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# Prediction of cutting temperature in orthogonal machining of AISI 316L using artificial neural network

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ABSTRACT

In this study, an approach based on artificial neural network (ANN) was proposed to predict the experimental cutting temperatures generated in orthogonal turning of AISI 316L stainless steel. Experimental and numerical analyses of the cutting forces were carried out to numerically obtain the cutting temperature. For this purpose, cutting tests were conducted using coated ($TiCN + Al_2O_3 + TiN$ and $Al_2O_3$) and uncoated cemented carbide inserts. The Deform-2D programme was used for numerical modelling and the Johnson–Cook (J–C) material model was used. The numerical cutting forces for the coated and uncoated tools were compared with the experimental results. On the other hand, the cutting temperature value for each cutting tool was numerically obtained. The artificial neural network model was used to predict numerical cutting temperatures by means of the numerical cutting forces. The best results in predicting the cutting temperature were obtained using the network architecture with a hidden layer which has seven neurons and LM learning algorithm. Finally, the experimental cutting temperatures were predicted by entering the experimental cutting forces into a formula obtained from the artificial neural networks. Statistical results ($R^2$, RMSE, MEP) were quite satisfactory. This demonstrates that the established ANN model is a powerful one for predicting the experimental cutting temperatures.


## 1. Introduction

Stainless steel is a material which has rapidly become widespread in recent years. This material can be used in a variety of areas as it resists corrosion excellently, can be used at low and high temperatures, is easy to shape and has a pleasant aesthetic appearance. The major factors which affect the machinability of this kind of material negatively are its lower thermal conductivity and the presence of strengthening elements such as chrome, nickel and molybdenum in its chemical composition. Because of chip removal process is a complex process, a theory that fully discloses the cutting process is not easy to suggest. Therefore sometimes, it is not possible to measure experimentally each case which occurs during cutting. Especially, finite element method is a numerical analysis method that is widely used to predict some data (such as cutting force and cutting temperature) during cutting. However, finite element solutions result in more realistic and closer to the experimental data depend on to used material model and friction conditions being close to the friction conditions in the actual cutting conditions [1]. When the studies done in this regard subject to an overall evaluation, it will be seen that Johnson–Cook material model used is more suitable in simulations of the cutting processes [2–4] because, Johnson–Cook material model is able to express analytically the material behaviour at high strain rates and temperatures. Umbrello et al. [5], in their study, investigated the variation of the cutting temperature and the cutting forces using the five different Johnson–Cook material models for AISI 316L stainless steel. The closest results to cutting temperature and the cutting force values that experimentally measured, material model developed by Tounsi et al. [6] was prepared. For this reason in this study, this material model was used.Since the metal cutting process is complicated, it is not easy to offer a theory which precisely clarifies the procedure of cutting. While many studies performed in this area exist, there still are differences between theory and practice. Many experimental and numerical studies to identify the optimal conditions for the cutting process have been carried so far [7–11]. Yaldiz et al. [12] dealed with a comparison of experimental results and consistent fuzzy rule-based model for estimating the cutting forces in turning. In cutting experiments, AISI 1040 steel was used as the workpiece material. Feed force, radial force and

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**Nomenclature**

| | |
|---|---|
| $A$ | yield stress (MPa) |
| $o$ | output value |
| $Al_2O_3$ | aluminum oxide |
| $P$ | number of pattern |
| ANN | artificial neural network |
| $R^2$ | absolute fraction of variance |
| $B$ | hardening modulus (MPa) |
| RMSE | root mean square error |
| BP | back propagation |
| SCG | scaled conjugate gradient learning algorithm |
| $C$ | strain rate sensitivity parameter |
| $T$ | temperature of work material (°C) |
| $Ct$ | cutting tools |
| $T_r$ | room temperature (°C) |
| $Fc$ | main cutting force (N) |
| $T_m$ | melting temperature of work material (°C) |
| $Ff$ | feed force (N) |
| $Tc$ | cutting temperature (°C) |
| $f$ | feed rate (mm/rev) |
| TiCN | titanium carbo-nitride |
| $f_t$ | transfer function |
| TiN | titanium nitride |
| $h$ | heat transfer coefficient of work material (kW/m$^2$ °C) |
| $t$ | target value |
| $ij$ | processing elements |
| $V$ | cutting speed (m/min) |
| $k_p$ | shear flow stress of chip (MPa) |
| $w_{ij}$ | the weights of the connections between $i$th and $j$th processing elements |
| LM | Levenberg–Marquardt learning algorithm |
| $w_{bi}$ | the weights of the biases between layers |
| $m$ | shear friction factor |
| $X_j$ | the output of the $j$th processing element |
| $M$ | thermal softening coefficient |
| $\bar{\sigma}$ | yield stress (MPa) |
| MEP | absolute mean error percentage (%) |
| $\dot{\bar{\varepsilon}}$ | strain rate (sn$^{-1}$) |
| NET$_i$ | the weighted sum of the input to the $i$th processing element |
| $\dot{\bar{\varepsilon}}_o$ | reference strain rate (sn$^{-1}$) |
| $n$ | strain hardening index |
| $\bar{\varepsilon}$ | equivalent plastic strain rate (sn$^{-1}$) |
| $np$ | number of processing elements in the previous layer |
| $\tau$ | shear stress at the tool–chip interface (MPa) |

