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Razvoj sistema za nadzor obrabe orodja pri struženju na temelju nevronskih mrež

Development of a Neural-Networks Tool-Wear Monitoring System for a Turning Process

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Prispevek podaja rezultate razvoja sistema za nadzor obrabe orodja pri struženju v trdo, v laboratorijskih razmerah, z uporabo sodobnih metod umetne inteligence kakor so nevronske mreže. Eden od najbolj pomembnih dejavnikov, ki vplivajo na zanesljivost postopka struženja, je stanje orodja, zato je sistem za spremljanje stanja orodja razvit tako za laboratorijske kakor tudi razmere v praksi. Prispevek prikazuje raziskave, povezane z izbiro metod in strategije za določanje obrabe orodja po struženju, na podlagi serije laboratorijskih preizkusov. Nadzor stanja orodja je izvajan po posredni metodi na podlagi merjenja rezalnih sil, ki so najboljši pokazatelj stanja orodja med delovanjem, kombinirano z nevronskimi mrežami. Prav tako je predstavljena topologija nevronske mreže, uporabljene za struženje.

(Ključne besede: nadzor orodij, obraba orodij, struženje, sile rezanja, mreže nevronske)

This paper presents the results of developing a tool-wear monitoring system for hard turning in laboratory conditions. The system is based on modern artificial intelligence methods such as neural networks (NNs). One of the most dominant factors influencing the reliability of the turning process is the condition of the tool; thus, systems for monitoring tool conditions have been developed both in practice and in the laboratory. The paper describes research connected to the selection of methods and strategies for determining the tool-wear condition after turning on the basis of a set laboratory system model. The tool monitoring is performed by an indirect method on the basis of cutting force as one of best determiners of tool condition in the online working regime, combined with one of the artificial intelligence methods, i.e. neural networks. The paper also presents the topology of the neural network used for the training.

(Keywords: tool wear monitoring, turning, cutting forces, neural networks)

0 UVOD

Sodobni postopki izdelave zahtevajo zmanjševanje stroškov, ki pa jih lahko uresničimo takole: z ostrejšimi rezalnimi pogoji, s krajšimi časi izdelave in zmanjšanjem izmečka. Da bi vse to izpolnili v različnih izdelovalnih postopkih, je treba skrajno izkoristiti orodja in stroje. Stanje orodja med delom močno vpliva na zmanjšanje izmečka in zastojev v proizvodnji, ki se lahko vidijo neposredno skozi geometrijske, površinske in strukturne lastnosti obdelanih delov.

Povečevanje rezalnih sil je neposredno povezano z obrabo uporabljenega orodja, kar vodi k povečanju toplote in zato do sprememb strukture

0 INTRODUCTION

Modern procedures for part manufacturing impose cost reductions that can be realized in the following ways: increasing the turning regime, reducing the manufacturing time, and reducing the number of rejects. In order to accomplish this in various processing procedures, extreme efforts from tools and machines are required. The condition of the processing tool is very influential on reducing rejects and hold ups in manufacturing, which can directly be seen through the geometric, surface and structural properties and the characteristics of the processed part.

The increase in the cutting forces is directly linked to the wear condition of a processing tool, which obdelane površine in izmer obdelovanca. Ustrezen čas zamenjave orodja pomeni zelo pomembno sestavino v postopku obdelave, zato bo temu, na primeru struženja, posvečena posebna pozornost v tem prispevku. Številni avtorji so upoštevali mehanizme, ki vplivajo na pojav obrabe orodja pri struženju. Na primer Scheffer idr. [1] verjamejo da obstajata dve glavni značilnici, ki vplivata na zanesljivost pri struženju: rezalna hitrost in vrednost rezalne sile, ki se pojavi pri struženju. Raziskovalci, ki se ukvarjajo s to tematiko, so pokazali da, z vidika pričakovanja največje obstojnosti, večje spremembe hitrosti in rezalne sile niso dovoljene.

Iz izkušenj je znano, da obraba na prosti ploskvi neposredno vpliva na kakovost obdelane površine ter, da na porušitev rezalnega robu vpliva kotanjasta obraba cepilne ploskve, ki nastaja zaradi kemičnih, difuzijskih pojavov med rezanjem. Izkušnje govorijo tudi, da pojav obrabe orodja poteka nepretrgano in postopno, zato lahko določimo stopnjo obrabe orodja, ker pa se porušitev orodja pojavi trenutno, je izjemnega pomena nepretrgan nadzor orodja za zaznavo porušitve in pravočasno odzivanje. Sklenemo lahko, da druge metode uporabimo za nadzor porušitve orodja in navzkrižje v povezavi z nadzorom obrabe orodja.

0.1 Nadzor obrabe orodja

Sistemi za nadzor obrabe orodja tako stare kakor tudi nove generacije kot merno veličino uporabljajo postopkovne parametre, ki so posredno povezani z obrabo orodja in so lahko: sile ali vibracije, zvočna emisija (ZE) ipd. Na postopek tudi vplivajo razmere, pri katerih ta poteka, kot npr. geometrijska oblika orodja, material orodja in obdelovanca ipd. Za modeliranje nelinearnih odvisnosti, ki se lahko izločijo iz merilnih signalov postopkovnih razmer, obrabe orodja ali porušitve orodja se uporablja nevronske mreže, sisteme mehke logike ali kombinacijo obeh metod. Balazinski idr. [2] so dognali, da se inteligentne nevronske mreže in nevronske mehke tehnike močno preučujejo in pomenijo najbolj izbirano inteligenčno mrežo metod (umetna inteligenca - UI) za spojitev nadzorovanih značilnosti. Vendar, pri tržno dosegljivih sistemih prevladuje pristop "eno zaznavalo/eno orodje v postopku" in je uporaba metod UI redkokdaj uporabljana. V svojem preglednem članku Siek [3] trdi, da se je v preteklem času večina raziskovalcev ukvarjala z nalogami določanja obrabe ali porušitve. Obraba orodja je pojem, ki ni enotno definiran in ga je

leads to a heat increase and hence to a structure change of the processed surface of the workpiece and its dimensions. Timely and appropriate tool replacement represents a very important component in processing, and therefore in turning, to which significant attention will be given in this paper. Many authors have considered mechanisms influencing the tool-wear process during turning. For example, Scheffer et al. [1] believe there are two principal characteristics influencing the reliability of turning: cutting speed and the value of the force appearing during turning. Research dealing with this topic has shown that, from the point of view of the optimum tool-life expectancy, large variations in speed and cutting force are not allowed.

