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OPTIMIZATION OF TURNING NST 37.2 STEEL WITH UNCOATED CARBIDE CUTTING TOOLS

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Abstract: Selection of optimimum machining parameters is an essential factor in process planning for efficient metal cutting operations. In this study, an artificial neural network-based tool wear predictive model and a genetic algorithm-based optimization model were developed to determine the optimum cutting parameters for turning NST 37.2 steel with uncoated carbide cutting inserts. Multi-layer, feed-forare, back –propagation network was used in predictive model, while maximum metal removal rate (MRR) was used as the objective function and tool wear as samples NST 37.2 steel bars with 25mm diameter and 400mm length s workspiece and Sandvice Coromant® uncoated carbide inserts with International Standard Organizxation (ISO) designation SNMA 12406. Dry machining at different cutting conditions with cutting speed (v), feed rate (f) and depth of cut (d) ranging from 20.42-42.42 mm/min, 1.0-2.2 mm/rev and 0.2-0.8mm, respectively were carried out. Eight passes of 50mm length of cut were machined at each conediiton, the spindle power and tool wear (flank and nose) were measured during each cutting operation. Results have shown that the predictive model had acceptable accurancy and optimum cutting parameters obtained were: v =42.32mm/min, f = 2.19 mm/rev and d = 0.8mm.

Keywords: Optimization, turning, genetic algorithm, artificial neural network, NST 37.2 steel.

INTRODUCTION

NST 37.2 steel is one of the commercial carbon steel grades produced by the Delta Steel Company (DSC), Aladja, Delta State, Nigeria. It is commonly used as structural member in building construction and for production of machine components. In the machining industry, carbon steels are popularly being machined with the convectional high speed steel (HSS) cutting tools, which are known to have short tool life due in part to the reduction in tool properties at elevated temperature generated at the cutting edge during the cutting operation. In most cases, the steel is heat treated by normalization process prior to machining and then quenched and tempered again after the machining operations, which leads to increase in manufacturing time and cost of production. In recent times, the need for an economic production of machined components from materials with supreme properties which are difficult-to-cut has led to the development of different harder and tougher cutting tool materials such as ceramic and carbide grade tools (Mursec and Cus, 2003; Cus *et al.*, 1997). However, application of these new generation cutting tool materials is not yet popular in the machining industry in Nigeria. Thus, there is need to determine the optimum machining parameters for turning NST 37.2 steel using these new generation cutting tools, in order

to promote their rapid adoption in the machining industry in Nigeria.
Prediction of tool wear and tool condition monitoring has been extensively studied using artificial neural networks (ANN) by many researchers (Sick, 2002). Sunil and Saundra (2000) defined neural network as a parallel processing architecture in which knowledge is represented in the form of weights between highly interconnected processing elements. A number of researchers have reported the application of neural network systems in tool conditioning monitoring and prediction of tool wear or tool life (Ozel and Nadgir, 2002; Elanayar and Shin, 1990: Elanayar and Shin, 1992).

Genetic Algorithms (GA) are adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetics (Goldberg, 1999). The basic concept of GA is designed to simulate processes in natural system necessary for evolution, specifically those that follow the principles first laid down by Charles Darwin of survival of the fittest (Goldberg, 1999). As such they represent an intelligent exploitation of a random search within a defined search space to solve a problem (Goldberg, 1999). It has been applied in many fields of engineering. Not only does GA provide alternative methods to solving problem, it consistently outperforms other traditional methods in most of the problems link (Zbigniew and David, 2000). Genetic algorithm (GA), a global optimization method (Goldberg, 1999), can be applied in various application areas including facility layout design, machining condition determination, building design, system-parameter estimation, and process-parameter optimization (Caldas and Norford, 2002; Islier, 1998; Cook et al., 2000; Daren, 2001; Edward et al., 2002, Tang and Li, 2002). An effective GA representation, meaningful fitness evaluation, good selection and variation are the keys of the success in GA applications. The appeal of GAs comes from their simplicity and elegance as robust search algorithms as well as from their power to discover good solutions rapidly for difficult high-dimensional problems.

