Numerical modeling and optimization of machining duplex stainless steels

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The shortcomings of the machining analytical and empirical models in combination with the industry demands have to be fulfilled. A three-dimensional finite element modeling (FEM) introduces an attractive alternative to bridge the gap between pure empirical and fundamental scientific quantities, and fulfill the industry needs. However, the challenging aspects which hinder the successful adoption of FEM in the machining sector of manufacturing industry have to be solved first. One of the greatest challenges is the identification of the correct set of machining simulation input parameters. This study presents a new methodology to inversely calculate the input parameters when simulating the machining of standard duplex EN 1.4462 and super duplex EN 1.4410 stainless steels. JMatPro software is first used to model elastic–viscoplastic and physical work material behavior. In order to effectively obtain an optimum set of inversely identified friction coefficients, thermal contact conductance, Cockcroft–Latham critical damage value, percentage reduction in flow stress, and Taylor–Quinney coefficient, Taguchi-VIKOR coupled with Firefly Algorithm Neural Network System is applied. The optimization procedure effectively minimizes the overall differences between the experimentally measured performances such as cutting forces, tool nose temperature and chip thickness, and the numerically obtained ones at any specified cutting condition. The optimum set of input parameter is verified and used for the next step of 3D-FEM application. In the next stage of the study, design of experiments, numerical simulations, and fuzzy rule modeling approaches are employed to optimize types of chip breaker, insert shapes, process conditions, cutting parameters, and tool orientation angles based on many important performances. Through this study, not only a new methodology in defining the optimal set of controllable parameters for turning simulations is introduced, but also the optimum set of process input variables for turning duplex stainless steels is defined.

**Keywords:** 3D-FEM; duplex stainless steel; JMatPro; VIKOR method; FANNS; machining performance index

1. Introduction

Empirical machining models are of limited use: They are generally only calibrated to be valid for a limited process range. Meanwhile, due to the simplification, analytical machining models are only partially suitable for describing complex processes such as can be described by finite element modeling (FEM). FEM can provide a comprehensive and in some cases complementary approach to empirical, mechanistic, or analytical approaches to study machining process. It makes possible to illustrate complex tools in...
2D or 3D configurations while simultaneously taking plasto-mechanical and thermal processes into consideration. However, it should be clear that in 2D-FEM of many machining operations: turning, drilling, milling, etc. (except broaching, sawing, etc.) the obtained final surface doesn’t correspond to the final one that is obtained in 3D-FEM. Thus, some prediction issues cannot have any realistic meaning (Klocke, 2011; Quiza & Davim, 2011).

The success and reliability of any FEM depends upon accurate mechanical (elastic constants, flow stress, friction, fracture stress/strain, etc.) and thermo-physical (density, thermal conductivity, heat capacity, etc.) data. Characterization of material flow stress behavior is needed for the extreme conditions of machining which involve plastic strains of 5–20, strain rates up to 10⁶ s⁻¹, temperatures between 500 and 1400 °C, temperature gradient (1000 °C/mm), high heating rates close to 10⁶ °C s⁻¹, and high cutting pressures of 1–3 GPa (Arrazola, Özel, Umbrello, Davies, & Jawahir, 2013). For this purpose, researchers recently applied modified constitutive equations, a great variety of which are exist in the literature (He, Xie, Zhang, & Wang, 2014; Hou & Wang, 2010; Li, Li, Wang, Liu, & Wu, 2013; Liu et al., 2013; Samantaray, Mandal, & Bhaduri, 2009; Song, Ning, Mao, & Tang, 2013; Wang et al., 2013). Some of the researchers have utilized Java-based Materials Properties (JMatPro) software to model the material properties and behavior of steels and Ni-based superalloys (Guo, Saunders, Miodownik, & Schille, 2007; Olovsjö, Hammersberg, Avdovic, Ståhl, & Nyborg, 2012; Saunders, Guo, Li, Miodownik, & Schille, 2004). Inverse identification of the constitutive model parameters has been proposed as an alternative method of defining the model coefficients, so that the models are valid over large ranges of conditions during machining (Klocke, Lung, & Buchkremer, 2013; Pujana, Arrazola, M’Saoubi, & Chandrasekaran, 2007; Shrot & Bäker, 2012; Umbrello, M’Saoubi, & Outeiro, 2007). Recent researches proposed methods for characterization friction and heat partition coefficients at the tool-work material interface in metal cutting operations (Arrazola & Özel, 2010; Attanasio & Umbrello, 2009; Bonnet, Valiorgue, Rech, & Hamdi, 2008; Heisel, Storchak, & Krivoruchko, 2013; Iraola, Rech, Valiorgue, & Arrazola, 2012; Puls, Klocke, & Lung, 2012; Rech et al., 2013; Smolenicki, Boos, Kuster, Roelofs, & Wyen, 2014; Ulutan & Özel, 2013). Several contributions have improved the FEM of serrated chip formation, chip flow, and chip breaking (Aurich & Bil, 2006; Buchkremer et al., 2014; Calamaz, Coupard, & Girot, 2008; Chagas, Barbosa, Barbosa, & Machado, 2013; Ducobu, Rivière-Lorphèvre, & Filippi, 2014; Guo & Yen, 2004; Lorentzon & Järvstråt, 2008; Rhim & Oh, 2006; Sima & Özel, 2010; Vaziri, Salimi, & Mashayekhi, 2011). Other works have focused on FEM of machining stainless steel materials (Koné, Czarnota, Haddag, & Nouari, 2011, 2013; Maranhão & Paulo, 2010; Outeiro, Umbrello, & M’Saoubi, 2006). Finally, recent works have also investigated the machining of duplex stainless steels experimentally (De Oliveira Junior, Diniz, & Bertazzoli, 2014; Koyee, Schmauder, & Eisseler, 2013; Koyee, Heisel, Eisseler, & Schmauder, 2014; Krolczyk, Legutko, & Gajek, 2013; Nomani, Pramanik, Hilditch, & Littlefair, 2013; Paro, Hänninen, & Kauppinen, 2001).

A vividly testimony to the potential interest on duplex stainless steels as a key research topic by various researches in the world is obvious when a search with the keywords ‘duplex stainless steel’ in popular database such as Science Citation Index-Expand or Scopus returns tens of recent publication. However, one can hardly find a research that addresses the FEM simulation of machining duplex grades. Furthermore, despite significant recent advances, FEM itself remains a ‘plug and play’ technique for predicting some process output, depending on the assumed boundary
conditions, including the friction. For example, it has been reported that FEM simulation of the same processes can produce different results (Arrazola & Özel, 2009).

To address the FEM simulation of machining DSS correctly, the plug and play technique must be limited first. For this purpose, this study introduces a new method of inverse identification through converting the overall differences between simulation results and experimentation ones into a single measure using Taguchi-VIKOR method. FEM modeling under mixed Taguchi design $L_{18}(2^3 \times 3^7)$ is performed to tune input parameters. Thermal contact conductance $h_{tc}$, cutting speed $v_c$, feed rate $f_r$, cutting tool–workpiece interface hybrid Coulomb $\mu_c$ and shear $\mu_s$ friction coefficients, Taylor–Quinney coefficient $\kappa_t$, percentage reduction of original flow stress $\%p$, and Cockcroft–Latham critical damage criterion $D_{crit}$ are considered as controllable input parameters. On the other hand, cutting experimentations are conducted and different performances are measured, recorded, and analyzed. The percentage difference between numerically and experimentally obtained performances such as thrust cutting force $\%E_t$, feed cutting force $\%E_f$, main cutting force $\%E_c$, chip thickness $E_h$, and tool nose temperature $\%E_T$ are considered as performance characteristics and are unified into a single index called VIKOR method. The derived indices are then optimized globally to determine the optimum set of input parameter using an effective neural network-based nature-inspired meta-heuristic algorithm known as Firefly Algorithm Neural Network System (FANNS). The optimum sets are next validated through experimentations. In the next stage of the research work, Taguchi optimization procedure is employed to numerically optimize the chip breaker types $CB$, insert geometries $Geo.$, cooling medium $CM$ such as still air, water-based and cryogenic coolants, cutting conditions such as cutting speed $v_c$ and feed rate $f_r$, and tool orientation angles such as normal rake $\alpha_n$ and inclination angle $\lambda$. Resultant cutting forces $(R)$, effective plastic stresses, chip-tool interface cutting temperatures, and tool wear rate are designated as performance characteristics. An expert system based on fuzzy rule modeling approach is adopted to derive a new index called numerical machining performance measure (NMPM). Finally, analysis of means (ANOM) is applied on the computed NMPMs to define the optimum levels of control factors. A schematic diagram summarizing the methodological framework developed in this study is shown in Figure 1.

Figure 1. Framework of the research.
2. Experimentations

2.1. Longitudinal turning operation

EN 1.4462 standard duplex and EN 1.4410 super duplex rods of circular cross section (diameter 55 mm, length 200 mm) were machined on a CNC lathe (Gildemeister CTX 420 Linear V5) having maximum drive power of 25 kW and speed range of 35–7000 revolutions/min. The tool holder was a Sandvik Coromat referenced PCLNL 2525 M 12, and the inserts were uncoated rhombic cemented carbide of ISO designation; CNMA 120412-IC20. They had neither chip breaker nor coating. The reason behind the selection of these basic-shape inserts was mainly to facilitate the optimization of the chip breaker geometry in the final stage of the study. The chemical composition and mechanical properties of the involved work materials are tabulated in Table 1.

In the literature, depth of cut has shown very little influence on chip thickness, contact stress at the tool–chip interface, tool wear rate, and average temperature (Astakhov, 2006). Therefore, in this study, the cutting tests are conducted at constant cutting depth of 1.5 mm with the following cutting data: cutting speed \( v_c = 80,160 \) and 240 m/min, and feed rate \( f_r = 0.15, 0.225 \) and 0.3 mm/rev. Finally, to avoid complications in cutting temperature measurements, the turning tests were carried out dry.

2.1.1. Cutting forces

The cutting force components \( F_c \), \( F_f \), and \( F_t \) are measured using piezoelectric dynamometer from Kistler. To ensure a steady state force signal and reduce the tool wear effect on cutting forces and temperatures, a new cutting edge per each experimental trial was employed. The effect of feed rate and cutting speed on the components of cutting force is shown in Figure 2. For instance, increasing the cutting speed from \( v_c = 80–240 \) m/min at constant \( f_r = 0.225 \) mm/rev while turning EN 1.4462 had reduced \( F_c \), \( F_f \), and \( F_t \) by 6.594, 40.613, and 19.8%, respectively. On the other hand, increasing feed rate from \( f_r = 0.15 \) to 0.3 mm/rev at constant \( v_c = 160 \) m/min while turning EN 1.4410 had increased \( F_c \), \( F_f \), and \( F_t \) by 47.39, 22.076, and 52.82%, respectively.