Based on experience, it is known that flank wear directly influences the quality of the processed surface, and that insert breakage is influenced by crater wear appearing because of a diffusion chemical reaction during processing. Experience says that the tool-wear process moves on continually and gradually, i.e., that the insert wear degree can be determined and one can react in time, while the breakage comes suddenly and continuous tool monitoring is essential for breakage detection. The conclusion is that other methods can be used for tool-breakage monitoring and collisions in relation to tool-wear monitoring.

0.1 Monitoring of tool wear

Systems for monitoring tool wear, both old and new generation, use process parameters that are indirectly linked to tool wear, i.e., force or vibration, acoustic emissions (AEs), etc. The process is also influenced by conditions under which the processing is taking place, like tool geometry, tool material and product, etc. For modelling non-linear dependencies that are separated from the measuring signal, processing conditions, tool wear or tool breakage, neural networks, fuzzy logic systems or a combination of both methods are used. Balazinski et al. [2] state that intelligent neural networks and neural fuzzy techniques are intensively studied and they present the most selected intelligence network (artificial inteligence - AI) methods for merging the monitored properties. However, with commercially available systems, the approach "one sensor/one tool per process" is dominant, and the application of the AI method can rarely be found. In his survey paper, Siek [3] established that, in the previous period, most researchers elaborated on the tasks of classifying wear or breakage. Tool wear is a term not uniformly defined and it has to be defined clearly before stating the treba jasno definirati pred izvajanjem nadzora. Porušitev orodja je vedno definirana in določena kot dve stanji: porušeno ali neporušeno (orodje). Določitev obrabe orodja mora uporabljati več ko dve stanji, da je mogoče nepretrgana ocena razmer pri obrabi ([4] in [5]).

Parametri za definiranje obrabe so povprečna in največja širina obrabe proste ploskve, pa tudi globina, dolžina in širina kotanje na cepilni ploskvi. Merilo, ki naj bi enolično definiralo obrabo, mora biti stalno, da bo predstavljalo stanje obrabe orodja. Če je obraba definirana v dveh skupinah (širina obrabe), to postane pogosto problem - lahko prepoznamo samo nova ter izrazito obrabljena orodja. Za nadziranje obrabe v praksi je treba postaviti več skupin obrabe, ki so praktično zelo obetajoča strategija nadzora. Lahko rečemo, da je obraba nepretrgan in monotono naraščajoči postopek, zato naj bi za nepretrgano ocenjevanje bilo najbolj ustrezno fizikalno postopanje.

Zadnja leta je opazno izrazito delo na uporabi metode umetne inteligence (UI) pri nadzoru obrabe orodja. Tako Balazinski idr. [2] primerjajo uporabo treh metod UI: nevronsko mrežo z veriženjem naprej, mehki sistem za podporo odločanju ter mehki sklepni sistem, ki temelji na umetni nevronski mreži. Žarišče ni samo na natančnosti napovedi obrabe orodja, temveč tudi na praktični uporabnosti predstavljenih metod. Ozel in Nadgir [6] predlagata uporabo nevronskih mrež za učenje z vzvratnim razširjanjem napake, za napovedovanje obrabe proste ploskve pri struženju v trdo. Merjenje sil, nastalih v rezalnih postopkih, je izvedeno z dinamometrom, ki omogoča merjenje treh komponent sile.

V tem primeru sta razmerje sil in razmere v postopku vključeni kot značilnosti vstopne ravni nevronske mreže; skrita raven ima 30 nevronov, izstopna raven pa sestoji iz osem nevronov, ki so bili binarna ponazoritev eksperimentalno merjene obrabe proste ploskve oziroma osem značilnic razmer pri obrabi orodja. Za napoved obrabe proste ploskve so bili zajeti dobri rezultati z uporabo te metode nevronske mreže.

Kothamasu in Huang [7] ter Scheffer idr. ([1] in [8]) tudi predlagajo drugo metodo, ki temelji na kombinaciji statičnih in dinamičnih nevronskih mrež.

1 PREDLOG MODELA SISTEMA ZA NADZOR

Predlagani model sistema za nadzor orodja je lahko v bistvu opazovan skozi štiri sklope

monitoring task. Tool breakage is always defined and classified by two states, broken or not broken. The tool-wear classification has to use more than two tool states, i.e., it should be a continual evaluation of the wear condition ([4] and [5]).

The parameters defining wear are the average and maximum width of the flank wear, as well as the depth, length and widths of the crater wear. Criteria that should define wear as uniform need to be fixed in order to present the state of the tool wear. If wear is defined in two groups (wear width), it becomes quite wide and one can recognize only new and significantly worn tools. To monitor wear in practice, it is necessary to establish several wear groups, which in practise represents a very promising monitoring strategy. It can be said that wear is a continual and monotonously increasing process; therefore, continual evaluation would suit the physical processing most appropriately.