The objective of the study was to develop an artificial neural network-based tool wear predictive model and a genetic algorithm-based optimization model to determine the optimum cutting parameters for turning NST 37.2 steel with new generation uncoated carbide cutting inserts using the maximum metal removal rate (MMRR) as the objective function and tool wear as constraints.

MATERIALS AND METHODS

Workpiece

Samples of NST 37.2 steel bars were obtained from Delta State Company (DSC), Aladja, Nigeria. The chemical composition and the mechanical properties of the steel are shown in Tables 1 and 2, respectively. The microstructure of the steel is shown in Figure 1.

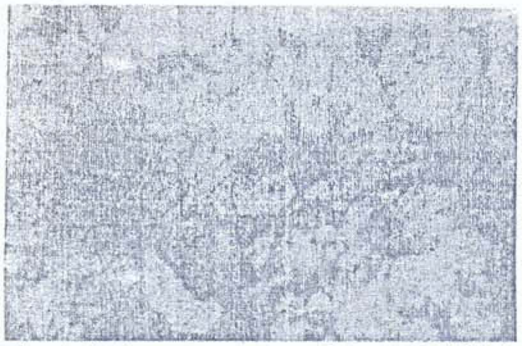

Fig. 1: Microstructures of the NST 37.2 steel (x 100)

Table 1: Chemical composition by weight (%) of NST 37.2 steel

Element	Composition by weight (%)
C	0.331
S	0.011
Si	0.15
Mn	0.69
P	0.018
Fe	98.8

(Source: Asafa, 2007)

Table 2: Mechanical properties of NST 37.2 steel

Properties	Average value
Yield Strength (MN/m^2)	245.41
Tensile Strength (MN/m^2)	342.33
Elongation (%)	18.48
Reduction in Area (%)	15.05
Young Modulus (GPa)	198.50
Hardness (BHN)	48.5
Density (g/cm^3)	8.15

(Source: Asafa, 2007)

Machining operations

Straight turning operations were carried out on M300 Harrison-type lathe with speed range of 40 and 2500 rpm. The lathe was driven by 2.25 kW Kapak inductions motor. Carbide inserts produced by Sandvic Coromant® were used for the machining trials. A tool holder was used to hold the inserts. The machining conditions investigated are listed in Table 3, while the experimental setup is shown in Figure 2. For each of the machining condition, eight passes of 50 mm length of cut were made without application of coolant. At the end of each pass, spindle power, nose wear and flank wear were measured using digital multimeter and by means of machine vision system developed by Fadare and Oni (2009), respectively.

The tool rejection criteria for roughing operation were used in the machining experiments in accordance to International Standard Organization (ISO) 3685 Standard (ISO, 1977). The cutting insert was rejected and further machining discontinued when any or combination of the following criteria was reached: Flank wear ≥ 0.7mm, Nose wear ≥ 0.5mm, Surface roughness ≥ 6.0μm and Catastrophic failure.