Table 1. Properties of the work materials.

| Chemical composition (Weight) | EN 1.4410 | EN 1.4462 |
|------------------------------|-----------|-----------|
| Carbon                       | .015      | .018      |
| Chromium                     | 24.92     | 22.42     |
| Nickel                       | 6.91      | 5.44      |
| Molybdenium                  | 4.06      | 3.12      |
| Manganese                    | .75       | .84       |
| Silicon                      | .25       | .37       |
| Nitrogen                     | .3        | .18       |
| Phosphor                     | .021      | .025      |
| Sulfur                       | .0007     | .003      |
| Copper                       | .1        | –         |

**Mechanical properties**

|               | EN 1.4410 | EN 1.4462 |
|---------------|-----------|-----------|
| Yield strength (MPa) | 579       | 514       |
| Tensile strength (MPa) | 826       | 737       |
| Hardness (BHN)     | 236       | 212       |
| Elongation (%)     | 40        | 41        |
2.1.2. Cutting temperatures

Although infrared (IR) cameras are quite expensive, they remain one of the most promising solutions for temperature measurement since they allow for a non-contact, extensive measurement of temperature. Thus, the problem of perturbation of the heat flow in the tool and changes the results is avoided. The fast response of the IR camera lets high, cutting speeds to be used in machining experiments, since it can capture the transient changes and the stages of chip formation and entanglement around the workpiece, the tool holder, and the tool post. In this study, high-resolution thermo-graphic camera Image IR8300 by InfraTec was used to film the chip formation and measures the chip temperature. Each film made for an experimental trial is composed of 800 images. The IR camera is placed straight above the rake face of the tool. The lens of the camera is protected against possible impacts of the chips flying about. The images in the films are examined, and the mean of maximum temperature in the middle of the chips is recorded. Figure 3 shows the setup of IR camera.
The dependency of maximum chip temperature on the cutting condition and the machined material can be seen in Figure 4. Examining the mean maximum chip temperature values, the average maximum chip temperature when machining EN 1.4410 was higher than EN 1.4462 by 3–5%. Experimental results have shown that high cutting speed and feed rates will not always lead to high chip temperatures. This seems in contradiction with the known proportional relations between cutting conditions and cutting temperature. The most likely explanation to this is that when the cutting speed and feed rate are increased, higher rate of removed volume is expected. In this case, the higher heat flux entering the chip resulting from the higher interface temperature is divided over a larger volume, hence lower intensity.

Due to the continuous entanglement of the DSS chips around the cutting tool and workpiece surface, the chip surface was not always available for direct observation by the IR camera. Furthermore, due to the concave surface of the scanned workpiece, highly reflective nature of DSS, surface and difficulties in accurately measuring surface emissivity, the erroneous temperature reading of tool–chip interface was inevitable (see Figure 5). During the early efforts to compare the maximum chip temperatures, similar

**Figure 4.** Dependency of maximum chip face temperature on the cutting conditions.

**Figure 5.** Problems associated with IR camera temperature measurement during machining DSS.
problems of measuring maximum chip temperature due to the obstructed chip’s free face have also been encountered. Therefore, the application of the obtained maximum chip temperature results is restricted only to the experimentation phase. Instead, the calibrated IR images of the black tool tip with emissivity value of 0.93 were obtained very shortly (0.25 sec) after the feed was halted and the temperature of the cutter at the end of steady cutting is recorded. The experimentally measured temperature data are then utilized to validate the results obtained in the simulation phase.

Figure 6 maps the experimentally measured maximum tool surface temperatures at location of 0.5 mm < 45° from the origin of the nose curvature. It can be seen that the maximum temperature on the tool face increases with cutting speed. With the increase in feed rate, the cross section of chip and tool–chip contact length increases and consequently friction rises. This is also involves the increase of temperature.

2.1.3. Micrographs of the chips

The serrated chip geometries, which were detected in some machining occasions, have to be correctly configured and measured. Thus, the chips are carefully collected and prepared for detailed analyses. Among many chip-related measurements, maximum and minimum chip thickness and degree of serration are recorded using two different techniques. In the first, the collected chips are embedded in transparent epoxy, polished using increasingly finer diamond grit, and etched in chemical solution. Despite the process time-consuming nature and reduction of the 3D structures to 2D planes, this method enabled the ease tracings of the streamline of material flow and paths of the grains. The variation of plastic deformation during a chip formation cycle is clearly shown in Figure 7(a). Higher plastic deformation during the loading stage and lower plastic deformation during the unloading stage of the chip formation cycle have influenced the grain shapes, so that in the zone of high plastic deformation, the grains are severely deformed and in the zone of low plastic deformation, the grains are moderately deformed. The tips of the cracks can be clearly observed at the boundary between the zones. The chip structure shown in Figure 7(b) is an example of saw-tooth continuous transitional chips obtained when DSSs are machined.

In the second measurement technique, the chips are photographed and measured using a high magnification optical microscope. The average values of five consecutive chip thickness ratios \( h_{\text{max}}/h_{\text{min}} \) are defined as the degree of serration:

![Figure 6. Dependency of tool tip temperature on the cutting conditions.](image-url)
where \( h_{\text{max}} \) and \( h_{\text{min}} \) are the perpendicular distances measured from the bottom of the chip to the peaks and valleys, respectively (see Figure 7(c)). The presence of fragments is also revealed by showing the image of free side of the chip. Only in the cases when \( H \approx 1 \), a smooth continuous chip is expected. Otherwise, the higher the ratio \( H \), the more serrated the type of the chip is. Comparing the cutting of DSS, EN 1.4462 has generally led to produce friendlier to the machine, thinner and more segmented types of chips. This is possibly due to the higher content of chip breaking elements, such as phosphor and sulfur (see Table 1). In general, as cutting speed and feed rate are increased, there are increases in the degree of serration (\( H \)) as observed in the Figure 8. It is also observed that cutting speed, which adversely affected the \( h_{\text{max}} \), has contributed positively in the chip thinning process through reducing the consecutive distance between the peaks.

3. Prerequisite conditions of machining numerical simulations

3.1. Control factors

Since the success and reliability of machining modeling depends upon accurate mechanical and thermo-physical data, a brief description of the involved FEM control factors is considered important here, so that deeper understanding of the simulation of cutting DSS is gained.

3.1.1. Damage

One of the reasons behind the poor machinability of standard and super DSS is their high tensile strength. Therefore, when machining of DSS, tensile stress is expected to play an important role. In this research, the effect of tensile strength is included in the material response employing Cockcroft–Latham’s damage criterion, which is expressed mathematically as follows:

\[
D = \int_0^{\varepsilon_f} \sigma_1 d\varepsilon
\]
where $\varepsilon_f$ is the effective strain, $\sigma_1$ is the principal stress, and $D$ is a material constant. Cockcroft and Latham’s criterion states that when the integral of the largest tensile principal stress component over the plastic strain path in Equation (2) reaches the critical value $D_{\text{crit}}$, usually called damage value, fracture occurs or chip segmentation starts, the flow stress is reduced to a lower value $\%p$, which is expressed as percentage of the original flow stress (Umbrello et al., 2007).

3.1.2. Friction

In this study, Zorev’s friction model is adopted to overcome the shortcomings of the Coulomb and the shear friction law simultaneously. So that in the range of low normal pressure, the Coulomb law is applied while for high normal pressures, the shear friction law is used. This can be expressed by means of the following formulation:

$$\tau_f(x) = \begin{cases} 
\tau_p : \mu \sigma_n \geq \tau_p, & (l_p < x < l_c) \quad \text{Sticking region} \\
\mu \sigma_n : \mu \sigma_n < \tau_p, & (0 < x < l_p) \quad \text{Sliding region}
\end{cases}$$

(3)

where the $\tau_f$, $\sigma_n$, and $\mu$ are the frictional stress, normal stress, and coefficient of friction, respectively (Zorev, 1963).

3.1.3. Thermal contact conductance $h_{lc}$

The thermal contact conductance $h_{lc}$, also known as the heat transfer coefficient, describes the heat flux of two solids in contact and is defined as follows:

$$h_{lc} = \frac{q}{\Delta T}$$

(4)

Figure 8. Dependency of the chip characteristics on the cutting conditions.
in which $\Delta T$ is the temperature difference at the contacting surfaces and $q$, the heat flux, defined as:

$$h_{tc} = \frac{d}{dA} \left( \frac{dQ}{dt} \right)$$

(5)

where $A$ is the area of contact surface and $Q$ is the conducted heat in (J). It is recognized that thermal contact conductance is a function of several parameters, the dominant ones being the type of contacting materials, the macro- and micro-geometry of the contacting surfaces, the temperature, the interfacial pressure, the type of lubricant or contaminant, and its thickness (Rosochowska, Balendra, & Chodnikiewicz, 2003).

3.1.4. Taylor–Quinney coefficient

As the mechanical behavior is affected by temperature (softening effect), the plastic deformation is accompanied by heat generation which results in temperature rise. The heat generation due to this phenomenon is described by the following relationship:

$$\dot{q}_p = \kappa \varepsilon_{\dot{p}}$$

(6)

where $\dot{q}_p$ is the volumetric heat generation due to plastic work in (W/m$^3$), $\varepsilon_{\dot{p}}$ is the von Mises equivalent plastic strain, and $\kappa$ is the Taylor–Quinney coefficient which represents the proportion of plastic works converted into heat. (Haddag & Nouari, 2013) have shown strong dependency of $\kappa$ on both strain and strain rate for various engineering materials. Within the confines of their constitutive framework, the assumption that $\kappa$ is constant is inconsistent with the rate independence of the stored energy of cold work, which is a fundamental consequence of thermodynamics. It would seem that the only justification for a priori assumptions on $\kappa$ is a lack of information on the stored energy of cold work. Therefore, this coefficient is considered as an unknown input value that has to be inversely determined in the next cutting simulations.

3.2. Prediction of chip serration

Serrated chips (also called segmented or non-homogeneous chips, see Figure 7(c)) are semi-continuous with large zones of low shear strain and small zones of high shear strain; hence, the latter zone is called shear localization. Metals with low thermal conductivity and strength that decreases sharply with temperature (thermal softening) exhibit this behavior (Kalpakjian & Schmit, 2006). Adiabatic shear bands have been observed in the serrated chip during high strain rate metal cutting process of titanium (Sima & Özel, 2010), carbon steel (Rhim & Oh, 2006), nickel-based alloys, and stainless steels (Lorentzon, Järström, & Josefson, 2009). Adiabatic shear bands are narrow zones with thickness of the order of few micro-meters where shear deformation is highly localized. Each material has a different susceptibility to adiabatic shear because it depends on properties such as heat capacity, heat conductivity, strength level, microstructure, geometry, defects, and strain rates. It is also known that adiabatic shear banding precedes material failures at high strain rates. Adiabatic shear banding is usually accompanied by a loss in stress capacity owing to intense thermal softening in the shear bands and, in many cases, shear bands serve as sites for crack initiation and growth during subsequent dynamic fracture (Odeshi, Al-ameeri, & Bassim, 2005). Localized adiabatic shearing can be considered a unique consequence of severe plastic
deformation at high strain rates. As both thermal and strain softening lead to rapid deformation localization, a shear band forms via a nearly adiabatic process. Also of note is that grain refinement can occur within shear bands and severe plastic strain (which can reach 5–20) can also appear within these shear bands (Xue, Liao, Zhu, & Gray, 2005).

In order to capture the formation of chip serrations numerically, a material model which accounts for thermal and strain softening should be employed. In last several years, numerous attempts have been made to predict serrated chip formation by finite element method. However, it was found to be difficult to predict the shear band and the serrated chip formation by the FEM technique, especially in three-dimensional configuration. In addition to the improper meshing size and strategy, the application of conventional flow stress models is one of the main reasons.

