DEVELOPMENT OF A WEAR MONITORING SYSTEM FOR TURNING TOOLS USING ARTIFICIAL INTELLIGENCE

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SUMMARY

Tool wear during metal cutting operations is a continuous source of economic loss for the manufacturing industry. Complete tool failure after a certain degree of wear has occurred, can also have catastrophic consquences. One problem with monitoring tool wear is that the rate of wear and its geometric growth is always unique. This in effect means that a statistical approach for optimising the use of tool inserts cannot be realised, because too much losses will still occur together with the possibility of catastrophic failure. An alternative approach to achieve optimal tool use and prevent costly failures is on-line sensor-based monitoring of the tool inserts. In this research, a method is proposed for cost-effective on-line monitoring for turning tool inserts, based on Artificial Intelligence (AI) modelling, with the focus on turning operations.

To establish Tool Condition Monitoring (TCM) methods in industry, a generic method is required that can be applied to different types of operations. In this study, hard turning and interrupted cutting of Aluminium are investigated. A method is proposed that can effectively monitor the wear of the tool inserts used in these operations. It was shown that more than one wear mode can monitored in this way. Cutting conditions (*e.g.* speed, feed rate and depth of cut) can be included to ensure that the accuracy of the system is not affected if these conditions vary or change. A sensor-integrated tool holder was developed during the course of this work and it was shown how this tool can be used to reconstruct the cutting forces of a machining operation. A calibration procedure for the sensor-integrated tool was also developed.

The specific AI methods used in this research is Neural Networks (NNs). It was shown that using a novel fomulation of NNs, accurate monitoring can be achieved under shop floor conditions. This is achieved by training a combination of static and dynamic NNs. The new method is compared with other formulations and methods for further improvement are also investigated. Furthermore, an innovative training algorithm for on-line training of the NNs is also presented, after investigating many conventional and new optimisation algorithms. Achieving reliable and accurate wear monitoring under shop floor conditions is very significant since this has never been achieved to satisfaction up to date. In this case, using cost-effective custom developed hardware, advanced signal processing techniques and a novel formulation of NNs, the degree and rate of wear can be predicted at any given time. Comprehensive reviews of metal cutting, tool wear, modelling techniques, TCM and commercial TCM systems form part of this study as relevant background information.

Keywords: *condition monitoring, wear, neural networks, machine tool, vibration, machining, lathe, artificial intelligence.*

Ontwikkeling van 'n slytasiemoniteringstelsel vir draaibeitels deur gebruik te maak van kunsmatige intelligensie

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OPSOMMING

Slytasie van beitels wat gebruik word vir metaal sny operasies is 'n voortuderende bron van ekonomiese verliese in die vervaardigingsbedryf. 'n Katastrofiese faling van die beitel as gevolg van slytasie het ook ernstige gevolge. Die feit dat die geometrie en die tempo van die slytasie altyd uniek is, maak 'n statistiese benadering om die gebruik van die beitels te optimeer problematies. So 'n metode sal nie die moontlikheid van 'n katastrofiese faling uitskakel nie en sal steeds ekonomiese verliese meebring. 'n Alternatiewe metode om optimale gebruik van snybeitels aan te help en falings te voorkom is sensorgebaseerde monitering. Hierdie navorsing stel 'n koste-effektiewe metode voor vir intydse monitering van draaibeitels deur die gebruik van kunsmatige intelligensie. Om Masjiengereedskap ToestandsMonitering (MTM) metodes in die bedryf te vestig, word 'n generiese metode benodig wat op verskillende operasies toegepas kan word. In hierdie werk is die draai van verharde staal en die onderbroke draai van Aluminium ondersoek. 'n Metode word voorgestel wat die slytasie van beitels gedurende hierdie operasies betroubaar kan monitor. Daar word ook aangetoon hoe meer as een slytasiemodus op 'n beitel gemonitor kan word. Die masjineringsparameters kan ook in ag geneem word om te verseker dat die stelsel nie deur snytoestand variases beïnvloed word nie.

