	72,9766	1,5974	1,4033	1,5755	0,6767	1,5997
5.	89,59	1,2261	2,9438	0,8768	0,4224	2,1102
6.	77,3172	0,2184	2,8271	5,0068	1,9761	1,6398
7.	76,7329	1,2499	3,419	0,8668	0,4137	2,1541
8.	71,4226	0,8111	1,2602	3,33	1,3376	1,2869
9.	78,3444	1,3788	1,422	1,6674	0,7104	1,5821
10.	74,9697	1,0642	1,5767	2,0003	0,831	1,4994
11.	75,1765	1,1894	1,8672	1,5469	0,661	1,633
12.	79,9521	1,742	1,205	1,5399	0,6681	1,6454
13.	71,0584	0,8159	2,3007	1,8955	0,7854	1,6123
14.	79,8531	1,5932	0,3439	5,4488	2,17	1,3258
15.	87,8129	1,6075	3,5003	0,6245	0,3497	2,4016
16.	71,5664	1,6482	2,8673	0,8454	0,4108	2,0639
17.	74,9438	0,6955	2,7845	1,755	0,7306	1,7597
18.	71,4768	0,971	0,919	3,7881	1,5172	1,2318
19.	85,0128	0,4805	3,8122	1,6294	0,6802	2,1107
20.	78,3126	0,1202	1,2983	19,0971	0,4619	1,1362

Preglednica 2. *Naključni podatki za testiranje UNM*
Table 2. *Random data for testing of an ANN*

	v m/min	*f* mm/rev	*a* mm	T_p min	C_p \$	R_a µm
21.	89,9495	0,7281	3,4458	1,1863	0,5219	2,1102
22.	74,553	1,7638	0,2244	8,0028	3,1619	1,2967
23.	82,6487	0,6876	1,2062	3,5362	1,418	1,3288
24.	74,0273	0,2431	1,806	7,2782	2,8602	1,2978
25.	73,8974	1,762	1,1272	1,7375	0,7401	1,5742
26.	87,1717	0,9584	3,3609	0,9852	0,4535	2,1335
27.	79,641	1,6031	1,7164	1,217	0,5464	1,7586
28.	76,9498	1,6444	0,9989	1,9916	0,8362	1,5227
29.	71,2062	0,1035	2,5027	12,71	4,9709	1,4469
30.	71,7795	1,648	2,9632	0,8213	0,4028	2,0959
31.	83,7713	0,1625	1,0278	16,6952	6,5277	1,1129
32.	86,8299	1,1085	1,2473	2,0882	0,8689	1,5145
33.	74,9683	1,6027	3,0694	0,7887	0,3928	2,1427
34.	86,3879	1,6548	2,8	0,8724	0,4092	2,3131
35.	84,4258	0,5777	0,2982	16,0698	6,2926	1,0234
36.	85,9883	0,9272	2,5233	1,3111	0,5716	1,8497
37.	88,8055	1,62	2,0845	0,9329	0,4491	1,9605
38.	79,7766	0,7753	1,1405	3,4408	1,382	1,3112
39.	86,8305	1,1165	1,6594	1,5993	0,6835	1,6467
40.	83,3854	1,2646	2,9355	0,9087	0,4316	2,0654

nadaljevanje postopka optimiranja. Sledi iskanje ekstrema funkcije (y), ki je simulirana z nevronsko mrežo. Vsi koraki postopka se izvedejo samodejno v dveh sekundah. V stolpcu 2 in 3 preglednice 3

continuation of the optimization process. Searching for the extreme of the function (y), simulated by neural network, then follows. All the steps of the process are executed automatically within a time of 2 sec-



Sl. 3. *Zmanjševanje napak pri nadzorovanem učenju različnih nevronskih mrež*
Fig. 3. *Decrease of errors during supervised training of different neural networks*