Unfortunately, a universal material model suitable for all cutting simulations remains one of the main unaccomplished tasks. Due to the typical machining high strain, strain rate temperature, and temperature gradient, it is not always easy to determine the flow stress curves experimentally. Additionally, experimental methods such as split Hopkinson bar test are quite expensive and require a large number of experiments to conduct. On the other hand, empirical material laws which describe the flow stress as a function of strain, strain rate, and temperature contain specific material constants that have to be determined by regression analyses or by the least-squares method and verified experimentally. During the last three decades, many of such models are suggested. The most notably are the engineering-based and physically based models. Results of the first evaluative simulations trials carried out in this study have shown that chip morphologies predicted by engineering-based model such as Johnson–Cook (JC) model and physically based model such as Zerilli–Armstrong lacked the formation of the shear bands and strain localizations which are often denoted as characteristics of chips formed during machining materials that possess high ultimate and yield strength and low thermal conductivity such as duplex stainless steels. For example, the following conditions were considered in a 3D-FEM and extruded 2D-FEM modeling:

- Tool: normal rake angle = −5°, relief angle = 7°, inclination angle = 0°, radius of the cutting edge = 0.03 mm, and tool material is tungsten carbide (WC).
- Work material: EN 1.4462
- Work material models: (a) JMatPro and (b) JC model. The JC constitutive model is given by equation:

\[ \sigma = (A + B\varepsilon^n) \left( 1 + C \ln \left( \frac{\dot{\varepsilon}}{\dot{\varepsilon}_0} \right) \right) \left( 1 - \left( \frac{T - T_r}{T_m - T_r} \right)^m \right) \]  

(7)

where \( \sigma \) is current von Mises flow stress; \( A \) is initial yield strength; \( B \) is strain hardening coefficient; \( \varepsilon \) is equivalent plastic strain; \( n \) is strain hardening exponent; \( C \) is strain rate coefficient; \( \dot{\varepsilon} \) is equivalent plastic strain rate; \( \dot{\varepsilon}_0 \) is reference plastic strain rate; \( m \) is thermal softening exponent; \( T \) is current temperature; \( T_m \) is melting temperature; \( T_r \) is reference temperature at which material constants are determined (Nasr, Ng, & Elbestawi, 2007).

The elastic-plastic, viscosity, and thermal softening terms are represented by the first, second, and third brackets of the above equation, respectively. The procedure of computing the constants of Johnson–Cook model from JMatPro stress flow curves involved the following steps:
The value of \( A \) is calculated from the yield stress of the metal given in Table 1, that is, \( A = 514 \) MPa.

At \( T = T_r \) and \( \dot{\varepsilon} = \dot{\varepsilon}_0 \), the curve \( \ln(\sigma - A) \) vs. \( \ln(\varepsilon) \) is plotted. The values of \( B \) and \( n \) are extracted from the intercept and slope of this plot, respectively.

Substituting the values of \( A, B, \) and \( n \) in Equation (7) and assuming \( T = T_r \) which eliminates the thermal softening term, the strain rate coefficient (\( C \)) is obtained from the slope of the graph \( \{\sigma/(A + Be^n)\} \) vs. \( \ln(\dot{\varepsilon}) \).

At \( \dot{\varepsilon} = \dot{\varepsilon}_0 \), the viscosity term is eliminated. The exponent (\( m \)) is obtained from the slope of the graph \( \ln[1 - \{\sigma/(A + Be^n)\}] \) vs. \( \ln\{(T - T_r)/(T_m - T_r)\} \). Finally, the overall correlation coefficient was found satisfactory at \( R^2 = 0.85567 \). The JC parameters of the EN 1.4462 DSSs are given in Table 2.

- Cutting regime: cutting speed \( v_c = 100 \) m/min and uncut chip thickness \( f_c = 0.25 \) mm.
- Damage criteria: \( D_{\text{crit.}} = 50 \) MPa and \( \%p = 20 \).
- Shear coefficient \( \mu_t = 0.4 \) and \( h_{tc} = 45 \) N/(mm s K).
- Mesh size = 20 \( \mu \)m and aspect ratio = 7.
- Stress flow curves of the work material are illustrated in Figure 9.

The left and right sides of the Figure 10 show the states of the deformation zones for JMatPro and JC models, respectively. For instance, Figure 10(b) shows the plastic strain distribution in the deformation zone, while Figure 10(c) presents the temperature distribution in the deformation zones. As clearly seen from the figures, the formation of transitional or saw-tooth chip types is hardly predicted in the chips correspond to the JC

### Table 2. Parameters of the Johnson–Cook model for EN 1.4462.

| Parameter | \( A \) (MPa) | \( B \) (MPa) | \( n \) | \( C \) | \( m \) | \( \dot{\varepsilon}_0 \) (1/s) |
|-----------|--------------|--------------|------|------|------|----------------|
| Value     | 514          | 612.96       | .1801| .01194| .9765| 1               |

Figure 9. EN 1.4462 JC and JMatPro flow stress curves at \( \varepsilon = 1 \).
model. Furthermore, the morphologies of the chips when cutting stainless steel materials are often related with chip up-curling and side-curling are also hardly noticed in JC material model cases. On the other hand, FEM results employed JMatPro flow stress curves seem to perform better in terms of the prediction of chip curling and formation adiabatic shear bands phenomenon. Therefore, the option of implementing flow stress data generated by JMatPro software is adopted. A text file was first generated for each workpiece material with chemical composition and mechanical properties shown in Table 1 and copied into the keyword file of the actual simulation. The software is also used to model the elastic and thermo-physical behavior of the work material.

3.3. Finite element simulations

The classical representation of cutting process by 2D models of chip formation suitable for orthogonal cutting has a limited assistance to tool and process designers. Moreover, the obtained final surface does not correspond to the final one that is obtained in 3D. Consequently, some prediction performances like residual stresses cannot have any realistic meaning. For these reasons, the oblique turning models are designed in 3D-FEM environment. The predicted thermo-mechanical properties of the work materials are shown in Figure 11.

The simulations are carried out with commercial software DEFORM-3D v10.1. The software is based on the implicit updated Lagrangian formulation. The workpiece, each 10 mm size, was considered as a plastic object and meshed with approximately 140,000 elements. The tool considered a rigid object meshed with more than 100,000 elements. It is oriented according to the cutting angles set in experimental test and moves along a straight path. The cutting tool material was uncoated tungsten carbide (WC) and assigned directly from the available material database of the software. Thermal and mechanical properties of WC tools are tabulated in Table 3.

To improve the gradients of temperature, stress, strain, and strain rate distributions, the mesh is refined in the vicinity of areas of cutting tool and the workpiece where the primary and secondary shear zone will be located. However, fixing the minimum element size at a very fine one could make the computation very expensive in terms of
running time and size of the final database. Therefore, the minimum mesh element size of the workpiece and aspect ratio was fixed at ¼ of the minimum uncut chip thickness and 7, respectively. The top sides of the workpiece as well as all sides of the cutting tool were allowed to exchange heat with the environment; the convection coefficient is considered constant at 0.02 N/(s mm K), which is the default value for dry cutting in DEFORM 3D. On the other hand, meshing of the cutting tool model expected to be a decisive factor for the simulation of the heat flux, temperature, and stresses in the material decohesion/deformation zone (Niesłony, Grzesik, Chudy, & Habrat, 2014). Therefore, the meshing density on the tool is increased in the potential chip-tool contact surface, while the rest of the tool is meshed with relatively coarser mesh. The mesh and boundary conditions for the finite element model are shown in Figure 12.

### 3.4. Design of the FEM experiments

When the experimental design is a full factorial one, the final number of experiments is usually large, because all the possible combinations should be introduced in the design. In order to allow improvement in the methodology of simulation tests and study the entire control factors space with the smallest possible number of experiments, the concept of design of experiment (DOE) is applied. DOE is defined as process of planning of an experiment so that appropriate data will be collected, which are suitable for further statistical analyses resulting in valid and objective conclusions. One of the robust methods of experimental design is Taguchi method, which provides a simple, efficient, and systematic approach for the optimization of experimental designs for performance.

![Figure 11. Temperature-dependent mechanical and physical properties of the work materials.](image-url)
quality and cost. To evaluate the effect of each control factor or its interaction effects on the process outputs, Taguchi employs standard orthogonal arrays. After conducting the experiments and collecting the desired outputs according to the Taguchi arrays, the values of outputs have to be transferred into signal-to-noise (S/N) ratios. Usually, there are three S/N ratios available, \( \eta \), depending on the type of characteristic; the lower-the better (LB), the higher-the better (HB), and the nominal-the better (NB). Owing to the non-beneficiary nature of the considered performances (outputs) here, the LB is adopted as:

\[
\eta_{ij} = -10 \log_{10} \left( \frac{1}{n} \sum_{i=1}^{n} Y_{ijk}^2 \right)
\]

where \( \eta_{ij} \) is the S/N ratio for the response \( j \) of experimental number \( i \), and \( Y_{ijk} \) is the experiment result for the response \( j \) of the experiment \( i \), in the \( k \)th replication; \( n \) is the total number of replications, and \( Y_0 \) is the nominal response. Thereafter, analysis of means (ANOM) and analysis of variance are performed on the S/N ratio of orthogonal array to identify the optimal factor level combination and estimate the error variance for the effects and variance of the prediction error, respectively (Keleştemur, Arıcı, Yıldız, & Gökçer, 2014).

In this study, the eight considered control factors are as follows: (1) thermal contact conductance \( h_{tc} \), (2) cutting speed \( v_c \), (3) feed rate \( f \), (4) Coulomb friction coefficient \( \mu_c \), (5) shear friction coefficient \( \mu_t \), (6) Taylor–Quinney coefficient \( \kappa_t \), (7) percentage decrease in flow stress \( %\sigma_p \), and (8) Cockcroft–Latham critical damage value \( D_{\text{crit}} \). The third and fourth control factors are referred to the cutting conditions and are included in the design to give the design more flexibility in dealing with other sets of cutting conditions that are planned in the second stage of the study. Taguchi mixed design L\(_{18}\) \( (2^4 \times 3^7) \) is adopted so that the underestimation and overestimation problems are
avoided by keeping the most parameter levels at three. Additional advantage of this factorial design is the reduction of experimentation trials from 18 to 9, because cutting speed and feed rate are the only input variables that can be designated as controlled factors during experimentation phase of the study. The control factors and their levels and the orthogonal array are shown in Tables 4 and 5, respectively.