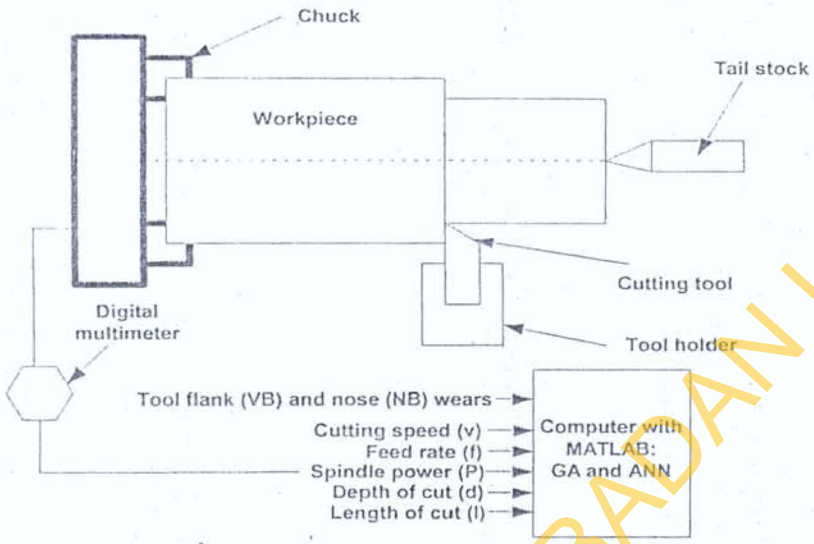

Fig. 2: Experimental setup

Table 3: Machining conditions

Cutting parameter	Value		
Speed, v (mm/min)	20.42	29.06	42.42
Feed Rate, f (mm/rev)	1.0	1.8	2.2
Depth of Cut, d (mm)	0.2	0.4	0.8

3 Development of the neural network-based tool wear predictive model

Neural Network Toolbox for MATLAB® (Howard and Beale, 2000) was used to design the multi-layer, feed-forward, back-propagation neural networks. The basic steps involved in designing the network were: collection/generation of input/output dataset; pre-processing of data (partitioning of dataset); design of the neural network objects; training and testing of the neural network; simulation and prediction with new input data sets; and analysis and post-processing of predicted result.

The cutting speed (v), feed rate (f), depth of cut (d), length of cut (l) and spindle power (P) were used as input parameters, while flank and nose wear were used as output parameters. The configuration of the network is shown in Figure 3. The input/output dataset were first normalized with MATLAB® function, '*prestd*', in order to obtain inputs with zero mean and unity variance. In addition, principal component analysis was carried out on the dataset using a Matlab function, '*prepca*'. The concept was to eliminate those components that contribute less than 99% to the variation in datasets. The output of the network was later converted to the original format of the dataset with '*postd*'. Eight-eight (88) of the dataset was used as training dataset, while 24 was as the test dataset.

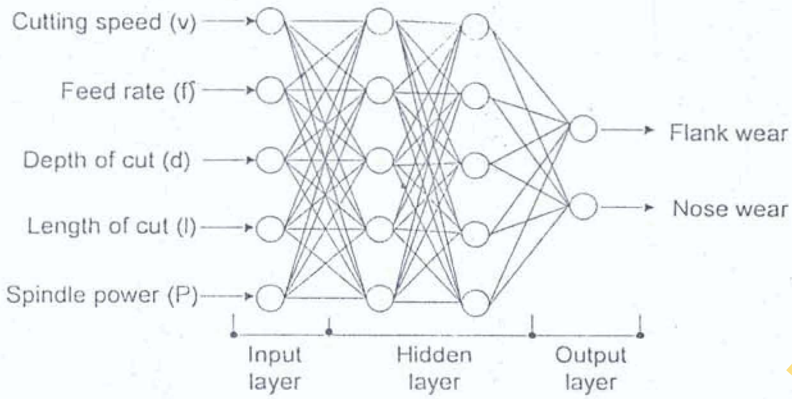

Fig. 3: Configuration of Artificial Neural Networks

Levenberg-Marquardt learning algorithm was used together with Bayesian regularization in training the neural networks. The '*logsig*', '*tansig*' and '*purelin*' activation functions were used in the input, hidden layer, and output layer, respectively. Four different networks structures (5-20-5-2, 5-5-20-2, 5-10-5-2 and 5-20-2) were investigated in order to determine the best network structure required for the predictive model..

Development of the genetic algorithm-based optimisation model

The Genetic Algorithm (GA) was implemented with self written codes using MATLAB 6.5. The search procedure of obtaining optimum cutting parameters was implemented as shown in the flow chart (Figure 4).