Preglednica 3. *Primerjava rezultatov*
Table 3. *Comparison of results*

	UČENJE / TRAINING				PRESKUŠANJE / TESTING		
	z (T_p, C_p, R_a)	y (T_p, C_p, R_a)	z - y		z (T_p, C_p, R_a)	y (T_p, C_p, R_a)	z - y
1.	0,795	0,7945	0,0005	21.	0,7456	0,7442	0,0014
2.	0,6796	0,6786	0,001	22.	0,3257	0,3255	0,0002
3.	0,7666	0,7664	0,0002	23.	0,5474	0,5467	0,0007
4.	0,7153	0,716	-0,0007	24.	0,3516	0,3499	0,0017
5.	0,7846	0,7847	-0,0001	25.	0,698	0,698	0
6.	04443	0,4443	0	26.	0,7703	0,77006	0,00024
7.	0,7853	0,78531	-0,00001	27.	0,7518	0,7502	0,0016
8.	0,5644	0,5655	-0,0011	28.	0,6731	0,6726	0,0005
9.	0,7057	0,7055	0,0002	29.	0,2161	0,216	0,0001
10.	0,6739	0,673	0,0009	30.	0,7927	0,8047	-0,012
11.	0,7179	0,7162	0,0017	31.	0,1829	0,1816	0,0013
12.	0,7172	0,7171	0,0001	32.	0,6641	0,6629	0,0012
13.	0,6813	0,6827	-0,0014	33.	0,7956	0,8146	-0,019
14.	0,4294	0,429	0,0004	34.	0,7872	0,787	0,0002
15.	0,8095	0,8107	-0,0012	35.	0,191	0,1909	0,0001
16.	0,7904	0,7905	-0,0001	36.	0,7383	0,739	-0,0007
17.	0,6913	0,6937	-0,0024	37.	0,781	0,7811	-0,0001
18.	0,5327	0,5289	0,0038	38.	0,5551	0,5532	0,0019
19.	0,6942	0,6941	0,0001	39.	0,7111	0,7122	-0,0011
20.	0,1661	0,1658	0,0003	40.	0,782	0,7808	0,0012

so prikazane po enačbi (13) izračunane vrednosti funkcije (z) ter vrednosti (y), ki jih napove UNM.

Slika 3 prikazuje monotono zmanjševanje vrednosti vseh napak *(NT, NNT, NU NNU*) s številom iteracij med postopkom učenja in preskušanja za različne konfiguracije mrež in različne učne parametre. Najmanjša napaka testiranja je dosežena blizu iteracije 830 z mrežo št. 55. Slika 3 prikazuje zgradbo najboljše nevronske mreže (št. 55).

onds. The columns 2 and 3 of Table 3 show the values of the function (z), calculated according to Equation (13), and the values (y) predicted by the ANN.

Figure 3 shows the uniform falling of the value of all errors *(ETst, ETstMax, ETrn, ETrnMax*) with the number of iterations during the training and testing process for different network configurations and different training parameters. The smallest error of testing (*ETst*) is reached near iteration 830, with network No. 55. Figure 3 shows the architecture of the best neural network (No. 55).

4 OBRAVNAVA REZULTATOV

Izvedeni so potrditveni preizkusi za ovrednotenje usmerjenih in žarkovnih nevronskih mrež. Usmerjene nevronske mreže dajo bolj natančne rezultate, vendar pa terjajo več časa za učenje in testiranje. Žarkovne mreže zahtevajo več nevronov kot standardne usmerjene nevronske mreže z učnim algoritmom vzvratnega širjenja napake (BPN), toda njihova izdelava traja le delček časa, ki je potreben za učenje usmerjene mreže. Preglednica 4 prikazuje izbrane optimalne rezalne parametre ter ustrezajoče vrednosti veličin, ki temeljijo na največjih vrednostih posredne funkcije (y), ki jo napove UNM. Prva vrstica prikazuje optimalne rezane pogoje, izračunane z matematičnim orodjem [9], druga vrstica pa rezalne pogoje, določene s postopkom UNM.

4 DISCUSSION OF RESULTS

Verification experiments are performed to evaluate feed-forward and Radial Basis networks. The Radial basis neural networks require more neurons than the standard feed-forward neural networks with the Back Propagation (BPN) Learning Rule. However, the conceiving of radial basis neural networks lasts only a part of the time necessary for the training of the feed-forward network. Table 4 shows the selected optimum cutting conditions and the corresponding values of the variables based on maximization of the implicit function (y) predicted by the ANN. The first line shows the optimal cutting conditions calculated by the mathematical tool [9], whereas the second line shows the cutting conditions determined by the ANN approach.