4. Results of the DOE

The first stage of performing numerical simulations has confirmed the strong influence of control factors on the cutting performances. Among the performances that have been strongly affected were the cutting temperatures, cutting forces, strain rates, and chip morphologies. Figure 13 depicts the impact of sets of control factors on the cutting temperature and chip morphology after cutting 8 mm of the workpiece length. It is difficult to draw clear conclusion points on the parametric effect of each control factor based on

| Factors                                | Sym. | Unit          | Levels       |
|----------------------------------------|------|---------------|--------------|
| Thermal contact conductance            | \( h_{tc} \) | N/(s mm K)   | 100 1000     |
| Cutting speed                          | \( v_c \) | m/min        | 80 160 240   |
| Feed rate                              | \( f_r \) | mm/rev       | .15 .225 .3  |
| Coulomb friction coefficient           | \( \mu_c \) | –            | .5 .75 1     |
| Shear friction coefficient             | \( \mu_t \) | –            | .6 .9 1.2    |
| Taylor–Quinney coefficient            | \( \kappa_t \) | –          | .8 .9 1      |
| Reduction in flow stress               | \%p  | –            | 10 30 50     |
| Critical damage value                  | \( D_{crit} \) | MPa        | 50 100 150   |

Table 4. Control factors and levels for the design of simulation experiments.

| Control factors |
|-----------------|
| \( h_{tc} \) (N/mm s K) | \( v_c \) (m/min) | \( f_r \) (mm/rev) | \( \mu_c \) | \( \mu_t \) | \( \kappa_t \) | \%p | \( D_{crit} \) (MPa) |
| 100             | 80             | .15            | .5             | .6             | .8             | 10 | 50             |
| 2               | 100            | 80             | .225           | .75            | .9             | .9  | 30            |
| 3               | 100            | 80             | .3             | 1              | 1.2            | 1   | 50            |
| 4               | 100            | 160            | .15            | .5             | .9             | .9  | 50            |
| 5               | 100            | 160            | .225           | .75            | 1.2            | 1   | 150           |
| 6               | 100            | 160            | .3             | 1              | .6             | .8  | 30            |
| 7               | 100            | 240            | .15            | .75            | .6             | 1   | 30            |
| 8               | 100            | 240            | .225           | 1              | .9             | .8  | 50            |
| 9               | 100            | 240            | .3             | .5             | 1.2            | .9  | 10            |
| 10              | 1000           | 80             | .15            | 1              | 1.2            | .9  | 30            |
| 11              | 1000           | 80             | .225           | .5             | .6             | 1   | 50            |
| 12              | 1000           | 80             | .3             | .75            | .9             | .8  | 10            |
| 13              | 1000           | 160            | .15            | .75            | 1.2            | .8  | 50            |
| 14              | 1000           | 160            | .225           | 1              | .6             | .9  | 10            |
| 15              | 1000           | 160            | .3             | .5             | .9             | 1   | 30            |
| 16              | 1000           | 240            | .15            | 1              | .9             | 1   | 10            |
| 17              | 1000           | 240            | .225           | .5             | 1.2            | .8  | 30            |
| 18              | 1000           | 240            | .3             | .75            | .6             | .9  | 50            |

Table 5. L_{18} (2^{1+3}) orthogonal array.
the images shown, since at each cutting step, the values of performances change considerably. Therefore, statistical tools have to be employed to analyze the results and help emphasizing the effect of control factors separately.

Based on the Taguchi optimization procedure, the next step after recording the results of experimentation is to calculate the S/N ratio of obtained performance characteristics such as cutting forces in feed ($F_f$), cutting ($F_c$), and thrust ($F_t$) directions, strain, strain rate, principal stress, mean tool–chip interface temperature, chip temperature, and chip thickness for each simulation. Owing to the non-beneficial nature of the studied performances, the lowest value is always desirable. Therefore, Equation (8) is employed in this case. The simulation of randomly specified trials was repeated and no differences between replications were noticed (i.e. $k = 1$). The overall mean of ($\eta_{ij}$) associated with $n$ trials is then determined using the principles of analysis of means (ANOM). The level which returns maximum S/N ratio is designated as the optimum, since it optimizes the response and minimizes the effect of the noise factors simultaneously.

Figure 14 shows the results of performing ANOM after normalization. The mean S/N ratios are normalized between the worst ‘0’ and the best ‘1’. However, it should be noted here that explaining the main effect plots of each involved control factor on obtained performance characteristics is an enormous task and requires lots of paper space. For example, the optimum factor level combinations which minimize the main cutting force for machining EN 1.4462 and EN 1.4410 are $h_1^c, v_c^3, f_r^2, \mu_c^1, \mu_l^1, \kappa_l^3, %p^1 D_{\text{crit}}^1$, and $h_1^c, v_c^3, f_r^1, \mu_c^2, \mu_l^1, \kappa_l^3, %p^1 D_{\text{crit}}^1$, respectively. Another example, in the case of turning 25 EN 1.4410, simulation results showed that increasing the cutting speed value from $v_c = 80$ m/min to $v_c = 240$ m/min had reduced the main effects of $F_c$, $F_f$, and $F_t$, strain, and chip thickness by 43.6%, 32.08%, 46.08%, 13.244%, and 39.44%, respectively. While the main effects of strain rate, normal stress, and chip/tool interface temperature had increased by 37.98%, 7.25%, and 19.045%, respectively.
5. Proposed methodology

The percentage of differences between the experimentally measured cutting forces, chip temperatures and thicknesses, and the FEM-predicted ones are computed using the percentage of difference expression (%E):

\[ \%E = \frac{Y_{\text{EXP}} - Y_{\text{FEM}}}{Y_{\text{FEM}}} \times 100 \]  \hspace{1cm} (9)

where \( Y_{\text{EXP}} \) represents the experimental performance values and \( Y_{\text{FEM}} \) the simulated performance values. To estimate the effect of the control factors and important interactions on the \( \%E \), percentage of contribution of each control factor on variance of the corresponding error percentage should be computed. The control factor that returns highest contribution percentage is designated as the prime factor. For the sake of more convenience, percentages are drawn in pie charts and shown in Figure 15. For instance, the control factors which are expected to play important roles in minimizing the percentage differences of feed force \( \%E_f \), cutting force \( \%E_c \), thrust force \( \%E_t \), tool temperature \( \%E_T \) and chip thickness \( \%E_h \) during turning EN 1.4462 were \( \mu_t, \kappa_t, \mu_i \) and \( h_{tc} \times v_c, \mu_i \) and \( h_{tc}, \mu_t \), respectively.

Results of \( \%E \) computations vs. the experimental order are illustrated in Figure 16. It can be seen that the predicted feed and thrust force components are generally underestimated except for some few cases at \( D_{\text{crit}} = 150 \text{ MPa} \). Fluctuations of \( \%E_f \) and \( \%E_t \) were generally in the range from \(-40 \) to \( 195\% \). On the other hand, \( \%E_c \) has shown better agreements with the range of approximately \(-40 \) to \( 45\% \). Furthermore, comparing the \( T_{\text{tool}} \) and \( h_{\text{max}} \), the \( \%E \) between experimental and FEM values also fluctuate between overestimation and underestimation, with very few cases where the absolute \( \%E \) is less than \( 5\% \). These results show the strong impact of control factors on the outputs of the
5.1. VIKOR-based Taguchi

The VIKOR method was developed for multi-criteria optimization of complex systems. It determines the compromise ranking-list, the compromise solution, and the weight stability intervals for preference stability of the compromise solution obtained with the initial (given) weights. This method focuses on ranking and selecting from a set of alternatives in the presence of conflicting criteria. It introduces the multi-criteria ranking index based on the particular measure of ‘closeness’ to the ‘ideal’ solution. On the other
hand, VIKOR-based Taguchi provides a systematic and efficient methodology for determining the optimum combination of the control factors such that the output is effective and has high performance and also is robust to the noise factors. The multiple-percentage of error problem at this stage is converted into a single-response problem as follow:

**Step 1.** Construction of the decision matrix: The decision matrix in this case is comprised of the values of S/N ratios for computed percentages of errors, that is, $\eta_{ij}$ of $\%E_j$ where $i = 1, 2, \ldots$, number of simulation experiments ($m = 18$), $j = 1, 2, \ldots$, number of performances percentage of errors ($n = 5$).

$$D = \begin{bmatrix} \eta_{11} & \eta_{12} & \cdots & \eta_{1n} \\ \eta_{21} & \eta_{22} & \cdots & \eta_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \eta_{m1} & \eta_{m2} & \cdots & \eta_{mn} \end{bmatrix} \quad (10)$$

**Step 2.** Calculation of normalized ratings by the vector normalization:

$$r_{ij} = \left( \frac{\eta_{ij} - \min(\eta_j)}{\max(\eta_j) - \min(\eta_j)} \right) \quad (11)$$

**Step 3.** Calculate the relative weight of performances using the standard deviation method:

$$w_j = \frac{\text{STDV}_j}{\sum_{j=1}^{n} \text{STDV}_j} \quad (12)$$

where $\text{STDV}_j$ is the standard deviation of performance $j$. The summation of the individual weights should always yield one.

**Step 4.** Calculate weighted normalized ratings ($\vartheta_{ij}$):

$$\vartheta_{ij} = w_j r_{ij} \quad (13)$$

**Step 5.** Identification of positive ideal and negative ideal solutions ($A^*$ and $A^-$): The positive ideal solution, $A^*$ ($A^*_i; i = 1, 2, \ldots, m$), is made of all the best values (maximum S/N ratio) and the negative ideal solution, $A^-$ ($A^-_i; i = 1, 2, \ldots, m$), is made of all the worst values (minimum S/N ratio) at the responses in the weighted normalized decision matrix. They are calculated using Equations (14) and (15), where $J$ is the set of cost type criteria and $J'$ is the set of benefit type criteria.

$$A^* = \{ \vartheta_{1}^*, \ldots, \vartheta_{m}^* \} = \{ (\max \vartheta_{ij}|j \in J), (\min \vartheta_{ij}|j \in J') \} \quad (14)$$

$$A^- = \{ \vartheta_{1}^-, \ldots, \vartheta_{m}^- \} = \{ (\min \vartheta_{ij}|j \in J), (\max \vartheta_{ij}|j \in J') \} \quad (15)$$

where $J = \{ j = 1, 2, \ldots, n|\vartheta_{ij}, \text{ if desired response is large} \}$; $J' = \{ j = 1, 2, \ldots, n|\vartheta_{ij}, \text{ if desired response is small} \}$.

**Step 6.** Compute the values of utility measure $S_j$ and regret measure $R_j$ by respective relations:
\[ S_i = \sum_{j=1}^{n} w_j \left( \frac{\vartheta_j^+ - \vartheta_j^-}{\vartheta_j^+ - \vartheta_j^-} \right) \]

\[ R_i = \max_j \left( w_j \left( \frac{\vartheta_j^+ - \vartheta_j^-}{\vartheta_j^+ - \vartheta_j^-} \right) \right) \]

**Step 7.** Compute the VIKOR index \((Q_V)\) values for attribute \(j = 1, 2, \ldots, n\), by the relation

\[ Q_V = \xi \left( \frac{S_i - S^+}{S^- - S^+} \right) + (1 - \xi) \left( \frac{R_i - R^+}{R^- - R^+} \right) \]

where \(S^+ = \min_j S_j\), \(S^- = \max_j S_j\); \(R^+ = \min_j R_j\), \(R^- = \max_j R_j\).

\(\xi\) is introduced as weight of the strategy of the maximum group utility, usually \(\xi = 0.5\).

**Step 8.** Rank the alternatives, sorting by the values \(S\), \(R\), and \(Q_V\). The results are three ranking lists.

**Step 9.** For given attribute weights, propose a compromise solution, alternative \(A_{b1}\), which is the best ranked by \(Q_V\), if the following two conditions are satisfied:

**Condition 1:** “Acceptable advantage”: \(Q_V(A_{b2}) - Q_V(A_{b1}) \geq (1/(m-1))\), where \(A_{b1}\) and \(A_{b2}\) are the first and second-best alternatives in the ranking order by \(Q_V\).

**Condition 2:** “Acceptable stability in decision making”: alternative \(A_{b1}\) must also be the best ranked by \(S\) and/or \(R\). This compromise solution is stable within a decision-making process, which could be ‘voting by majority rule’ (when \(\xi > 0.5\) is needed) or ‘by consensus’ (when \(\xi \approx 0.5\)) or ‘with veto’ (when \(\xi < 0.5\)). If one of the conditions is not satisfied, then a set of compromise solutions is proposed, which consists of:

(a) Alternatives \(A_{b1}\) and \(A_{b2}\) if only condition 2 is not satisfied.
(b) Alternatives \(A_{b1}, A_{b2}, \ldots, A_{bi}\) if condition 1 is not satisfied; \(A_p\) is determined by the relation \(Q_V(A_{b2}) - Q_V(A_{b1}) \approx (1/(m-1))\) (Rao, 2013).