'n Sensor-geïntegreerde beitelhouer is ook ontwikkel en daar word aangetoon hoe die kragkomponente van 'n draai operasie daarmee bepaal kan word. Kalibrasieprosedures vir die sensor-geïntegreerde beitelhouer is ook ontwikkel. Die spesifieke kunsmatige intelligensie metode wat in hierdie navorsing aangewend word, is Neurale Netwerke (NNe). Daar word aangetoon hoe akkurate monitering van beitelslytasie op die fabrieksvloer moontlik is deur middel van 'n unieke formulering van NNe. 'n Kombinasie van statiese en dinamiese NNe word opgelei om die slytasie intyds te voorspel. Die nuwe metode word vergelyk met ander formulerings, en metodes vir verdere verbetering word ook ondersoek. 'n Innoverende opleidingsalgoritme vir intydse opleiding van die dinamiese NNe word ook voorgestel na ondersoek van verskeie konvensionele en nuwe optimeringsalgoritmes. Die feit dat betroubare en akkurate slytasiemonitering op die fabrieksvloer berwerkstellig is, is 'n belangrike bydrae van hierdie werk omdat so iets nie voorheen geïmplementeer is nie. In hierdie werk is koste-effektiewe hardeware ontwikkel en gebruik saam met gevorderde seinprosessering en 'n unieke NN formulering om die waarde en tempo van die slytasie op engige gegewe tydstip te voorspel. Omvattende studies in metaalsny, beitelslytasie, modelleringstegnieke, MTM en kommersiële MTM stelsels word as relevante agtergrondmateriaal vir hierdie navorsing ingesluit.

Sleutelwoorde: *toestandsmonitering, slytasie, neurale netwerke, masjiengereedskap, vibrasie, masjinering, draaibank, kunsmatige intelligensie.*

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NOMENCLATURE

UPPERCASE

A	constant (SOM), approximations (wavelet analysis), pulse magnitude (strain gauges)
$\mathbf{A}$	calibration matrix
A_c	area of chip load (mechanistic model)
B	constant (SOM), pulse magnitude (strain gauges)
BL	length of groove backwall wear
BW	width of groove backwall wear
C	constant (Taylor equations)
C_o	wave velocity (strain gauges)
C_x	covariance
D	workpiece diameter , details (wavelet analysis), NN initialisation space
E	modulus of elasticity , signal entropy (wavelet analysis)
F_{cw}	cutting force due to tool flank wear (mechanistic model)
F_f	frictional cutting force (mechanistic model)
$\mathrm{F_f}$	feed force (orthogonal and oblique cutting)
$\mathrm{F_r}$	radial force (oblique cutting)
F_n	normal cutting force (mechanistic model)
F_s	sampling rate
$\mathrm{F_t}$	tangential force (orthogonal and oblique cutting)
F_{tw}	thrust force due to tool flank wear (mechanistic model)
Fx,y,z	directional static forces (turning)
Fxd	natural frequency of tool holder feature (hard turning)
G_L	gauge length (strain gauges)
I	second moment of area
$\mathbf{I}$	identity matrix
K	kurtosis
$\mathrm{K_D}$	depth of the crater wear (hard turning)
$\mathrm{K_f}$	specific feed pressure constant (mechanistic models)
K_f	frictional cutting pressure (mechanistic model)
$\mathrm{K_L}$	approximate length of the crater wear (hard turning)
K_M	crater wear centre from edge
K_n	normal cutting pressure (mechanistic model)
$\mathrm{K_t}$	specific cutting pressure constant (mechanistic models)
K_T	crater wear depth
KT	depth of groove backwall wear
$\mathrm{K_V}$	volume of crater wear (hard turning)