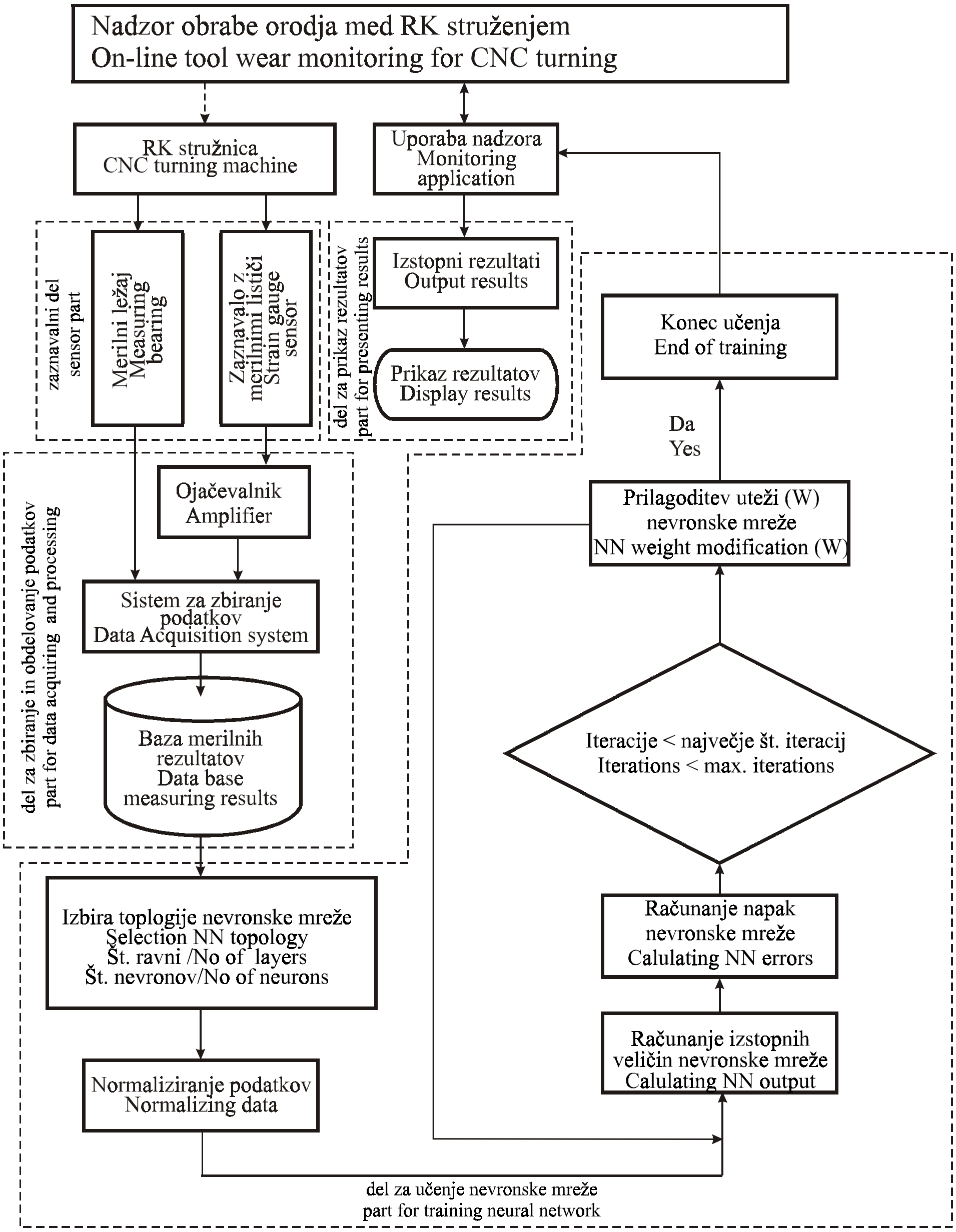
Recent years have seen intensive work to apply the artificial intelligence (AI) method for monitoring tool wear. Thus, Balazinski et al. [2] compare the application of three AI methods: a feed-forward back-propagation (FF-BP) neural network, a fuzzy-decision support system (FDSS) and an artificial-neural-network-based fuzzy-inference system (ANNBFIS). The focus is not only on the accuracy of the tool wear prediction, but also on the practical usability of the presented methods. Ozel and Nadgir [6] propose the use of back-propagation neural networks for predicting flank wear during hard turning. Force-measuring tests that appear during the cutting processes are performed using a dynamometer that could measure three force components.

In this case, the force ratio and the processing conditions are included as a characteristic of the neural-network input layer; the hidden layer had 30 neurons, and the output layer consisted of 8 neurons, which was a binary representation of the experimentally measured flank wear, i.e., 8 condition characteristics of tool wear. For flank-wear predictions, good results were acquired using this neural-network method.

Kothamasu and Huang [7] and Scheffer et al. ([1] and [8]) also propose another method based on a combination of static and dynamic neural networks.

1 PROPOSAL FOR A MONITORING SYSTEM MODEL

The proposed tool-monitoring system model can basically be observed through four segments



Sl. 1. *Potek razvitega sistema nadzora orodja, ki temelji na nevronskih mrežah*
Fig. 1. *Algorithm of the developed tool-monitoring system based on neural networks*

sestavljene v celoto, ki uporablja nevronsko mrežo za učenje z vzvratnim razširjanjem napake in je povezana s krmilno enoto stroja, kot je prikazano na sliki 1.

Posebni sklopi sistema so:

- zaznavalni del,
- del za zbiranje, obdelovanje in analizo podatkov,
- del za učenje nevronske mreže,
- del za predstavitev rezultatov.

united in a whole, i.e., using back propagation, connected with the machine-managing unit, as shown in Figure 1.

The special segments of the system are:

- the sensor part,
- the part for data acquisition, processing and analyzing,
- the part for training the neural network,
- the part for presenting the results.

Zaznavalni del obdelovalnega stroja je narejen iz merilnega ležaja, ki je nameščen na sprednjem delu glavnega vretena stroja. Poleg merilnega ležaja je tukaj tudi drugo zaznavalo, ki deluje na načelu merilnih lističev, nameščenih na uporabljeno držalo orodja in posebno oblikovanih za ta primer merjenja rezalnih sil, ki se pojavljajo na tem orodju.

Del za zbiranje, obdelovanje in analizo podatkov vsebuje standardno kartico A/D ED 300, ki sprejema vstopne podatke iz sedanjih zaznaval, pretvarja jih v digitalne informacije ter pošilja v računalnik z bazo podatkov. Za tok informacij je odgovorna programska oprema, imenovana ED LINK, ki dopušča možnost programiranja hitrosti prenosa in vrsto vstopnih podatkov ([9] do [11]).

Nevronska mreža, vgrajena v obravnavni sistem je mreža z več ravnmi zaznavanja, z razširjanjem signala v eni smeri in je ena od najbolj znanih vrst nepovratnih mrež (brez povratnih zvez). Mreža ima tri ravni: vstopna ravnina vsebuje tri nevrone, vmesna skrita ravnina vsebuje m nevronov, izstopna ravnina ima en nevron.

Sistem programske opreme je oblikovan, da zbira in obdeluje informacije med delovanjem in upravlja delovanje komponent strojne opreme, zato lahko temelji na seriji omejitev za izvajanje nadzora obrabe orodja. Za določitev stopnje obrabe orodja lahko uporabimo primerjalno analizo krivulj obrabe, dobljenih pri sistemu učenja z uporabo nevronskih mrež. Določanje preostalega časa obstojnosti orodja temelji na podlagi razvoja obrabe, pridobljenega s primerjalno analizo krivulje obrabe in realnih razmer.

2 NEVRONSKA MREŽA ZA NADZOR OBRABE ORODJA

2.1 Predhodna obdelava in učenje

Kakor je že navedeno, ima nevronska mreža tri vstope, ki usmerjajo vrednosti iz zaznavala na nosilniku orodja, izmerjene velikosti sil iz merilnega ležaja in rezalne hitrosti. Z uporabo teh treh vrednosti nevronska mreža na izstopu določa vrednost obrabe proste ploskve VB v istem trenutku.