The procedure of calculating VIKOR indices for each work material case is started with the representation of decision matrix. S/N values are normalized using Equation (11). The criteria weights are then specified using the standard deviation method as per Equation (12). Thereafter, normalized decision matrices are calculated using Equation (13). The best and the worst values of all the criteria in weighted normalized decision matrices are identified using Equations (14) and (15). The values of utility (\(S\)) and regret (\(R\)) measures are calculated using Equations (16) and (17), respectively. The VIKOR index values \((Q_V)\) are calculated using Equation (18). For both work material cases, the values of the first and second ranked alternatives are in acceptable advantage range, that is, \(Q_V(A_{b2}) - Q_V(A_{b1})\) is always greater than \(1/(18-1) = 0.05882\). For example, the \(Q_V\) \((A_{b2})\) and \(Q_V\) \((A_{b1})\) of EN 1.4462 are 0.106 and 0.012, respectively, which satisfies condition 1, that is, \(0.106 - 0.012 = 0.094\) is greater than 0.05882. Both regret and utility measure values by consensus prove the stability in decision-making. Therefore, the values of \(Q_V\) are directly used in the next analyses. Based on the outcomes of the
VIKOR method, the best alternatives when cutting EN 1.4410 and EN 1.4462 were alternatives No. 15 and No. 6, respectively. Performing the ANOM, it can be proved that the optimum factor level sets when machining EN 1.4462 and EN 1.4410 are $h_{tc}^2 f_r^1 \mu_c^2 \mu_t^2 \kappa_t^3 \%p^2 D_{crit}^3$, and $h_{tc}^2 f_r^3 \mu_c^2 \mu_t^3 \kappa_t^3 \%p^2 D_{crit}^3$, respectively. The combination of these control factors should minimize the difference between experimental and numerical results. Figure 17 maps the effect of cutting speed interactions with the rest of control factors on the $Q_V$ values. The dark blue areas represent the favored regions where the difference between experimental and numerical performances is minimum.

5.2. Firefly algorithm neural network system

Unfortunately, owing to the missing impact of interactions in Table 5, the choice of the selecting the optimal set is not always straightforward. Additionally, the above optimum sets are case specific to the given cutting conditions. To comprehend the $Q_V$ so that it covers all the domain of the control factors and their corresponding interactions, an effective modeling technique is required. Unfortunately, the traditional modeling techniques such as response surface methodology were seen not quite efficient to accurately predict all values of $Q_V$. Furthermore, to account for all interactions, adopting quadratic model for example, comprise 44 terms which makes the problem even more complex. Therefore, a multi-layer perceptron (MLP) artificial neural network (ANN) is proposed to accomplish the task. Once, this step is accomplished, a recently developed stochastic optimization algorithm has to be integrated with the proposed ANN to minimize $Q_V$ and determine the optimum set at any required cutting condition.

5.2.1. Artificial neural network

Neural network is a logical structure with multi-processing elements, which are connected through interconnection weights. The knowledge is presented by the interconnection weights, which are adjusted during the training phase. The process of training a
neural network can be broadly classified into two typical categories: supervised learning and unsupervised learning. The first requires using both the input and the target values for each sample in the training set. The most common algorithm in this group is the back propagation, used in the Multi-Layer Perceptron (MLP), but it also includes most of the training methods for recurrent neural networks, time delay neural networks, and thrust basis networks. Unsupervised learning is used when the target pattern is not completely known (Quiza & Davim, 2011).

To establish a useful relationship between independent variables \((h_{tc}, v_c, f_c, \mu_c, \mu_b, \kappa_t, \%p, \text{ and } D_{crit})\) and dependent variable \((Q_V)\), supervised feed-forward MLP-neural networks with back propagation (BP) as learning algorithm were adopted. The back propagation algorithm consists of two phases: the forward phase, where the activations are propagated from the input to the output layer, and the backward phase, where the error between the observed actual and the requested nominal value in the output layer is propagated backwards in order to modify the weights and bias values. This procedure is repeated many times until the sum of squared error term reaches an acceptable level.

The MLP-neural networks used in this study have two layers: one hidden layer and one output layer (see Figure 18). The hidden layer uses a sigmoid-type transference function:

\[
F(\chi) = \frac{1}{1 + \exp(-b - \sum \omega_i \chi_i)}
\]

while the output layer uses a linear function:

\[
F(\chi) = b + \sum \omega_i \chi_i
\]

where \(\omega\) and \(b\) are the weights and biases of the network, respectively. To carry out the training process, all the inputs were normalized using the following equation:

![Figure 18. The neural network architecture used in the FANNS.](image-url)
The final output \( Q_{\text{NN}} \) of input vector \((8*1)\)-number of hidden neurons (N)-output feed-forward neural network structure can be mathematically expressed as:

\[
Q_{\text{NN}} = \log \text{sig} \left( \begin{bmatrix} \omega_{11} & \ldots & \omega_{18} \\ \vdots & \ddots & \vdots \\ \omega_{81} & \ldots & \omega_{88} \end{bmatrix} \times \begin{bmatrix} h_{bC} \\ \vdots \\ D_{\text{crit.}} \end{bmatrix} + \begin{bmatrix} b_1 \\ \vdots \\ b_N \end{bmatrix} \right) \times \begin{bmatrix} \omega_1 & \ldots & \omega_N \\ b_{N+1} \end{bmatrix} + b_{N+1}
\]

(22)

In this study, the MLP uses sigmoid transfer functions in the hidden layers. These functions are often called ‘squashing’ functions, because they compress an infinite input range into a finite output range. Sigmoid functions are characterized by the fact that their slopes must approach zero as the input gets large. This causes a problem when you use steepest descent to train a multi-layer network with sigmoid functions, because the gradient can have a very small magnitude and, therefore, causes small changes in the weights and biases, even though the weights and biases are far from their optimal values. The purpose of the resilient back propagation training algorithm (RPROP) is to eliminate these harmful effects of the magnitudes of the partial derivatives. Only the sign of the derivative can determine the direction of the weight update; the magnitude of the derivative has no effect on the weight update. The size of the weight change is determined by a separate update value. The number of learning steps is significantly reduced in comparison to the original gradient-descent procedure as well as to other adaptive procedures, whereas the expense of computation of the RPROP adaptation process is held considerably small. Another important feature, especially relevant in practical application, is the robustness of the new algorithm against the choice of its initial parameter (Riedmiller & Braun, 1993).

The scaling or normalization ensures that the ANN will be trained effectively without any particular variable skewing the results significantly. The weights and biases of the network are initialized to small random values to avoid immediate saturation in the activation functions. The neural networks trained using the gradient desendent with adaptive velocity and momentum back propagation algorithm to model \( Q_{\text{f}} \), where it is not easy to obtain analytical and good empirical relations. The optimum architecture was found out by varying network characteristics in MATLAB using trial and error technique. It was found that when the training function, RPROP; the number of hidden neurons, 13; maximum number of epochs to train, 100; the learning rate, 0.01; the increment to weight change, 1.2; decrement to weight change, 0.5; initial weight change, 0.07; and maximum weight change, 50, the root mean square of errors were the minimum.

Because neural networks are purely empirical models, validation is critical to operational success. Figure 19 shows the comparison of experimental results and modeling in verifying the network generalization capabilities. The results are almost identical.

5.2.2. Firefly algorithm (FA)

FA is one of the recent swarm intelligence methods developed by Yang (2010) in 2008 and is a kind of stochastic, nature-inspired, meta-heuristic algorithm that can be applied for solving the hardest optimization. The algorithm is inspired by the flashing lights of
fireflies in nature. Such flashing light may serve as the primary courtship signals for mating. Besides attracting mating partners, the flashing light may also serve to warn off potential predators. The algorithm has been formulated by assuming:

1. All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex.
2. Attractiveness is proportional to their light intensities. The less bright will be moving toward the brighter one. It will move randomly if there is no brighter one.
3. The brightness of a firefly is affected or determined by the landscape of the objective function.

The light intensity and attractiveness are in some way synonymous. While the intensity is referred to as an absolute measure of emitted light by the firefly, the attractiveness is a relative measure of the light that should be seen in the eyes of the beholders and judged by other fireflies. The attractiveness $\beta(\delta)$ and light intensities $I(\delta)$ of each firefly are considered to decrease monotonically depending on the distance $\delta$ as:

$$
\beta(s) = \beta_0 e^{-\gamma_a \delta^2/\delta_r} \tag{23}
$$

$$
I(s) = I_0 e^{-\gamma_a \delta^2/\delta_r} \tag{24}
$$

where $\beta_0$ and $I_0$ denote the maximum attractiveness and light intensities, respectively (i.e. at $\delta_r = 0$), and $\gamma_a$ is the light absorption coefficient, which controls the decrease of the light intensity. The light intensity $I$ of a firefly representing the solution $s_i$ and is proportional to the value of fitness function $I(s_i) \propto f(s_i)$. The distance between any
two fireflies $s_i$ and $s_j$ is expressed as the Euclidean distance by the base firefly algorithm, as follows:

$$\delta_{ij} = \|s_i - s_j\| = \sqrt{\sum_{k=1}^{d} (s_{ik} - s_{jk})^2}$$  \hspace{0.5cm} (25)$$

where $d$ denotes the dimensionality of the problem. The movement of the $i$th firefly is attracted to another more attractive firefly $j$. In this manner, the following equation is applied:

$$s_i = s_i + \beta_0 e^{-\gamma x^2} (s_j - s_i) + \alpha \psi_i$$  \hspace{0.5cm} (26)$$

where $\psi_i$ is a random number drawn from Gaussian distribution and $\alpha$ is the randomization parameter. In summary, FA is controlled by three parameters: the attractiveness $\beta$, the absorption coefficient $\gamma$, and the randomization parameter $\alpha$. Finally, the basic steps of the Firefly Algorithm (FA) can be summarized as the pseudo code and shown in Figure 20.

In order to obtain solutions that will provide useful information to the user during the phase of inverse identification of input parameters, neural network models should be integrated with the FA. The neural network models integrated with the FA optimizer were named FANNS and its architecture is shown in Figure 21.

The target of the optimization process in this study is to determine the optimal values of the input parameters that lead to the minimum value of ANN-predicted $Q_{NN}$ at any given cutting condition. The optimization problem can be defined as:

$$\text{Objective} = \max (1 - Q_{NN})$$  \hspace{0.5cm} (27)$$

The decision variables are $h_{tc}$, $v_c$, $f_r$, $\mu_c$, $\mu_t$, $\kappa_t$, $\%p$, and $D_{crit}$. They are constrained within the range of simulation experiments (refer to Table 4):

![Flow chart of the Firefly Algorithm (FA).](image-url)
5.2.3. Application of FANNS to the global optimization of VIKOR indices and validation of the results

The proposed FANNS approach has been applied to effectively model and optimize the VIKOR indices. The FA initializing optimization parameters were as follows: population size = 20, number of iterations = 2000, randomization ($\alpha$) = 0.5, attractiveness ($\beta_0$) = 0.2, and attractiveness variation ($\gamma_a$) = 1. The optimal sets of control factors that lead to the optimum $Q_V$ values are tabulated in Table 6, and the results of the FANNS are shown in Figure 22. The obtained optimization results showed that FANNS is highly reliable, converge consistently and quickly (the computation time was less than 3 min) to the optimum solution.