Population representation/initialization

A population of 100, string length of 5 and 10 generations were used in the model. The cutting speed varied from 20.42 to 42.42 mm/min, being speed range considered during the experiment. The depth of cut ranged from 0.2 to 0.8 mm while the feed rate was between 1.0 and 2.2 mm/rev. The cutting length was between 0 and 400 mm. Therefore, a string of possible solution contains all the inputs to the trained neural network.

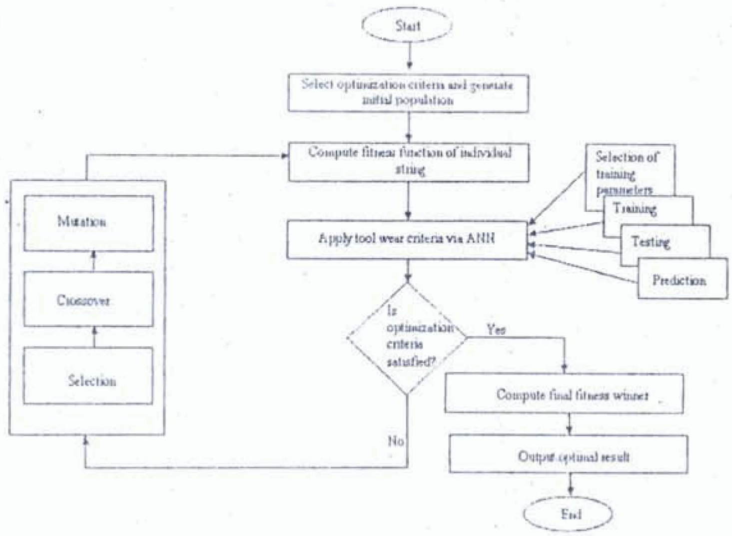

Fig. 4: Flow chart for the proposed genetic algorithm-based optimization model

Evaluation of objective function

The objective function to be optimized was the maximum metal removal rate (MMRR), which is expressed mathematically as (Trent and Wright, 2000):

$$MMRR = v \times f \times d \qquad (1)$$

where v is surface speed (mm/min), f is feed rate (mm/rev) and d is depth of cut (mm). The ANN predicted tool wear for both flank and nose wear were applied as constraints in the optimisation of the objective function.

2Selection of Viable Strings in Population

The selection function chooses parents for the next generation based on their fitness function. The Roulette's wheel deterministic selection algorithm was used for the randomized selection of viable strings among the population in each generation. Once a solution had been chosen as the first parent in the mating pool, it could not be used as the second parent anymore. However, if a solution was used as the second parent, it could be elevated to the position of the first parent during further selection. The technique undermines the firs parent from condescending while allowin the second parent to be elevated.

Crossover

Crossover enables the algorithm to extrac the best genes from different individuals an recombines them into potentially superic children. One point crossover mechanisı was used to combine two individual string to generate another two different strings. . crossover probability of 0.5 which connote that each string is crossed in half and eac half is then combined with second half (another string was utilized.

Mutation

Mutation adds to the diversity of population and, thereby, increases tl likelihood that the algorithm would genera individuals with better fitness values. Sin the symbols in the strings were continuo variables, small values of variation we applied to the strings using the Gaussi distribution. Gaussian adds a randc number, or mutation, chosen from Gaussian distribution, to each entry of t parent vector. A normalized random numbers of zero (mean) and 0.5 (standard deviation) were added to the cutting speed while 0 and 0.01 were added to the depth of cut and feed rate.