K_{Vfr}	full range of crater wear volume
K_{Vmd}	maximum deviation from true crater wear volume
K_{Vrms}	rms deviation from true crater wear volume
K_{VTCMS}	crater wear volume predicted by the monitoring system
K_{Vtrue}	measured crater wear volume
K_W	width of the crater wear (hard turning)
L	length of cut along shaft (turning), surface profile sample length, gauge length (strain
M	number of files to compress
N	nose wear
NL_1	notch wear length on main cutting edge
NL_2	notch wear length on secondary cutting edge
NW_1	notch wear width on main cutting edge
NW_2	notch wear width on secondary cutting edge
P_L	pulse length (strain gauges)
R_a	roughness average
P_{xx}	power spectral density of X
P_{xy}	cross spectral density of X and Y
R_t	theoretical surface roughness (turning)
R_z	rms surface roughness
S	signal, skewness
SD	depth of secondary face wear
SW	width of secondary face wear
T	tool life (taylor equation), pulse period (strain gauges), time interval, sampling time
T_R	reference tool-life
V	cutting speed (orthogonal and oblique cutting)
V_c	chip speed (orthogonal and oblique cutting)
V_0	Wheatstone bridge excitation voltage
V_R	reference cutting speed
VB	flank wear
$VB(i)$	on-line wear estimation at step i
VB_A	area of flank wear (hard turning)
VB_{Afr}	full range of flank wear area
VB_{Amd}	maximum deviation from the true flank wear area
VB_{ATCMS}	flank wear area predicted by the monitoring system
VB_{Atrue}	measured flank wear area
VB_{Arms}	rms deviation from the true flank wear area
VB_{avg}	average flank wear (hard turning)
VB_L	approximate length of the flank wear (hard turning)

VB_{max}	maximum flank wear
VB_{notch}	notch wear
VB_p	width of the plastic flow region (mechanistic model)
W_C	coating effect factor
W_g	chip-groove effect factor
X_{rms}	rms of X

LOWERCASE

a	neuron output, wavelet scale function
$a_1, a_2 \ldots a_p$	AR parameters
b	chip width (orthogonal and oblique cutting), length of flank wear, neuron bias
$b_1, b_2 \ldots b_q$	MA parameters
c	index of BMU, trigger channel
c_0, c_1	linear coefficients (mechanistic model)
doc	depth of cut
e_i	eigenvectors (PCA)
f	feed rate, neuron activation function
f	frequency of interest (strain gauges)
fh	upper frequency boundary
fl	lower frequency boundary
f_o	natural frequency (dynamometer)
f_r	resonant frequency (dynamometer)
h	depth of cut (orthogonal and oblique cutting)
h	height of surface profile
$h_{c(x),i}$	neighbourhood function (SOM)
i	cutting edge inclination angle (oblique cutting), neuron index (SOM), monitoring outer step, trigger threshold
i_e	effective inclination angle (mechanistic model)
k_{ij}	calibration matrix coefficients
l	tool overhang length
lm	cutting length per minute (turning)
m	input vectors (SOM)
$\mathbf{m}$	weight vector (SOM)
n	rotational speed of spindle (turning), constant (Taylor equation), dimension of input vectors (SOM), number of weight and bias values in the dynamic NN, total number of tool wear measurements, number of trigger events, index of ARMA models, mode of vibration
p	neuron input, order of AR model
q	order of MA model

r	tool nose radius
r_i	locality index (SOM)
r_n	tool nose radius (mechanistic model)
s	signal
t	index of learning step (SOM)
t_c	is the uncut chip thickness(mechanistic model)
tol	convergence tolerance
u	sequence for MA model
V	voltage (calibration)
w	neuron weight, width of cut (mechanistic model)
x	distance from tool tip (mechanistic model)
$\boldsymbol{x}$	weight vector of dynamic NN, sample vector (SOM)
Δw	width of element (mechanistic model)
$\bar{x}$	mean value