To validate the global FANNS results, the experimental cutting conditions should be identical to the numerical ones. Therefore, three longitudinal turning experiments per each work material were carried out at the exact optimum cutting conditions as listed in Table 6. The averages of the measured performances are computed and used to calculate the percentage difference between the numerical and experimental ones using Equation (9).

\[
\begin{align*}
100 & \leq h_{tc} \leq 1000 \text{ N/(s mm K)} \\
80 & \leq v_c \leq 240 \text{ m/min} \\
0.15 & \leq f_c \leq 0.3 \text{ mm/rev} \\
0.5 & \leq \mu_c \leq 1 \\
0.6 & \leq \mu_t \leq 1.2 \\
0.8 & \leq \kappa_t \leq 1 \\
10 & \leq \%p \leq 50 \\
50 & \leq D_{crit} \leq 150 \text{ MPa}
\end{align*}
\] (28)
The percentage difference between numerically obtained cutting forces, chip temperature, and maximum chip thicknesses, and the experimental ones for each work material are tabulated in Table 7. It can be seen that the calculated performances are in close agreement to the experimental results. The global optimum difference percentages are also compared with difference percentages of the rank No. 1. The lower percentages of difference confirm the advantage of FANNS application in identifying the input parameters while simulating the machining of duplex stainless steels.

### 5.3. Extension of FANNS application: a case study

One of the aims of this study was to define a robust approach, so that the optimum set of control factors at any given cutting speed and feed rate is accurately determined. In this section, the adaptability of the described approach to the changing cutting speeds and feed rates is examined. Three arbitrary experimental cutting tests per each work material were conducted. The optimum sets of control factors at the exact cutting speeds
Table 7. Validation numerical and experimental results.

| EN  | $F_f$ (N)      | $F_c$ (N)      | $F_t$ (N)      | $T_{tool}$ ($^\circ$C) | $h_{max}$ (mm) |
|-----|----------------|----------------|----------------|------------------------|----------------|
|     | Exp. | Num.  | Exp. | Num.  | Exp. | Num.  | Exp. | Num.  | Exp. | Num.  |
| 1.4462 | 385.167 | 369.941 | 935.654 | 9,720.614 | 298.646 | 290.139 | 134.635 | 140.519 | .3346 | .3516 |
| %E  | -4.116 | 3.745 | -2.139 | 4.187 | 5.125 | |
| 1.4410 | 761.152 | 723.686 | 1485.63 | 1569.54 | 517.254 | 491.827 | 142.714 | 148.709 | .5535 | .5843 |
| %E  | -5.177 | 5.346 | -5.169 | 4.031 | 5.254 | |
Table 8. Optimum sets of control factors at fixed cutting speed and feed rates.

| Parameter | Unit     | A.1. | A.2. | A.3. |
|-----------|----------|------|------|------|
| $v_c$     | m/min    | 75   | 150  | 225  |
| $f_r$     | mm/rev   | .325 | .175 | .2   |
| $h_{tc}$  | N/(s mm K) | 665.558 | 771.698 | 820.049 |
| $\mu_c$  |           | .53225 | .66125 | .69922 |
| $\mu_t$  |           | .69525 | .70525 | .84552 |
| $\kappa_t$ |         | .98308 | .90325 | .97825 |
| $\%p$    |           | 24.7349 | 21.1528 | 19.8571 |
| $D_{crit.}$ | MPa    | 65.7898 | 77.6984 | 71.2524 |
| EN 1.4462 | $h_{tc}$  | N/(s mm K) | 795.523 | 826.375 | 862.815 |
| $\mu_c$  |           | .99125 | .84258 | .87134 |
| $\mu_t$  |           | 1.04321 | 1.06925 | 1.08125 |
| $\kappa_t$ |         | .98995 | .94582 | .92545 |
| $\%p$    |           | 30.7425 | 22.2481 | 26.4358 |
| $D_{crit.}$ | MPa    | 92.506  | 100.678 | 111.452 |
| EN 1.4410 | $h_{tc}$  | N/(s mm K) | 795.523 | 826.375 | 862.815 |
| $\mu_c$  |           | .99125 | .84258 | .87134 |
| $\mu_t$  |           | 1.04321 | 1.06925 | 1.08125 |
| $\kappa_t$ |         | .98995 | .94582 | .92545 |
| $\%p$    |           | 30.7425 | 22.2481 | 26.4358 |
| $D_{crit.}$ | MPa    | 92.506  | 100.678 | 111.452 |

and feed rates were determined using the proposed FANNS (see Table 8); meanwhile numerical models, each at the exact optimum set of optimized control factors, were prepared and executed. Figure 23 shows the measured and predicted cutting performances for EN 1.4410 and EN 1.4462. The average of absolute percentage differences between the experimental and numerical results for each material case is 3.8652 and 4.9956%, respectively. Considering the wide range of applied cutting speeds and feed rates, the proposed methodology of inversely identifying the simulation input factors shows excellent results with respect to the examined performances.

![Figure 23](image-url)
6. Inverse identification of the Usui’s wear law constants

Tool wear is a major consideration in all machining operations. It adversely affects tool life, quality of machining surface, and its dimensional accuracy, and consequently, the economics of cutting operations. Tool wear and the changes in tool geometry during cutting manifest themselves in different ways, generally classified as flank wear, crater wear, nose wear, notching, plastic deformation of the tool tip, chipping and gross fracture (Kalpakjian & Schmit, 2006). The allowable average wear land for various machining operations is usually determined by the width of flank wear (VB) which occurs on the relief (flank) face of the tool.

To characterize tool wear for a cutting operation, there exist two main approaches: empirical tool life models and tool wear rate models. In order to derive a reliable empirical tool life model, a large number of experimental tests are essential which is usually time-consuming, cost-intensive, restricted to the investigated tool–workpiece combinations and cannot predict the influence of work material or tool materials on the values of constants in the models. On the other hand, tool wear rate models involve process variables that are not directly measurable or very difficult to measure during a cutting operation, such as normal stress and temperature on the tool face, chip temperature, and chip sliding velocity along the tool rake face. However, in the last several years, the FEM has been successfully applied to estimate such variables (Attanasio, Ceretti, Fiorentino, Cappellini, & Giardini, 2010). Consequently, a better understanding of the fundamentals of cutting mechanics, engineering analyses of tool wear, and systematic approach for the process optimization is possible.

Considering the Show’s equation of adhesive wear, tool wear rate model derived by Usui and co-workers involves variables such as temperature T, normal stress σn, sliding velocity vr at the contact surface, and two constants A and B. It is expressed as:

\[
\frac{dW}{dt} = A \sigma_n v_r \exp\left(-\frac{B}{T}\right)
\]  

Their results have shown that both the flank and crater wear rates have the same functional form. The variables in Usui’s wear rate model can be predicted by FEM simulation of cutting process or combining analytical method and FEM (Yang & Liu, 2002). In this study, the procedure of calculating the Usui’s wear model constants can be simply summarized as follows:

1. Conduct tool life experimentations under dry condition using a typically recommended insert grade to machine stainless steels to determine the wear rate \((dW/dt)\).
2. To estimate the variables in Equation (29), prepare identical to the experimentations, fully coupled thermo-mechanical, and FANNS-optimized 3D-FE models, and run the simulations.
3. Collect the numerically estimated \(\sigma_n\), T, and \(v_r\).
4. Fit the nonlinear Usui’s model to determine the constants A and B.

Seven arbitrary multi-pass dry turning tests of EN 1.4410 and EN 1.4462 DSS bars were performed on a variable spindle speed CNC lathe using rhombic 80° CNMA 120412-IC20 uncoated cemented carbide inserts. The solid bars had outside diameter of 55 mm. Constant material volumes of 29,405 mm³ (i.e. 6 mm in thrust and 60 mm in axial directions) were removed per each experimental trial. An optical microscope with magnification 200 times was then used to measure the maximum wear on the flank
surface after each cutting pass. Thereafter, logarithmic plots of tool wear vs. cutting time were drawn, and the slopes \( \frac{dW}{dt} \) were determined. Meanwhile, the 3D-FE cutting simulations were carried out based on the proposed procedure. The tool is considered rigid with no wearing possibility. Values of \( T, \sigma_n, \) and \( v_s \) were directly extracted from simulation results. Matlab function nonlinear model fit was then utilized to fit the model and test its adequacy through ANOVA. The adjusted correlation factor \( (R_{adj}) \) was in very good agreement with predicted correlation factor \( (R_{pre}) \) which supports the prediction power of the model and was generally above 0.94. The root mean square of errors (RMSE) for EN 1.4462 and EN 1.4410 Usui wear models were 0.000314 and 0.000469, respectively. The final forms of Usui’s wear model for each workpiece material case are given as:

\[
\left( \frac{dW}{dt} \right)_{EN \ 1.4462} = 6.0478 \times 10^{-9} \sigma_n v_s \exp\left(-\frac{1172.8}{T}\right) \quad (30)
\]

\[
\left( \frac{dW}{dt} \right)_{EN \ 1.4410} = 7.1704 \times 10^{-9} \sigma_n v_s \exp\left(-\frac{992.5203}{T}\right) \quad (31)
\]

7. Optimization of Turning EN 1.4410 and EN 1.4462 DSS

In the second stage of this study, a hypothetical benchmark analysis based on the Taguchi optimization procedure is suggested. The objective was to select the best combination of criterions such as chip breakers type, tool geometry, process and cutting conditions, and cutting tool orientation angles for an effective machining of EN 1.4462 and EN 1.4410 DSS. For this purpose, Taguchi’s mixed design L\(_{18}(2^{1} \times 3^{7})\) is once again seen the most appropriate because of its attractive characteristics which combines the highest possible number of levels along with largest number of criterion and smallest number of experiments. Another attractive characteristic of the design is that the interaction between column 1 and 2 is orthogonal to all columns and hence can be estimated without sacrificing any column. The interaction can be estimated from the 2-way table of columns 1 and 2. The studied criterion and their corresponding levels are listed in Table 9. Columns 1 and 2 can be combined to form a 6-level column. Each level in column three represents an insert designation which is often commercially available. The next sub-sections briefly describe the studied criterion.

| Factors                  | Symbol | Unit      | 1   | 2   | 3   |
|--------------------------|--------|-----------|-----|-----|-----|
| Chip breaker type        | CB     | –         | M3  | M   | PP  |
| Insert shape             | Geo.   | –         | DNMG| CNMG| WNMG|
| Cooling medium           | CM     | –         | Still air | Water | Cryogenic |
| Cutting speed            | \( v_c \) | m/min   | 75  | 150 | 225 |
| Feed rate                | \( f_r \) | mm/rev   | .1  | .175| .25 |
| Rake angle               | \( a_n \) | degree  | 0   | -6  | -12 |
| Inclination angle        | \( \lambda \) | degree | 0   | -6  | -12 |
7.1. Control factors

7.1.1. Chip-breaker type

In particular designed for machining stainless steels, chip breakers such as M3 M type are adapted with geometric features that improve the tool’s life due to a reinforced cutting edge at the area where notch wear tends to occur when machining stainless steel, causing poor surface finish and risk of edge breakage (see Figure 24). On the other hand, PP-type chip breakers, which are also recommended for machining stainless steels, are characterized by having 3-step smart dot structures which provides smooth chip evacuation with a wide range of feed rates, and smooth taper cutting edge to reduce cutting forces.