RESULTS AND DISCUSSION

Selection of best network structure for the tool wear predictive model

The performances of the different network structures investigated are given in Table 4 in terms of the sum of square error (SSE), sum of square weight (SSW), number of effective parameters (NOEP) and number of iteration required for convergence during the training process. Comparing the results for the networks, the network structure 5-20-5-2 with the smallest SSE of 0.7466 and number of iteration of 90 was selected for the development of the tool wear prediction model. Similarly, the predictive performance of multilayer percetron artificial neural networks trained with six backpropagation learning algorithms for forecasting of solar radiation data have shown to be dependent on the learning algorithm (Fadare *et al*, 2010) and network structure such as type and number of neurons in the input and hidden layer, and number of layers in the hidden layer in the network (Fadare and Olugasa 2009). In these previous studies, the network structure (5-10-1) and Levenberg-Marquardt (LM) learning algorithm were identified as the optimum network parameters required for best performance.

Table 4: Performance of the ANN tool wear predictive model

Network Architecture	*SSE*	*SSW*	*NOEP*	*Number of iterations*
5-20-5-2	0.7466	88	145	90
5-5-20-2	27.68	32	*39*	578
5-10-5-2	8.42	63	80	250
5-20-20-2	97.77	3	11	2000

Cutting Condition Optimization Model

Optimum machining parameters (cutting speed, feed rate and dept of cut) for maximum metal removal rate (MMRR) without violating the tool flank wear constraint was determined with the optimization model. The algorithm was run for different numbers of population and generation in order to study the effects of population number and generation number on the maximum MRR at the beginning of the first generation and the end of the last generation for chosen population and generation numbers. The optimum performance of the optimization model was achieved at population of 100 and generation size (number) of 100, while the optimum cutting parameters were obtained as cutting speed (v) of 42.32 mm/min, feed rate (f) of 2.19 mm/rev, and depth of cut (d) of 0.8 mm with the corresponding maximum metal removal rate (MMRR) of 74.14 mm^3/min. Similarly, Ko and Kim (1998) has also applied genetic algorithm model to determine the optimum cutting parameters for turning high carbon steel (JIS, S45C) with Tungsten carbides tools (TNMG 160412-B20) using the same objective function (MMRR) and tool wear as constrain and obtained optimum parameters (d = 0.3 mm, f = 0.055 mm/min, v = 1200 rpm and MMRR = 19.8 mm^3/min), while Chien and Tsai (2003) obtained optimum cutting parameters (v = 88.94 m/min, d = 1.5411 mm, f = 0.179 mm/rev and MMRR = 24.54 x 10^{-3} mm^3/min) for turning 6 cm length of 17-4PH stainless steel with Valenite VN8 (P10) coated TiN cutting tools. The maximum metal removal rate (74.14 mm^3/min) obtained in this study for turning mild steel was higher than the value for high carbon steel (19.8 mm^3/min) and stainless steel (24.54 x 10^{-3} mm^3/min) reported by Ko and Kim (1998) and Chien and Tsai (2003), respectively. The relative softness of mild steel compared to high carbon steel and stainless steel and the high mechanical properties of the new generation cutting tool used in this study may be attributed to the high maximum metal removal rate obtained.

CONCLUSIONS

The following conclusions are drawn from the study.

- The neural network-based tool wear model with network structure of 5-20-5-2 trained with automatic Bayesian regularization gave the best performance despite the small dataset used in the training.
- Generally, the magnitude of flank wear was significantly higher than nose wear in all the cutting conditions considered except at cutting condition (v = 20.42 mm/min, d = 2.2 mm and f = 0.4 mm) where nose wear was higher than flank wear.
- The optimisation model with population and generation numbers equal to 100 gave the best performance.
- Optimum cutting condition was found to be: cutting speed of 42.32 mm/min, feed of 2.19 mm/rev and DOC of 0.8mm with corresponding MRR of 74.14 mm^3 /min

REFERENCES

Asafa, T.B. 2007. Investigation on tool wear prediction and optimization of cutting conditions in Machining Aladja NST 37.2 Steel. Unpublished M.Sc. Dissertation of Mechanical Engineering Department, University of Ibadan, Nigeria.

Caldas, L. G. and Norford, L. K. 2002. A design of optimization tool based on a genetic algorithm. *Automatic Constrain.* 11, 2: 173–184.