Za potrebe postopka učenja je bila oblikovana serija, ki vsebuje 30.900 vstopnih vektorjev in enako število natančnih vrednosti izstopnih spremenljivk. Pri oblikovanju serije je bila posebna pozornost posvečena predstavniškim

The sensor part of the machine tool is made of a measuring bearing placed in the front bed of the machine tool's main spindle. In addition to the measuring bearing, there is also another sensor working on the principle of a measuring strain gauge, placed on the processing tool holder and designed specially for this case, for measuring the cutting forces appearing on the tool itself.

The part for data acquisition, processing and analyzing contains a standard A/D card ED 300, which receives input data from the existing sensors, converts them to digital information, and sends them to a computer database. For information flow, the composite software named ED LINK is responsible, allowing the possibility for programming the conditioning speed and the type of input data ([9] to [11]).

The neural network built into the system is a multi-layer perception network with signal spreading in one direction (feed-forward topology), and one of the best-known types of feed-forward neural networks. The network has three layers: the input layer contains three neurons, the intermediate hidden layer contains m neurons, and the output layer has one neuron.

The software system is designed to acquire and process the information in an online work regime and to manage the work of hardware components, so it can be based on set limitations for the monitor processing and the tool wear. To establish the degree of tool wear we can utilize comparative analysis of the wear curves obtained by system training using neural networks. Determining the leftover tool duration is set on the basis of the wear trend gained by a comparative analysis with the wear curve and real conditions.

2 NEURAL NETWORK FOR TOOL-WEAR MONITORING

2.1 Pre-processing and training set

As already stated, the neural network has three inputs to which the force values from the sensor on the tool holder, the measured force size from the measuring bearing, and the cutting speed are directed. Using these three values, the neural network at its output evaluates the values of flank wear VB in the same time moment.

For the requirements of the training process, a set was formed containing 30,900 input vectors and the same number of precise values of output variable. In creating the set, special attention was podatkom, tako da so izbrani podatki pokrili celotno območje mogočih vrednosti vstopnih parametrov in ustrezali dejanskim spremembam razmer. Serija za učenje je oblikovana tako, da zagotovi, da nevronska mreža pravilno oceni odvisnost vstopnih vrednosti in izstopne spremenljivke na celotnem območju vstopnih veličin.

Zato da bi imeli učinkovito učenje so bile vse veličine v seriji za učenje poprej normalizirane. Normaliziranje je bilo izvedeno tako, da je vsaka vstopna in izstopna veličina v seriji za učenje imela povprečno vrednost enako nič in je bil standardni odmik omejen na enotno vrednost. Za i-to vrednost vstopnega vektorja, iz spremenljivk, zaznanih z merilnim ležajem FRprom, lahko zapišemo enačbo za normalizacijo v naslednji obliki:

given to data representatives, i.e., data were selected to cover all the intervals of possible values of input variables and to be appropriate for the real change conditions. The training set formed in such a manner ensured that the neural network correctly approximated the dependence of input values and output variables on the whole range of input sizes.

In order to have efficient training, all the sizes in the training set were previously normalized. Normalization was performed in such a way that every input and output size in the training set had an average value equal to zero, and a standard deviation reduced to the unit value. For the i-th value of the input vector from the variable registered by the measuring bearing FRprom, normalization formula can be written in the following way:

$$\hat{p}_i = \frac{p_i - p_{sr}}{s_p} \tag{1}$$

kjer je:

where:

$$p_{sr} = \frac{1}{N}\sum_{i=1}^{N} p_i \tag{2}$$

srednja vrednost in:

is an average value, and:

$$s_p = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(p_i - p_{sr})^2} \tag{3}$$

standardni odmik vstopnega vektorja, določenega prek celotne serije za učenje (N = 30.900). Enačbe za preostale spremenljivke v seriji za učenje bi lahko zapisali podobno.

Pred postopkom učenja, ne glede na normaliziranje podatkov, je bilo treba izpeljati izbiro topologije nevronske mreže. Ker so vrednosti izstopne spremenljivke VB odvisne edino od trenutnih vrednosti vstopnih spremenljivk, je bila večravenska zaznavna mreža z razširjanjem signala v eni smeri izbrana kot topologija mreže. Poleg tega teorija navaja, da je funkcija, ki jo mora nevronska mreža oceniti, izrazito nelinearna; zato je bila za prožilno funkcijo nevronov v skriti ravnini izbrana sigmasta funkcija ([12] in [13]):

is a standard deviation of the promess variable input vector defined over the whole training set (N = 30,900). The formulas for other variables in the training set can be written similarly.

Before the training process, apart from data normalization, it was necessary to select the neural-network topology. Since the values of the output variable VB depend solely on the momentary values of the input variables, a multi-layer perception network with a signal spreading in one direction (feed-forward topology) was selected for the network topology. In addition, the theory stated that the function that the resultant neural network had to approximate was distinctly non-linear; hence, for the output function of the neurons in the hidden layer a sigmoid function ([12] and [13]) was selected:

$$y(net_i) = \frac{2}{1+e^{-net_i}} - 1 \tag{4}$$

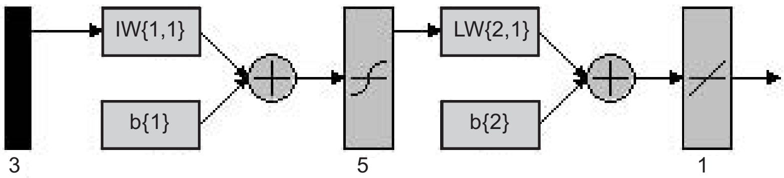
kjer je:

where:

$$net_i = \sum_{j=1}^{M} w_{ji}x_j - b_i, \tag{5}$$

vsota vrednosti vstopne mreže, pomnožena z ustreznimi koeficienti uteži nevrona.

is the sum of the input network sizes multiplied by the appropriate neuron weight coefficients.



Sl. 2. *Topologija nevronske mreže*
Fig. 2. *Neural-network topology*

Uporabljena mreža ima tri ravni: vstopno, skrito in izstopno, kar je prikazano na sliki 2; predstavlja zadostno število ravni za problem, ki ga obravnava, upoštevajoč dejstvo, da več ravensko zaznavanje z eno skrito ravnino lahko oceni poljubno dejansko zvezno funkcijo.