Preglednica 4. *Rezultati, pridobljeni z UNM*
Table 4. *Results obtained by ANN*

Model	v m/min	f mm/rev	a mm	T_p min	C_p $	R_a μm
idelana rešitev [9] ideal solution	87,01	1,8	3,6	0,576	0,341	2,46
UNM / ANN; y	86,6	1,74	3,64	0,576	0,328	2,41

Model	MRR mm^3/min	T min	F N	P kW	čas optimiranja s optimization time s
idelana rešitev ideal solution	557598,1	58,6	132,0	0,53	24
UNM / ANN; y	557581,3	60	128,6	0,56	2

Očitno je, da optimizacijski postopek, temelječ na UNM, zagotovi zadovoljiv približek k pravi optimalni rešitvi. Slika 4 prikazuje prostor rešitev, ki je omejen z določenimi omejitvami in ekstrem optimizacijske funkcije s pripadajočimi optimalnimi rezalnimi pogoji.

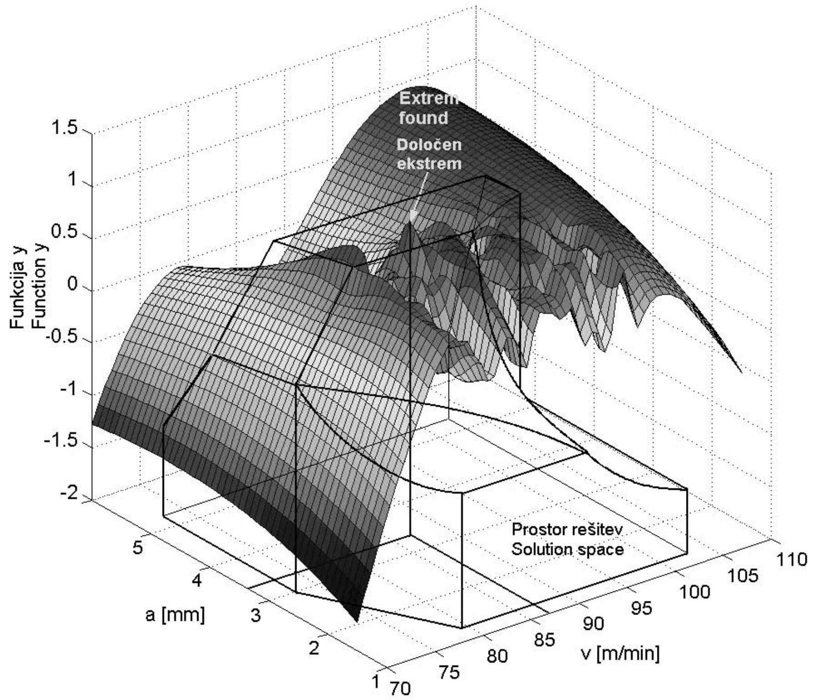
V opisanem delu uporabljena mreža (št. 55) je bila preizkušena s prej citiranimi metodami v literaturi s primerjanjem njenih rešitev z rešitvami iz [6] in [2]. Nevronski algoritem je napisan v MatLab-u 5.3 in deluje na osebnem računalniku.

V preglednici 5 so povzete glavne značilnosti teh problemov. Problem 1 je predlagan postopek z uporabo rutine UNM, ki je predstavljen v prispevku. Problem 2 predstavlja optimizacijski postopek z uporabo genetskih algoritmov. Tako parametri kakor nizi omejitev so enaki kakor v primeru 1. V problemu 3 je uporabljena tehnika LP. Na sliki 3 so prikazani

Clearly, the ANN-based optimization approach provides a sufficient approximation to the true optimal solution. Figure 4 shows the solution space limited by defined constrains and the extreme of the optimization function with relevant optimum cutting conditions.

The network (No.55) used for the work reported here was tested with the problems previously cited in the literature by comparing its solutions with those of [6] and [2]. The neural network algorithm was written in MatLab 5.3 and runs on a PC.