GREEK SYMBOLS

$\alpha(t)$	learning rate function (SOM)
α_{en}	effective normal rake angle (mechanistic model)
α_n	normal rake angle (mechanistic model)
α_r	rake angle (oblique cutting)
β	clearance angle
β_n	end condition parameter
ε_{out}	reported peak strain (strain gauges)
ε_R	peak strain (strain gauges)
ϕ_c	shear angle (oblique cutting)
γ^2	coherence function
γ_{eL}	effective lead angle (mechanistic model)
η	average accuracy with respect to the full range of wear, chip-flow angle (oblique cutting)
η_c	chip-flow angle (mechanistic model)
λ_i	eigenvalues (PCA)
μ_x	mean of vector population (PCA)
ρ	mass density of tool holder material, correlation coefficient
σ	minimum accuracy with respect to the full range of wear
σ^2	variance
σ_{eff}	effective stress (mechanistic model)
σ_o	tool tip normal stress (mechanistic model)

σ_w	normal tool flank stress (mechanistic model)
τ_o	tool tip shear stress (mechanistic model)
τ_w	shearing tool flank stress (mechanistic model)
ω	frequency
$\Delta\xi$	sections on tool (mechanistic model)
ψ	wavelet function
ψ_s^2	frequency band energy from PSD function

ABBREVIATIONS

3-D	Three Dimensional
A/D	Analogue to Digital
AC	Adaptive Control
ACC	Adaptive Control Constraint
ACO	Adaptive Control Optimisation
ADELINE	Adaptive Linear Neuron Network
AE	Acoustic Emission
AI	Artificial Intelligence
ANOVA	Analysis of Variance
AR	Auto-Regressive
ARD	Automatic Relevance Determination
ARMA	Auto-Regressive Moving Average
ART	Adaptive Resonance Theory
ASPS	Automated Sensors and Signal Processing Selection
BHN	Brinell Hardness Number
BMU	Best-Matching Unit (SOM)
BW	Bandwidth
CAD	Computer Aided Design
CBN	Cubic Boron Nitride
CF	Crest Factor
CNC	Computer Numerical Control
CWT	Continuous Wavelet Transform
DN	Dynamic Network
DWT	Discrete Wavelet Transform
ECT	Equivalent Chip Thickness
ETOP	Energy Trajectory Optimisation Program
EUR	Euro
EWMA	Exponentially Weighted Moving Average
FEM	Finite Element Method
FF	Feedforward
FFT	Fast Fourier Transform

FRF	Frequency Response Function
GA	Genetic Algorithm
GEOMC	Global Economical Optimal Machining Conditions
IDD	Independent Identically Distributed
IDWT	Inverse Discrete Wavelet Transform
KBES	Knowledge-Based Expert Systems
KFM	Kohonen Feature Map
LFOP	Leap-Frog Optimisation Program
MLP	Multilayer Perceptron
MRR	Metal Removal Rate
NC	Numerical Control
NFS-S	Supervised Neuro-Fuzzy System
NN	Neural Network
OMC	Optimal Machining Conditions
OR	Operations Research
PC	Personal Computer
PCA	Principal Component Analysis
PLS	Partial Least Squares
PSD	Power Spectral Density
PSOA	Particle Swarming Optimisation Algorithm
RAMV	Ratio of Absolute Mean Value
RAN	Resource Allocation Network
RBF	Radial Basis Function
RMC	Recommended Machining Conditions
RNN	Recurrent Neural Network
SEM	Scanning Electron Microscope
SeTAC	Sequoia Triaxial Acceleration Computer
SLP	Single Layer Perceptron
SN	Static Network
SOF	Statistical Overlap Factor
SOM	Self-Organising Map
SPC	Statistical Process Control
SQSD	Spherical-Quadratic Steepest Descent
SS	Stainless Steel
SURE	Stein's Unbiased Risk Estimate
TCM	Tool Condition Monitoring
TCMS	Tool Condition Monitoring System
TDL	Tapped Delay Line
TDNN	Time Delay Neural Network
TMC	Technical Machining Conditions