7.1.2. Cutting insert shapes

In metal cutting, the primary goal was to achieve the most efficient separation of chips from the workpiece. One of the main factors that contribute in optimizing chip morphology is the insert shape. For this reason, the selection of the right cutting tool geometry is critical. The three basic insert shapes which have to be investigated in this study were diamond 55°, rhombic 80°, and trigon 80°. Other geometric features, such as clearance angle, tolerance, size, thickness, nose radius, and cutting edge preparation, were identical.

7.1.3. Cooling medium

Following the determination of the optimum thermal contact conductance of the tool–chip interface ($h_t$) using FANNS approach, the influence of environmental heat convection in dry, wet, and cryogenic conditions on the cutting processes is investigated and optimized. A window for heat exchange was defined as shown in Figure 25. It was restricted to the secondary and tertiary deformation zones on the inserts using a cylindrical shape of 1.2 mm radius and 3 mm length and was not intended to change any other boundary conditions in the finite element model. Local convection coefficients in wet and cryogenic cutting were assigned in the areas covered by the window, while the rest of the cutting tool is still subjected to air convection. The convection coefficients of dry, wet, and cryogenic cutting mediums are taken from the literature as: 0.02, 10, and 5000 N/(s mm K), respectively (Pu et al., 2014; SFTC, 2010).

Figure 24. Investigated chip breakers characteristics.
7.1.4. Cutting conditions

For all simulation trials, the finishing and semi-finishing set of cutting conditions are selected according to the maximum and minimum levels of cutting speed \( (v_c) \) and feed rate \( (f) \) as follows:

(a) Finishing:

\[
150 \leq v_c \leq 225 \text{ m/min} \\
0.1 \leq f_r \leq 0.175 \text{ mm/rev}
\]  

(b) Semi-finishing:

\[
75 \leq v_c < 150 \text{ m/min} \\
0.175 < f_r \leq 0.25 \text{ mm/rev}
\]

7.1.5. Tool orientation angles

Tool inclination angles affect many performances such as cutting forces, chip thickness, tool–chip contact length, chip flow angle, etc. When machining DSS, the formed chips are tough, abrasive to the tooling, and tend to entangle around cutting tool, workpiece, and tool post. A proper cutting insert inclination and rake angle for example may cause the chips to flow to a position at which they are less likely to become entangled and rub and scratch the finished surface of the workpiece. Geometry of oblique cutting process with straight cutting edge is shown in Figure 26. The process is performed with
tools having the tool cutting edge angle $k_r \neq 90^\circ$ and tool inclination angle $\lambda \neq 0^\circ$. The rake angle may be measured in more than one plane, and hence, more than one rake angles can be defined for a given tool and angle of obliquity. The different rake angles in oblique cutting are named as: normal ($\alpha_n$), velocity ($\alpha_v$), and effective ($\alpha_e$) rake angles. The flow of chip is at an angle to the normal to the cutting edge. The angle between normal to the cutting edge and chip velocity vector is called chip flow angle ($\Delta$). The shear angles could also be measured in different planes, such as a plane normal to the cutting edge ($\phi_n$) and plane of effective rake angle ($\phi_e$). Since chip flow and shear angles are often designated as dependent cutting variables, and the rake and inclination angles as independent cutting variables, therefore, when constructing the 3D-FE models, cutting tools are only positioned according to the combination of inclination and rake angles.

7.2. 3D-FE models

Due to the incorporation of chip breaker geometry in the array of control factors, a great deal of geometrical resolution is essential. Therefore, the 3D-CAD models of the cutting inserts are created in Solidworks first and exported as Standard for the Exchange of Product model data (STEP) files into Transmagic software to increase the resolution. The models are saved in Standard Tessellation Language (STL) format and exported to the Deform-3D environment. Both workpiece and cutting tools are meshed with grids of varying tetrahedral mesh densities so that the highest densities of meshes are assigned to the locations where temperature, strain, strain rate, ..., etc. have the highest gradient. The total number of mesh elements in workpiece and cutting tool were 80,000 and 250,000, respectively. In addition to the described geometrical parameters, the cutting tools had identical nose radius of 0.8 mm, cutting edge radius of 30 $\mu$m, and clearance angle of 5°. The WC cutting tools are considered rigid and are worn out under Usui’s
wear model. Other FEM settings such as elasto-visco plastic and thermo-mechanical properties of the workpiece, the boundary conditions, and process conditions are covered under previous sections of this study.

7.3. Simulation results and discussion

Once the turning simulations has been finished, cutting performances such as cutting forces, temperatures, …, etc. have been extracted. The S/N ratio of each performance is computed based on its beneficial or non-beneficial status. Almost all performances considered in this study were non-beneficial; therefore, lower is better concept applied and the values of S/N ratios are computed using Equation (8). To eliminate the complexity of problem, instead $F_f$, $F_c$, and $F_t$ components, resultant cutting force ($R$) has been considered:

$$R = \sqrt{F_f^2 + F_c^2 + F_t^2}$$ \hspace{1cm} (34)

The main effect of each control factor on each performance is determined by the ratio of sum of all S/N ratios corresponding to a factor at particular level to number of repetition of factor level. The optimum combinations corresponding to maximum average effect are directly depicted in the main effect plots as shown in Figure 27 below. Statistical analysis of variance (ANOVA) is performed to specify statistically significant control factors.

Figure 28 exhibits the percentage of contribution of each control factor on the variance of the corresponding cutting performance. In the following sub-sections, the effects of control factors on each single cutting performance are described.

![Figure 27. Main effect plots of the effect of control factors on the cutting performances during turning EN 1.4410 and EN 1.4462 DSSs.](image-url)
7.3.1. **Influence of control factors on the resultant cutting forces**

Based on a quick review of the results, the following conclusion points can be drawn:

1. The optimum insert designations which minimize $R$ during turning EN 1.4462 and EN 1.4410 can be described in ISO norms as: WNMG 060408-PP and CNMG 120408-PP, respectively.

2. In spite of the advantageous aspects of increasing cutting speed, applying coolant, and cryogenic conditions in increasing the productivity and reducing the overall $R$ values, results have shown a limited influence of these control factors on the mean $R$ values. This statement is supported by the slopes of the $R$ curves in Figure 27.

3. Among the considered control factors, feed rate had shown the strongest impact on the resultant cutting forces (see Figure 28).

4. The optimum values of cutting tool orientation angles expressed by ranges of investigated rake and inclination angles are $-6^\circ$ and $0^\circ$, respectively.

7.3.2. **Influence of control factors on the effective strain**

Without relating the hardening parameters in the loading function to the experimental uniaxial stress-strain curve, the work-hardening theory of plasticity cannot be applied in practical terms. In order to correlate the test results obtained by different load programs, the introduction of any strain and stress variables, that are functions of plastic strain and plastic stress, and can be plotted against each other is considered useful. These variables are often called effective strain and effective stress.

DSSs are a group of stainless steel alloys that are characterized by high work-hardening rate. They are machined at very high strain rates which increase the work-hardening rate and causing higher resistance to plastic deformation. Generally, the following observation points can be made:

![Figure 28. The percentage contribution of FEM control factors in the cutting performances variances.](image-url)
(1) The average effective plastic strain when machining EN 1.4462 was 13.2% lower than the corresponding EN 1.4410.

(2) Employing chip breaker type PP has generally caused lower effective strain values.

(3) Detrimental control factors vary considerably per work material family.

(4) Higher values of effective strains are observed when the cooling medium on the tool is cryogenic.

(5) Main effects of effective strain decrease with increasing cutting speed.

(6) Mean effective strains are found to be minimum at the feed rate range of 0.1–0.175 mm/rev and inclination angle range of 6°–12°.

(7) Minimum effective strain value when cutting EN 1.4462 and EN 1.4410 at \( a_n = 0^\circ \) and \( a_n = -12^\circ \), respectively.

7.3.3. Influence of control factors on the effective stress

Effective plastic stress is considered a relevant characteristic of the cutting process which characterizes the level of resistance to cutting. The correlation between the state of this performance imposed by the cutting tool in the layer being removed and the fracture strain of the work material could be used to estimate the physical efficiency of the cutting process. In summary to the results, the following conclusions can be drawn:

(1) The effective stress encountered in cutting EN 1.4410 12% higher than EN 1.4462.

(2) The optimum control factor level combinations of cutting EN 1.4462 and EN 1.4410 were \( CB^1 \ Geo. \^1 CM^2 v_c^1 f_r^1 \alpha_n^3 \lambda_2^2 \) and \( CB^1 Geo. \^2 CM \^1 v_c^2 f_r^1 \alpha_n^2 \lambda_2 \), respectively.

(3) Increasing the rake angle in negative direction and inclination angle in positive direction generally increases the effective stress.

(4) The minimum effective plastic stress of 1261.48 MPa and 1492.01 MPa when cutting EN 1.4462 and EN 1.4410 was recorded at experiment No. 9, respectively.

(5) When cutting EN 1.4462, process conditions such as \( v_c, f_r, CM \), and \( v_c \times CM \) interaction have contributed to the effective stress values by 48%. On the other hand, when cutting EN 1.4410, they had contributed by as much as 66%.

7.3.4. Influence of control factors on the tool–chip interface temperature

Mean contact temperature at the tool–chip interface (also is referred to as the cutting temperature) is the basic tribological characteristics of the tool–chip interface. It plays a major role in the formation of crater on the tool face and leads to failure of tool by softening and thermal stresses. This temperature is the most suitable parameter to correlate the tribological conditions with tool wear. Control factors that affect the tool–chip interface temperature are workpiece and tool material, tool geometry, cutting conditions, and cutting medium. Fortunately, most of these factors are included in the original design of simulation experimentations. Figure 29 depicts the state of cutting temperature distribution in the primary and secondary deformation zones of the workpiece. The results of the numerical studies on temperatures in cutting DSS can be summarized as follows:
(1) Mean cutting temperatures at dry cutting when machining EN 1.4462 and EN 1.4410 were 36.3 and 53.5% higher than at corresponding cryogenic process conditions.

(2) The contribution of water-based coolant in lowering the cutting temperature has not exceeded 7.8% in both material cases.

(3) Minimum mean cutting temperature when cutting EN 1.4462 and EN 1.4410 has been recorded at experimental run 16 and 15, respectively.

(4) Cooling medium, cutting condition, and their interaction accounts for most of contributions in cutting temperature variations.

(5) The optimum control factor level combinations of cutting EN 1.4462 and EN 1.4410 were $CB^2 Geo^3 CM^3 \nu^1 f^3 \alpha^2 \lambda^1$ and $CB^1 Geo^2 CM^3 \nu^1 f^2 \alpha^3 \lambda^2$, respectively.

(6) The average cutting temperature when machining EN 1.4462 was 9.85% lower than the corresponding EN 1.4410.