V vstopni kakor tudi izstopni ravnini je bilo število nevronov določeno s številom vstopnih veličin, tako je vstopna ravnina vsebovala tri nevrone, ki ustrezajo vstopnim spremenljivkam (FRtool, FRprom, Vm/min), izstopna ravnina pa je vsebovala en nevron, katerega izstopna veličina je imela vrednost ocenjene velikosti obrabe proste ploskve VB.

Število nevronov v skriti ravnini je bilo določeno s preizkusi, s primerjanjem lastnosti mreže z različnimi števili nevronov v skriti ravnini. Med preizkusi je bila mreža testirana z dvema do sedmimi nevroni v skriti ravnini in za vsako topologijo so bile izvedene številne ponovitve z enakimi serijami za učenje mreže, tako da so bile značilnosti vsake topologije določene kar se da primerno. Mreže z majhnim številom nevronov (dvema ali tremi nevroni) v skriti ravnini niso pokazale zadovoljivih rezultatov, kar bi lahko pripisali nezadostno bogati strukturi mreže in kar kaže na majhno zmožnost funkcije približevanja. Mreže s petimi ali več nevroni v skriti ravnini se zadovoljivo približajo odvisnosti razmerja med vstopnimi in izstopnimi veličinami, tako da je neka od teh topologij ustrezna za uporabo. Pri izbiri končne topologije je bila upoštevana splošna usmeritev, ki pravi, da naj bi bilo končno število nevronov v nevronski mreži čim manjše. S tem povečamo zmožnosti posploševanja mreže in se izognemo pojavu pretirane zahtevnosti. Ob upoštevanju omenjenih dejstev je bila izbrana kot dokončna struktura mreža s petimi nevroni v skriti ravnini.

Učenje nevronske mreže je bilo opravljeno s prožno spremembo osnovnega algoritma za učenje z vzvratnim razširjanjem napake, ki je bil oblikovan za nevronsko mrežo z drobljenjem prožilne funkcije, ki

The network used, as already said, had three layers: input, hidden and output, as shown in Figure 2; it presented a sufficient number of layers for the problem under observation, considering the fact that the multi-layer perception with one hidden layer could, with arbitrary accuracy 0, uniformly approximate any real continual function on the real final axis.

In the input as well as the output layer, the number of neurons was determined by the number of inputs, i.e., outputs, so that the input layer contained three neurons that corresponded to the input variables (FRtool, FRprom, Vm/min), and the output layer contained one neuron whose output gave the value of the estimated size of the flank wear VB.

The number of neurons in the hidden layer was determined by experiments comparing the network performances with a different number of neurons in the hidden layer. During the experiment, networks were tested with two to seven neurons in the hidden layer, and for every topology several trainings with the same training set were performed so that the performances of every topology could be estimated as objectively as possible. Networks with a small number of neurons (two and three neurons) in the hidden layer did not present satisfactory results, which can be attributed to an insufficiently rich network structure that implied a small capacity for the function approximation. Networks with five or more neurons in the hidden layer successfully approximated the input-output dependence, so any of those topologies was appropriate for implementation. In selecting the final topology, a general direction was used, saying that the total number of neurons in the neural network should be as small as possible, since in that way the generalization network abilities were increasing and the appearance of "over fitting" was avoided. Considering all the above mentioned, a network with five neurons in the hidden layer was selected for the final network structure.

Training of the ANN was performed with a "resilient" modification of the basic back-propagation algorithm that was designed for an ANN with skrči neskončno področje vstopne veličine v končni korak izstopne veličine (npr. sigmasta funkcija). Te funkcije bi lahko povzročale težave pri uporabi osnovnega algoritma za učenje z vzvratnim razširjanjem napake, ker ima gradient lahko zelo majhno vrednost in zaradi tega povzroča majhne spremembe pri utežnih koeficientih, ki vodijo k dolgem učenju. Zato je prožni algoritem uporabljen samo za označevanje delnih sklepov, da bi določili smer sprememb utežnih koeficientov, medtem ko je bila velikost spremembe določena s posebnim parametrom, čigar vrednost je bila med učenjem spreminjana po posebnem algoritmu ([14] in [15]).

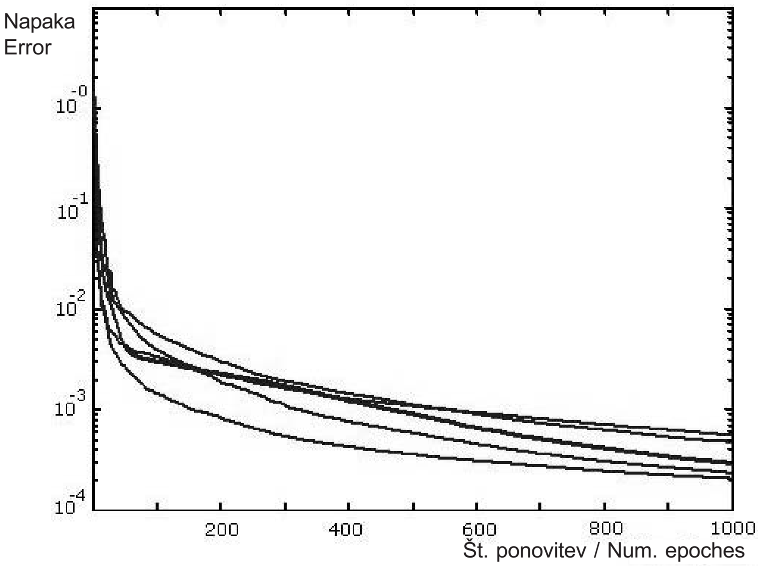
Končna topologija nevronske mreže je bila urjena večkrat z enako serijo za učenje, vsakokrat z novo, naključno ustvarjeno začetno vrednostjo utežnih koeficientov (sl. 3). Za največjo vrednost ponovitev je bilo vzeto število 1.000, ker je bilo ugotovljeno, da naslednje ponovitve niso znižale napake nevronske mreže pri neki značilni vrednosti. Vsako učenje nevronske mreže se konča z vmesno kvadratno napako (izračunano čez celotno serijo za učenje) v območju med 10^{-3} in 10^{-4}. Ta napaka je bila izračunana z normaliziranimi podatki; da bi torej dobili dejansko vrednost vmesne kvadratne napake je bilo treba pomnožiti dobljeno vrednost z vrednostjo standardnega odmika obrabe proste ploskve VB.