main cutting force were measured for three combinations of cutting speeds, feed rates and depth of cuts. The difference between experimental and predicted results was obtained as around 99.6%. These results demonstrate the potential of this approach for monitoring the cutting forces. Ucun and Aslantas [13] conducted the numerical simulations to determine the effect of coating type on the cutting forces, the tool stresses, and temperatures. The Lagrangian thermo-viscoplastic cutting simulation of AISI 4340 steel was conducted using two different coating types ($TiCN + Al_2O_3 + TiN$ and $Al_2O_3$) and uncoated carbide tool having same geometry. The predicted results indicated that $Al_2O_3$ coated tool showed minimum tool temperature value due to its decreasing thermal conductivity with increasing temperature and that the tool stress within the coating increases along the thickness with increasing cutting speed and feed rate.

Since the design of cutting tools, coating characteristics, the properties of workpieces and the cutting conditions are influential on the cutting temperature, the experimental and numerical approaches are not very appropriate for predicting it. In addition, as experimental studies require a lot of time and experiment sets are expensive, different approaches such as the artificial neural network which precisely predicted desired values have been preferred in studies in the recent years. The artificial neural network, which has been developed taking the working principle of the human brain as an example, can learn through examples and solve nonlinear problems. The ANN can be used in solving problems which cannot be modelled mathematically or are very difficult. The nonlinearity of artificial neurons allows for the ANN to be applied to many problems [14]. Nalbant et al. [15] conducted orthogonal cutting experiments for AISI 1030 steel at different parameters with coated (PVD-CVD coated cemented carbide) and uncoated inserts. The effects of cutting method, coating material, feed rate and cutting speed on the surface roughness of the workpiece are investigated. Surface roughness values are predicted by use of an ANN approach. Eventually the surface roughness values reached through the ANN ($R^2 = 0.99985$ for the training data and $R^2 = 0.99983$ for the testing data) are found to be very close to the results obtained by the experimental study. Kurt [16] investigated the variation by cutting parameters of the tool stresses occurring during the machining of the nickel-based super alloy Inconel 718. The cutting forces were measured experimentally and the stress distributions on the cutting tools were analysed by use of the finite element method (ANSYS). In addition, an ANN model is developed for predicting all cutting tool stresses. The $R^2$ value after the ANN training is very close to 1. Studies in the literature demonstrate that the ANN is a very powerful modelling technique [17,18]. Panda et al. [19] predicted flank wear in drilling using back propagation neural network (BPNN) and radial basis function network (RBFN). It has been observed from the present study that both BPNN and RBFN can predict the drill flank wear reasonably well. In addition to BPNN can predict the wear more accurately compared to RBFN. While the error in prediction is more in RBFN compared to that in the case of BPNN, RBFN can learn the pattern much faster compared to BPNN and could be used advantageously in online tool wear monitoring. Ravi et al. [20] presented the detailed study of thermally enhanced machining (TEM) of high chrome white cast iron (HCWCI) in which the effect of cutting parameters and surface temperature of the stock material on machinability characteristics (cutting forces and surface roughness) are analyzed using ANOVA and the ANN. The results show that TEM causes easy shearing of the material, leading to the reduction in cutting forces with expected improvement in tool life and surprisingly good surface finish. The confirmation tests suggest both second-order regression and ANN which are better predictive models for quantitative prediction of TEM of HCWCI, and ANN is more accurate of the two.

The objectives of this study are to predict experimental cutting temperatures using numerical cutting temperatures generated by means of FEM at different combinations of cutting tools, cutting forces and cutting parameters and to obtain experimental cutting temperatures using experimental cutting forces and the mathematical model derived by ANN.

## 2. Experimental details

### 2.1. Workpiece and cutting tools

Orthogonal turning tests using AISI 316L steel (see Table 1) as the workpiece material were carried out on a Johnford T35 CNC lathe with 10 kW spindle power and a maximum spindle speed of 6500 rpm (Fig. 1). Bars with 60.3 mm diameter and 240 mm cutting