Chien, W.T., Tsai, C.S., 2003. The investigation on the prediction of tool wear and the determination of optimum cutting conditions in machining 17-4PH stainless steel. Journal of Material Processing Technology 140 (1–3), 340–345.

Cook, D. F., Ragsdale, C. T. and Major, R. L.2000. Combining a neural network with a genetic algorithm for process parameter optimization. *Eng. Appl. Artif. Intell.* 13, 4: 391–396.

Cus, F.,Sokovic, J., Kopac, J., Balic, J. 1997. Model of complex optimization of cutting conditions. *International Journal of material processing Technology,* 64: 41-52.

Daren, Z. 2001. QSPR studies of PCBs by the combination of genetic algorithms and PLS analysis. *Comput. Chem.* 25, 2: 197–204.

Edward, E., Conrad, B. and Selwayan, S. 2002. Optimization of a neural network model for calibration of voltammetric data. *Chemom. Intell. Lab. Syst.*, 61,1–2: 35–49.

Elanayar, S.V.T., Shin, Y.C. 1990. Machining condition monitoring for automation using neural networks. *ASME Winter Annual Meeting*, Dallas, TX, USA. Pp 85-100.

Elanayar, S.V.T., Shin, Y.C. 1992. Robust tool wear estimation via radial basis function neural networks. *ASME Winter Annual Meeting*, Anaheim, C. A, USA. Pp 37-51.

Fadare, D. A., Olugasa T.T. and Falana A. 2010. Performance ranking of artificial neural network learning algorithms in solar radiation forecast. *Proceedings of the International Conference of the Nigerian Institute of Industrial Engineers (NIIE)*, April 22-24, 2010, *pp 104 – 112.*

Fadare, D.A. and Olugasa, T.T. 2009 An artificial neural network model for forecasting daily global solar radiation in Ibadan, Nigeria *Global Journal of Engineering and Technology*, 2(2):123–131.

Fadare, D.A. and Oni, A.O. 2009. Development and application of a machine vision system for measurement of tool wear. *ARPN Journal of Engineering and Applied Sciences*, 4(4):42-49.

Goldgerg, D.E. 1999. Genetic algorithm insearch of optimization and machine learning. Addison Wesley. USA. Pp. 2-5.

Howard D, Beale M. 2000. Neural network toolbox for use with MATLAB. User's Guide, Version 4. *The Math Works, Inc.* pp 133–205.

International Standard Organisation (ISO). 1977. Tool life testing with single-point turning tool. International Organisation for Standardisation. Ref No: ISO 3685 – 1977.

Islier, A.A. 1998. A genetic algorithm approach for multiple criteria facility layout design. *Int. J. Prod. Res.* 36(6): 1549-1569.

Ko, T.J., Kim, H.S., 1998. Autonomous cutting parameter regulation using adaptive modeling and genetic algorithms. *Precision Engineering*, 22 (4), 243–251.

Molinari, A., Nouari, M., 2002. Modeling of tool wear by diffusion in metal cutting. *Wear* 252, 135–149.

Mursec, B., Cus, F. 2003. Integral model of selection of optimal cutting conditions from different databases of tool makers. *International Journal of material processing Technology.* 133: 158-165.

Ozel, T. and Nadgir, A. 2002. Prediction of flank wear by using back propagation neural network modeling when cutting hardened H-13 steel with chamfered and honed CBN Tool. *International Journal of Machine Tool and Manufacture* 42: 287 – 297.

Sick, B. 2002. On-line and indirect tool wear monitoring in turning with artificial neural network: a review of more than a decade of research. *Mechanical System Signal Processing* 16(4): 487-546.

Summil Elanayar, V.T. and Saundra, K. 2000. Machining conditions monitoring for automation using neural networks. *International Journal of Material Processing Technology*. 105: 218 – 228.