Pri seriji za učenje je imel standardni odmik obrabe proste ploskve vrednost 0,0013, dejanska vrednost vmesne kvadratne napake pa je bila med 10^{-6} in 10^{-7}.

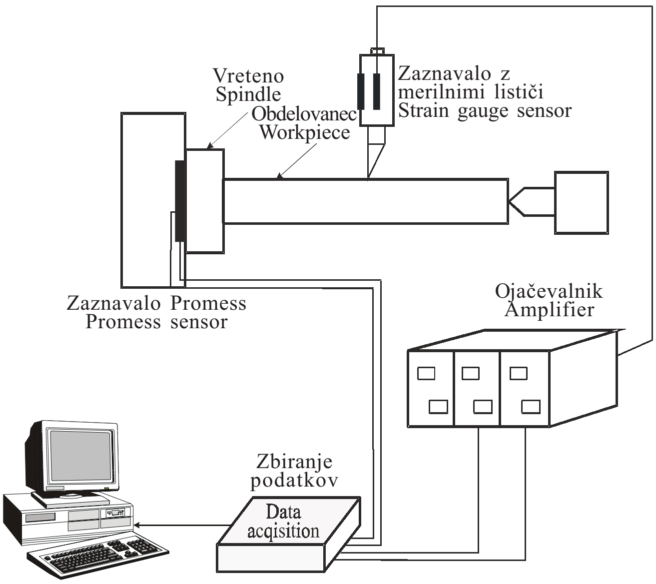
"squashing" activation functions, i.e., functions that compress the infinite input area into the final output interval (like a sigmoid function). These functions could cause a problem while using the basic back-propagation algorithm, since the gradient could have very small values and therefore cause small changes in the weight coefficients, which led to long-term training. Thus, the "resilient" algorithm utilized only the sign of partial inference in order to determine the direction of the weight-coefficient changes, while the change size was determined by a special parameter whose value was, during the training, changed, following the special algorithm ([14] and [15]).

The neural network's final topology was trained several times with the same training set, but each time with the new, randomly generated, initial values of the weight coefficients (Fig. 3). For the maximum value of iterations, the value 1,000 was adopted, since it was noticed that in the later iterations the neural-network error was not reduced by any significant value. Each neural-network training finished with an intermediate square error (calculated over the entire training set) in the interval between 10^{-3} and 10^{-4}. This error was calculated with the normalized data; so, to get a real value of the intermediate square error it was necessary to multiply the gained value by the value of the standard deviation of the flank wear VB.

On our training set, the standard deviation of flank wear had the value 0.0013, so the real value of the intermediate square error was between 10^{-6} and 10^{-7}.



Sl. 3. *Sprememba vmesne kvadratne napake med učenjem nevronske mreže*
Fig. 3. *The change of intermediate square error during neural-network training*



Sl. 4. *Osnovna zgradba eksperimentalnega merilnega sistema*
Fig. 4. *Basic configuration of the experimental measuring set-up*

3 IZVEDBA PREIZKUSOV

Parametri rezanja so bili izbrani tako, da so ustrezali industrijskim razmeram v realni proizvodnji. Parametri stroja za posamezni preizkus so podani v preglednici 1. Preizkusi so bili ponavljani v enakih razmerah kakor pri učenju,

3 EXPERIMENTAL SET-UP

The machine parameters were selected in order to respond to an industrial application in real manufacturing. The machine-tool conditions for every experiment are presented in Table 1. The experiments were repeated under the same conditions for the

Preglednica 1. *Eksperimentalni parametri*
Table 1. *Experimental parameters*

	Preiz. 1 Exp. 1	**Preiz. 2 Exp. 2**	**...**	**Preiz. 10 Exp. 10**
Obdelovalni stroj Machine tool	INDEX GU 600			
Držalo orodja Tool holder	PTGNL 25x25			
Ploščice Inserts	TNMG 220408			
Globina rezanja [mm] Cutting depth [mm]	1 mm			
Rezalna hitrost [m/min] Cutting speed [m/min]	200			
Material obdelovanca Workpiece material	Č.4730			
Število prehodov Number of passing	110	132	...	112
Skupni čas [min] Total time [min]	36	43	...	37
Premer [mm] Diameter [mm]	60	60	...	60
Dolžina prehoda [mm] Passing length [mm]	10	10	...	15

vrednotenju in urjenju modela nevronske mreže. V bistvu sta spreminjani rezalna hitrost in število učenj mreže. Bilo je skupno deset preizkusov, vsi so potekali z enako osnovno izoblikovanostjo. Vendar je bilo nekaj razmer pri preizkusih spreminjanih, da bi izločili motnje in ugotovili lastnosti ustreznega nadzorovanega signala. Posebna pozornost je bila na zagotavljanju, da so vse razmere pri preizkusih enake razen parametrov, ki so bili spreminjani nadzorovano. Osnovna izoblikovanost merilnega sistema pri preizkusih je prikazana na sliki 4 in sestoji iz RK stružniceopremljene z zaznavali za merjenje rezalne sile - zaznavalo Promess in posebej oblikovano zaznavalo z merilnimi lističi, pritrjenimi na držalo orodja.

possibilities of training, verifying and testing the neural-network model. Basically, the cutting speed and training number varied. There were ten experiments in total, all of them with the same basic configuration. However, some of the experimental conditions were changed to isolate disturbances and identify the properties of an appropriate monitoring signal. There was a special focus on ensuring that all the experimental conditions remained the same, except for the parameters that were changed under control. The basic configuration of the experimental measuring set-up is shown in Figure 4, and it contains a CNC lathe equipped with sensors for measuring the cutting force, those being: a promess sensor and a specially designed sensor with a measuring strain gauge placed on the tool holder.

4 REZULTATI

Izbrani model se je pokazal kot zanesljiva metoda za nadzor obrabe orodja med struženjem v trdo. Med raziskavo je bilo uporabljeno in preštudirano nekaj različnih izoblikovanj mrež za njihovo uporabo pri nadzoru obrabe orodja.

Poznano je, da so statične rezalne sile dober kazalnik obrabe orodja, vendar ustrezna analiza dinamičnih rezalnih sil lahko tudi poda zadovoljive značilnosti za nadzor obrabe. Slika 5 prikazuje komponente rezalne sile, izmerjene med nadzorom obrabe orodja.