Table 5 summarizes the main features of these problems. Problem 1 is the proposed approach presented in this paper, using the ANN routine. Problem 2 represents the optimization approach using genetic algorithms. Both the parameters and the constraint sets are the same as in Problem 1. Problem 3 uses the LP technique. The user-specified parameters of the neural ap-



Sl. 4. *Z algoritmom UNM določen ekstrem in optimizacijska funkcija (y)*
Fig. 4. *Optimization function (y) with the extreme found by the ANN algorithm*

Preglednica 5. *Primerjava rezultatov med predlagano GA in metodo LP*
Table 5. *Comparison of the results for proposed, GA and LP aproaches*

Model	Niz omejitev Constraint set	Iteracija Iteration	Optimalna rešitev / Optimum solution v_{opt} m/min	f_{opt} mm/rev	a_{opt} mm	C_p $	Čas optimiranja s Optimiz. time s
1 UNM ANN	obstojnost; rezalna sila; moč; hrapavost površine, tool-life; cutting force [10]; power; surface roughness;	1-100 1-150 1-830 1-1300	97,1 99 86,6 86,3	1,8 1,3 1,74 1,74	3,9 2,9 3,64 3,61	0,62 0,78 0,33 0,34	0,1 0,15 2 4
2 GA [6]	obstojnost; rezalna sila; moč; hrapavost; tool-life; cutting force; power; surface raughness;	1-400 400-800 900-1300	96,9 91,5 87,01	1,8 1,8 1,7	3,1 3,3 3,5	0,69 0,44 0,4	4 8 11
3 LP [2]	rezalna sila; moč; hrapavost površine; stroški obdelave. cutting force; power; surface raughness; cutting cost	1	85	1,8	3,7	0,39	2

parametri nevronskega postopka, ki jih navede uporabnik. V našem primeru so bili po obsežnem eksperimentiranju določeni: zgradba UNM, tip napake, pravilo učenja, vhodna/prenosna funkcija, največje št iteracij, stopnja učenja, vztrajnost učenja, in metoda klasifikacije. Parametri skritih ravni in pravilo učenja so zelo občutljivi na število omejitev. Ti se nastavijo navadno takrat, ko je program naložen.

V preglednici 5 je prikazana primerjava rezultatov za primere 1, 2 in 3. Iz rezultatov primera 1, ki je predstavljen v preglednici 5, je jasno, da predlagan postopek značilno prekaša postopka GA in LP. Predlagan postopek je našel optimalno rešitev 0,33 že pri 1 do 830 iteracijah, medtem ko je pri genetskem postopku potrebno od 900 do 1300 iteracij za dosego rešitve 0,4. To pomeni, da ima predlagan postopek za 22,1% boljšo rešitev kakor postopek GA in za 17,3% boljšo rešitev kakor postopek LP.

5 SKLEP

V prispevku je opisan razvoj nevronskega optimizicijskega postopka za določevanje karakterističnih optimalnih rezalnih parametrov pri opravilih struženja. Rezultati, dobljeni s primerjanjem predlaganega postopka s tistimi iz nedavne literature, potrdijo njegovo učinkovitost. Izvedena je primerjava rezultatov nevronskega postopka z rezultati genetskih algoritmov in metodo linearnega programiranja. V vseh primerih je ugotovljeno, da se bolje obnese v smislu napovedanih vrednosti ciljne funkcije. Čeprav utegne biti modeliranje z nadzorovanim učenjem računsko intenzivno, je predlagan postopek bolj ugoden od interaktivnih postopkov, še posebej v sistemih proizvodnje za

proach are presented in Figure 3. In this case, the architecture of the ANN, the error type, the learning rule, the input/transfer function, the maximum number of iterations, the learning rate, the momentum rate and the classification method were set after extensive experimentation. The hidden-layer parameters and the learning rule are very sensitive to the number of constraints. These are normally set once the software is operational.

The comparison of the results of Problems 1, 2, and 3, respectively, are shown in Table 5. From the results of Problem 1, presented in Table 5, it is clear that the proposed approach significantly outperforms the GA and LP approach. The proposed approach found an optimal solution of 0.33 for as low as 1 to 830 runs, the genetic-based approach required as many as 900 to 1300 runs to find solution of 0.4 This means that the proposed approach has a 22.1% improvement over the solution found by the GA approach, and 17.3% over the LP approach.

5 CONCLUSION

This paper outlines the development of a neural optimization approach to determining the characteristic optimum cutting parameters for turning operations. The results obtained from comparing the proposed optimization approach with those taken from recent literature prove its effectiveness. The results of the neural approach are compared with the results of genetic algorithms and the linear-programming method. In all cases, the proposed approach is found to perform better in terms of the predicted objective function values. Although global preference modelling via supervised learning may be computationally intensive, the proposed approach is more advantageous than interactive approaches, znanega kupca, pri katerih imajo v kratkem času opravka z velikim številom različnih izdelkov. Ker lahko na nevronski mreži temelječ postopek doseže skoraj optimalno rešitev, ga je moč uporabiti za izbiro rezalnih parametrov pri zapletenih obdelovancih, ki terjajo veliko obdelovalnih omejitev. Dobri rezultati, ki jih da ta metoda, pomenijo, da je mogoče metodo vključiti v inteligentni obdelovalni sistem za avtomatizirano načrtovanje sprotnega postopka. Integracija predlaganega postopka z inteligentnim obdelovalnim sistemom bo vodila k zmanjšanju proizvodnih stroškov, zmanjšanju proizvodnih časov, k večji prilagodljivosti pri izbiri rezalnih parametrov in k izboljšanju kakovosti izdelkov.

specially for job-shop production systems, where the products mix is diverse and dynamic. Since the neural-network-based approach can obtain a near-optimal solution, it can be used for the machining-parameter selection of complex machined parts that require many machining constraints. The implication of the encouraging results obtained from the present approach is that such an approach can be integrated online with an intelligent-manufacturing system for automated process planning. The integration of the proposed approach with an intelligent-manufacturing system will lead to a reduction in the production costs, a reduction in production times, flexibility in machining-parameter selection and an improvement of product quality.

6 LITERATURA
6 REFERENCES

[1] Phillips, D.T., C.S. Beightler (1970) Optimization in tool engineering using geometric programming. *AIIE Transactions* 5(1970), 355-360.

[2] Philipson, R.H., A. Ravindram (1979) Application of mathematical programming to metal cutting. *Mathematical Programming Study* (1979), 116-13.

[3] Milfelner, M., F. Čuš (2003) Simulation of cutting forces in ball-end milling. *Robot. comput. integr. manuf.* 19(2003), 99-106.

[4] Ghiassi, M.R., E. DeVor, M.I. Dessouky, B.A. Kijowski (1984) An application of multiple criteria decision making principle for planning machining operations. *IIE Transactions* 16(1984), 106-114.

[5] Lee, B.Y., Y.S. Tarng (2000) Cutting-parameter selection for maximizing production rate or minimizing production cost in multistage turning operations. *Journal of Materials Processing Technology* 7(2000), 61-66.

[6] Čuš, F., J. Balič (2003) Optimization of cutting process by GA approach. *Robot. comput. integr. manuf.* 19(2003), 113-121.

[7] Fourie, P.C., A. Groenwold (2002) The particle swarm optimization algorithm in size and shape optimization. *Struct. Multidisc. Optim*. 23(2002), 259-267.

[8] Li, X., S. Dong, P.K. Venuvinod (2000) Hybrid learning for tool wear monitoring. *Int. Journal of Advanced Manufacturing Technology* 16(2000), 303-307.

[9] Muršec, B., F. Čuš, J. Balič (2000) Organization of tool supply and determination of cutting conditions, *J. mater. process. technol* 100(2000), 241-249.

[10] Kopač, J. (2002) Rezalne sile in njihov vpliv na gospodarnost obdelave (Cutting forces and their influence on the economics of machining). *Stroj. vestn*. 3(2002), 121-132.

Naslov avtorjev: mag. Uroš Župerl
prof.dr. Franci Čuš
Univerza v Mariboru
Fakulteta za strojništvo
Smetanova 17
2000 Maribor
uros.zuperl@uni-mb.si

Authors' Address: Mag. Uroš Župerl
Prof.Dr. Franci Čuš
University of Maribor
Faculty of Mechanical Eng.
Smetanova 17
2000 Maribor, Slovenia
uros.zuperl@uni-mb.si

Prejeto:
Received: 29.7.2003

Sprejeto:
Accepted: 8.4.2004

Odprto za diskusijo: 1 leto
Open for discussion: 1 year