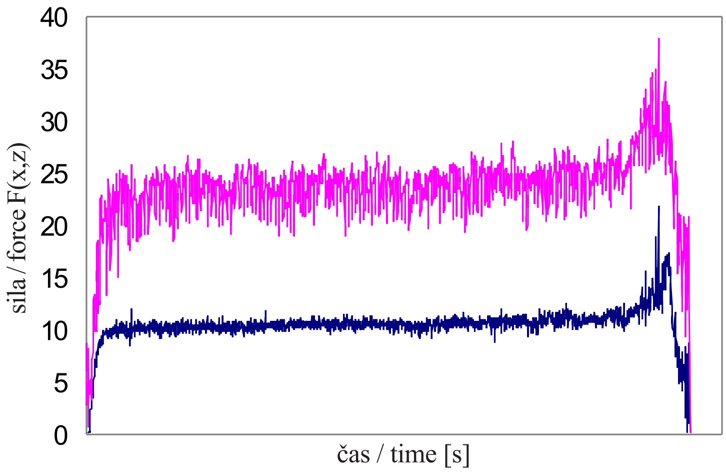
Obraba orodja (VB) je bila izmerjena po vsakem prehodu in vrednost vnesena v preglednico. Merjenje obrabe je bilo izvedeno z orodjarskim mikroskopom s 30-kratno povečavo. Rezalne ploščice, uporabljene pri preizkusih, so

4 RESULTS

The selected appropriate model was established to be a relatively reliable method for monitoring the tool wear during hard turning. During the research, several different network configurations were used and studied for their application in monitoring tool wear during hard turning.

It is known that static cutting forces are good tool-wear indicators; however, adequate dynamic analysis of the cutting forces can also give satisfactory properties for wear monitoring. Figure 5 presents the cutting-force components measured during tool-wear monitoring.

The tool wear (VB) was measured after each turning and the value suiting one passing was linearly put into the table. The wear measuring was performed using a Tool microscope with a 30 times magnification.



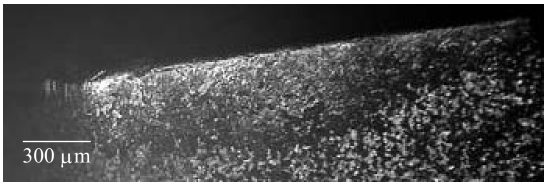
Sl. 5. *Rezalne sile, izmerjene med nadzorom*
Fig. 5. *Cutting forces measured during monitoring*

bile prekrite s prevleko iz TiN. Njihova pričakovana obstojnost se je nagibala k nenadnemu koncu, potem ko je prevleka izginila z rezalnega robu, kar naj bi bilo razvidno iz naglega in nenadnega skoka rezalne sile. Slika 6 kaže videz obrabljenih ploščic med izvajanjem preizkusov: a) ploščica iz preizkusa 1, b) ploščica iz preizkusa 3, c) ploščica iz preizkusa 5.

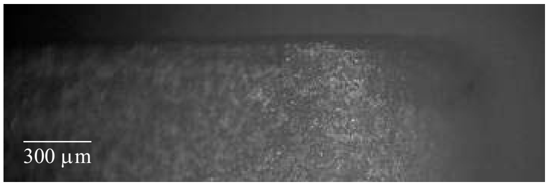
Slika 7 prikazuje razmerje med modelom ocenjenih vrednosti naučene nevronske mreže in natančnih vrednosti, dobljenih z merjenjem. Za boljši pregled slika 8 prikazuje normalizirane vmesne vrednosti ocenjenih vrednosti in izmerjenih rezultatov. Rezultati merjenja obrabe,

The cutting inserts used in the experiments were coated with TiN. Their tool-life expectancy had a tendency to decrease suddenly after the coating disappeared from the cutting part, which could be seen in a swift and sudden jump of the cutting force. Figure 6 shows the appearance of worn inserts during the experiments: a) tool insert from experiment 1, b) tool insert from experiment 3, c) tool insert from experiment 5.

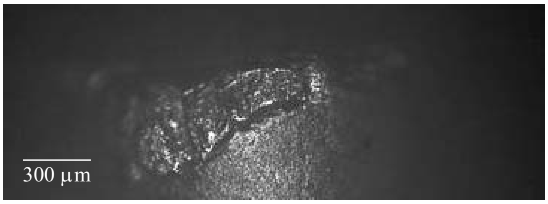
Figure 7 presents the agreement between the model of the estimated value of the trained neural network and the exact value gained from measurements. For a better survey, Figure 8 presents the normalized intermediate value of the estimated value gained from the model results and the measured results. The wear measuring results used



(a)

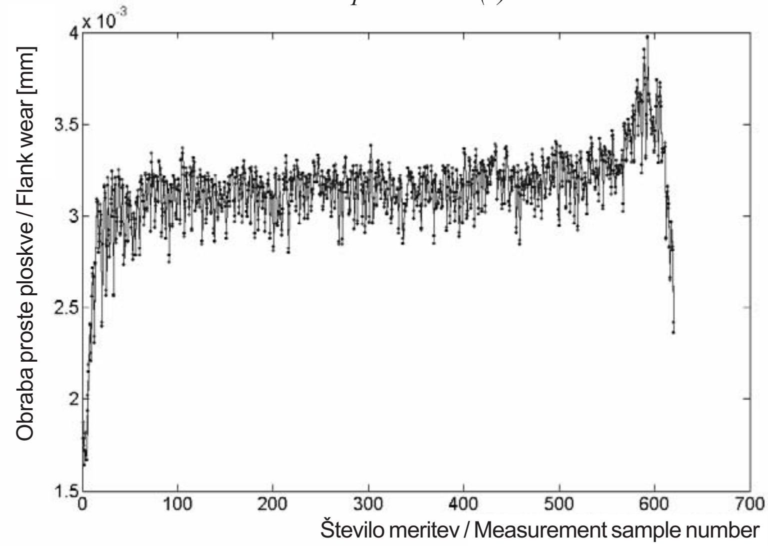


(b)

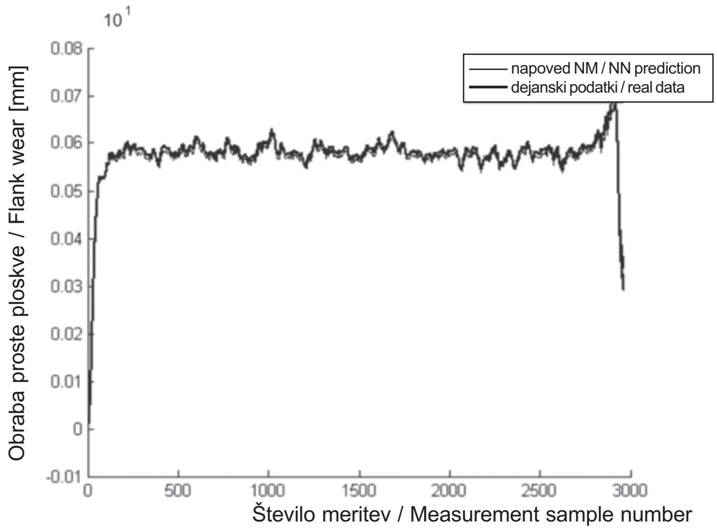


(c)

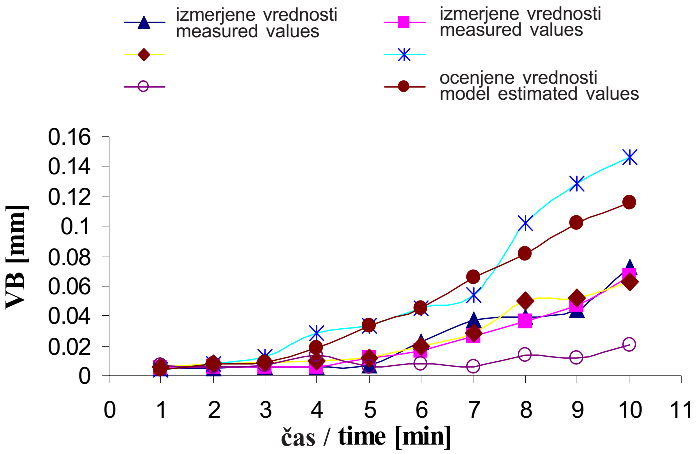
Sl. 6. *Obrabljena ploščica za preizkusne meritve: po preizkusu 1 (a), preizkus 3 (b) in preizkus 5 (c)*
Fig. 6. *Worn tool insert for experimental measurements: after experiment 1 (a), experiment 3 (b) and experiment 5 (c)*



Sl. 7. *Nevronska mreža za natančne in za ocenjene vrednosti*
Fig. 7. *Neural network exact value and estimated value*



Sl. 8. *Normalizirane vmesne vrednosti dejanskih izmerjenih in ocenjenih vrednosti*
Fig. 8. *Normalized intermediate values of real measurements and estimated values*



Sl. 9. *Deajnski izmerjeni rezultati*
Fig. 9. *Real measurement results*

uporabljeni za urjenje, so podani na sliki 9 za preizkuse 1 do 5. V vsakem primeru je bil model preverjen na podatkih, ki niso bili uporabljeni za učenje mreže.

Preglednica 2 prikazuje vmesne vrednosti parametrov izstopnih veličin in standardni odmik.

5 PRIHODNJE DELO

Pomanjkanje nevronskih mrež (podobno kakor pri številnih drugih preizkusnih modelih) zahteva dolgotrajno urjenje z normaliziranjem podatkov in vrednostmi, ki jih pričakujemo v dejanskih razmerah. Mreža ne more delovati brez predhodnega učenja. Da bi razrešili določen problem, je treba uporabiti tako numerične kot preizkusne metode. Glede na dejstvo,

for training were given in Figure 9 for Experiments 1 to 5. In each case, the model was tested on previously unseen data since these parameters remained constant during every individual test of the tool-life expectancy.

Table 2 presents intermediate value parameters of the input sizes and with the standard deviation.

5 FUTURE WORK

The lack of neural networks (as with many other experimental models) requires long-term training with data normalization of the values expected to be working in the real conditions. The network cannot work without previous training. To expand one's work, it is necessary to utilize both numerical and experimental methods. Considering the fact that the

Preglednic 2. *Parametri vstopnih veličin in standardni odklon*
Table 2. *Parameters of input sizes and standard deviation*

Vmesne vrednosti vstopnih veličin Intermediate value of input sizes	**Vmesne vrednosti izstopnih veličin Intermediate value of output size**
481,2658	0,0034
964,7022	
264,3197	
Standardni odklon vstopnih veličin Standard deviation of input sizes	**Standardni odklon izstopnih veličin Standard deviation of output size**
346,0206	0,0013
453,1569	
39,2540	

da je mrežo treba pri spremembi delovnih razmer ponovno učiti, štejemo lahko to za največjo pomanjkljivost pri uporabi nevronskih mrež v dejanski proizvodnji. Torej bi raziskave v prihodnje lahko vključile vgradnjo sedanjega sistema v obdelovalni RK stroj, namesto ločenih naprav kakor je to sedaj; s tem naj bi zagotovili, da bi sistem nadzora in obdelovalni stroj reagirala usklajeno - obdelovalni stroj bi se lahko ustavil, brž ko bi sistem ugotovil, da je orodje preveč obrabljeno. Ali drugače povedano, dinamične nevronske mreže zagotavljajo dodatne poprave naučene statične mreže pri praktičnem delovanju in lahko tudi razširijo sedanji model.

6 SKLEP

Prispevek je pokazal, da nevronske mreže lahko uporabljamo za učinkovito nadziranje obrabe med struženjem v trdo, z omenjenimi omejitvami. Po upoštevanju številnih mogočih ureditev modelov za nadzor obrabe, ki uporabljajo različne tipe razporeditev nevronskih mrež in temeljijo na vstopnih in izstopnih parametrih, je bila izbrana opisana z najboljšimi rezultati za izbrano število ravni mreže in nevronov. Model je bil postavljen tako, da se ga lahko precej preprosto dogradi z dinamično nevronsko mrežo, kar je ena izmed razmeroma novih raziskovalnih smeri na tem področju.

network should be re-trained from time to time, the training period can be considered as a major drawback in the application of neural networks in real manufacturing. However, future research could include the integration of the existing system into a CNC machine tool, instead of the currently separated device; this would ensure that the monitoring system and the machine tool could react synchronically, i.e., the machine tool could react by stopping once the over-worn tool is detected. More precisely, dynamic neural networks to ensure additional correction of the trained static network in an online work regime could also expand the existing model.

6 CONCLUSION

The paper presents neural networks (NNs) that can be used for efficient wear monitoring during hard turning, with the listed limitations. After considering many possible set ups for the wear-monitoring model using different configuration types of neural networks, and based on input and output parameters, the one selected performed with optimal results for the selected number of network layers and neurons. The model was set so it could be upgraded relatively easily with a dynamic neural network, which is one of the relatively new research directions in this field.

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