7.3.5. Influence of control factors on the strain rate

The flow stress curves shown in Figure 9 exhibit sensitivity to temperature and strain rate. This sensitivity is directly related with time and temperature dependency of the mechanisms that govern the deformation and the evolution of the deformation in the material. The main mechanism by which plastic strain takes place is thermally activated
motion of dislocations past obstacles that exist within the lattice over a wide range of strain rates and cutting temperatures. The material response is significantly affected by the nature and density of the obstacles (which may change as the deformation takes place). When dealing with metals, experimental results show that the stress required for plastic strain often reduces with the increase of temperature and with the decrease of plastic strain rate (Gilat & Wu, 1997). It can then be said that temperature and plastic strain rate greatly influence the material response. In general, the stress decreases with the increasing of temperature and decreasing the plastic strain rate. Actually, temperature and strain rate effects are coupled, since one influences the other. Temperature affects the rate of deformation, which is controlled mainly by a thermally activated mechanism. On the other hand, plastic strain at high rate generates significant heating and cause an increase in temperature which leads to mechanical instability and the localization of deformation into narrow sheets of material (the adiabatic shear bands), which act as precursor for eventual material failure (Davim & Maranhão, 2009). As generalization to the given results in Figures 30 and 31, the following concluding points can be depicted:

(1) Average strain rate values under cutting EN 1.4462 and EN 1.4410 are of $2.067 \times 10^5$ 1/sec and $3.23 \times 10^5$ 1/sec, respectively.
(2) Increasing cutting speeds from 100 to 300 m/min at lower feed rates of 0.1 mm/rev had drastically increased the strain rate values.

Figure 30. Contours of tool wear depth in three-dimensional models of cutting tools.

Figure 31. Contours of tool temperature distributions in three-dimensional models of cutting tools.
(3) Mean strain rate values in cryogenic cutting conditions during cutting EN 1.4462 and EN 1.4410 were, respectively, 9.158 and 11.863% lower than the corresponding still air conditions.

(4) $CB^2 Geo.^3 CM^3 v_c^1 f^2 z_n^3 \lambda^2$ and $CB^2 Geo.^2 CM^3 v_c^1 f^2 z_n^3 \lambda^3$ were the optimum control factor$_{level}$ combinations which have minimized the strain rate when cutting EN 1.4462 and EN 1.4410, respectively.

7.3.6. Influence of control factors on the tools wear

The Equation (34) has been used in conjunction with finite element simulation to model wear of WC tools in oblique cutting of DSS. The simulation results related to the tool wear were obtained in terms of tool wear rate, total wear depth, and tool temperature. Average values of tool wear rates are statistically analyzed and plotted as shown in Figures 27 and 28. Figure 30 maps the contours of tool wear depth in the nose area of the employed cutting tools after 7 mm longitudinal cutting. As it can be observed that the locations and intensity of tool wear depths are functions of work materials and control factor sets. Considering the effect of these factors, the summary of the findings is presented below.

(1) The optimum control factor$_{level}$ combinations which have minimized the tool wear rate during cutting EN 1.4462 and EN 1.4410 were $CB^2 Geo.^1 CM^3 v_c^1 f_r^1 z_n^3 \lambda^2$ and $CB^2 Geo.^1 CM^3 v_c^1 f_r^1 z_n^3 \lambda^2$, respectively.

(2) Major percentage of contributions of 69 and 72% in variance of tool wear rate were attributed to the process and cutting conditions and their interactions when cutting EN 1.4462 and EN 1.4410, respectively.

(3) The average tool wear rate when machining EN 1.4462 was 5.365% lower than the corresponding EN 1.4410.

(4) Contour profiles of tool wear depth shown in Figure 33 coincide with temperature distribution at rake and flank faces of the cutting tools in Figure 31. Maximum wear depths are occurred in positions at rake and flank surfaces where the tool temperature is the highest.

8. Numerical machining performance measure (NMPM)

The previous analyses of machining performances have showed different control factor$_{level}$ preferences. This will cause confusions to the process designer or the machinist who interested in finding the best compromise combination of control factors which simultaneously optimize the machining of DSS. Therefore, a new machining performance measure has to be defined. In this study, fuzzy logic system is employed to combine the normalized performances, such as the resultant cutting forces, effective stress, cutting temperature, and tool wear rate into a single characteristics index called machining performance index (NMPM).

Fuzzy logic unit is composed of four main sub units namely fuzzification, knowledge base, fuzzy inference engine, and defuzzification unit as shown in Figure 32. The fuzzifier converts the entered crisp value in to a suitable semantic value to be supplied to the fuzzy set for the first part of fuzzy rule. In the knowledge base units, information about of fuzzy rule base and membership functions is given. The fuzzy rule base is a database mainly for saving fuzzy rule, which is composed of if–then expression to
indicate a conditional descriptive sentence. ‘If’ is called the first part, and ‘then’ is called the conclusion part. They are used to describe the relationship between input and output. Fuzzy values are determined by the membership functions (μ) that define the degree of membership of an object in a fuzzy set. So far there has been no standard method of choosing the proper shape of the membership functions for the fuzzy sets of the control variables; the present investigation adopts a triangular shape membership function (see Figure 33).

For a rule:

\[ \text{Rule}_j: \text{If } x_1 \text{ is } (A_{i1}) \text{ and } x_2 \text{ is } (A_{i2}), \ldots, x_k \text{ is } A_{ik} \text{ then } y_i = B_j; j = 1, 2, \ldots, N. \]

where \( N \) is the total number of fuzzy rules, \( x_i \) \((i = 1, 2, \ldots, k)\) are the input variables, \( y_i \) are the output variables, and \( A_{ik} \) and \( B_j \) are fuzzy sets modeled by membership functions \( \mu_{Ai}(x_i) \) and \( \mu_{Bi}(y_i) \), respectively. Based on the Mamdani implication method of inference, the membership function of the output of fuzzy reasoning can be expressed as:

\[
\mu_{Bi}(y_i) = \max \{ \min \{ \mu_{Ai_1}(x_1), \mu_{Ai_2}(x_2), \ldots, \mu_{Ai_k}(x_k) \} \} \quad (35)
\]

Figure 32. Fuzzy Logic Unit (FLU).

Figure 33. Triangular membership function.
Finally, a defuzzification method, called the center-of-gravity method, is adopted to transform the fuzzy inference output $\mu_{B_i}(y_i)$ into a non-fuzzy value $y_0$:

$$y_0 = \frac{\int y_i \mu_{B_i}(y_i) dy}{\int \mu_{B_i}(y_i) dy} \quad (36)$$

The yielded value is the final crisp output value obtained from the input variables. It is worth mentioning here that in most cases, the membership functions are defined within a normalized interval (universe of discourse). Therefore, before the fuzzification can be started, the input values have to be scaled (normalized) so that they fit into the universe of discourse (Gupta, Singh, & Aggarwal, 2011).

Matlab software was used to construct the inference model of the NMPM. The S/N ratios of performance values were first adjusted to a notionally common scale between null and one, so that the digit ‘one’ represents the most desirable and ‘null’ is the least desirable alternative. The four input variables are assigned with the following fuzzy sets: Small (S), Medium (M), and Large (Lg). The output variable has the following nine levels: Extremely Low (EL), Very Low (VL), Low (L), Lower Medium (LM), Medium (M), Upper Medium (UM), High (H), Very High (VH), and Extremely High (EH). Mamdani implication method is employed for the fuzzy inference reasoning. The relationship between system input and output is expressed by an ‘if–then’ type. Totally $3^4$ fuzzy rules per material were formulated. Finally, the structural characteristics of the fuzzy inference system (FIS) in this study can be plotted as shown in Figure 34.

The main effect plots of the NMPM are presented in Figure 35. The figure indicates that the mean NMPM values of EN 1.4462 are generally higher than of EN 1.4410 and the final optimum factor level combinations for both materials are $CB^1$ Geo.$^3$ CM$^3$ $v_c^1$ $f_r^1$ $z_n^1$ $\lambda^2$ and $CB^2$ Geo.$^2$ CM$^3$ $v_c^1$ $f_r^1$ $z_n^2$ $\lambda^2$, respectively. Based on the NMPM values, it can be concluded that EN 1.4462 has better machinability in terms of the employed performances. Finally, performing ANOVA on the computed NMPMs has confirmed the major effects of process and cutting conditions and their interactions on the overall performance of cutting DSS (see Figure 36).

Figure 34. FIS-NMPM: 4 inputs, 1 output, 81 rules.
9. Conclusions

In this study, three-dimensional numerical simulations of oblique cutting of standard EN 1.4462 and super EN 1.4410 DSS have been investigated. A new approach for an effective and accurate simulation of DSS using JMatSoft’s-generated flow stress curves has been proposed. Taguchi design of experiments has been extensively used during the course of the study. Many FEM pre-processing variables are assigned as control factors for subsequent inverse identification process. The overall difference between the experimentally and numerically obtained results has been calculated and statistically analyzed based on the Taguchi optimization procedure. VIKOR method has been applied to combine the differences into one index. Thereafter, a new computational algorithm (FANNS) is suggested to effectively model and optimizes the indices in terms of the adopted control factors. Results of numerical simulation are validated and the approach prepared for the next stage of the investigation. In the second stage, a new methodology based on hypothetical numerical simulations is proposed to investigate the machining of DSS.
Parametric analysis of performances is undertaken, and many interim conclusion points are depicted. A new measure to evaluate machining performance of each of the employed DSS grades has also been suggested and the optimum machining setup is determined. Based on the experimental and numerical results and data analysis the following main conclusion points can be drawn:

1. JMatPro-generated elasto-visco plastic and thermo-mechanical properties can be effectively used to numerically simulate the machining of DSS.
2. Using time-dependent damage criteria such as Cockcroft-Latham damage criteria, JMatPro has outperformed the JC material model in prediction of chip serrations under similar thermo-mechanical material properties.
3. Pre-processing FEM control factors such as \( h_{tc}, \nu_c, \sigma, \mu_c, \mu_p, \kappa_p, \%p, \text{ and } D_{crit} \) have strong impacts on the percentage difference between experimental and numerical cutting performances.
4. The lowest mean values of the overall error percentages for cutting EN 1.4462 and EN 1.4410 were, respectively, at the following pre-processing control factor\(^{level}\) combinations; \( h_{tc}^2 \nu_c^1 f_r^1 \mu_c^2 \mu_p^2 \kappa_p^2 \%p^2 D_{circ}^3 \) and \( h_{tc}^2 \nu_c^2 f_r^3 \mu_c^2 \mu_p^2 \kappa_p^2 \%p^2 D_{circ}^3 \).
5. Validations of numerical results through experimentations have revealed that the proposed VIKOR-FANNS approach can efficiently minimize the overall percentage differences at any desired cutting conditions.
6. Hypothetical benchmark analysis based on the Taguchi optimization procedure can be numerically employed to select the best combination of criterions such as: \( CB, Geo., CM, \nu_c, f_r, \sigma_n, \text{ and } \lambda \).
7. Performing ANOM of the derived NMPM values has indicated that the final optimum factor\(^{level}\) combinations for cutting EN 1.4462 and EN 1.4410 are \( CB^1 Geo. \cdot CM^3 \nu_c^1 f_r^1 \sigma_n^2 \lambda^2 \text{ and } CB^2 Geo. \cdot CM^3 \nu_c^1 f_r^1 \sigma_n^2 \lambda^2 \), respectively.

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References
Arrazola, P. J., & Özel, T. (2009). Finite element modeling of machining processes. In T. Özel & J. P. Davim (Eds.), Intelligent machining: Modelling and optimization of the machining processes and systems (pp. 125–163). London: ISTE and Wiley.
Arrazola, P. J., Özel, T. (2010). Investigations on the effects of friction modeling in finite element simulation of machining. *International Journal of Mechanical Sciences, 52*, 31–42.

Arrazola, P. J., Özel, T., Umbrello, D., Davies, M., & Jawahir, I. S. (2013). Recent advances in modelling of metal machining processes. *CIRP Annals – Manufacturing Technology, 62*, 695–718.

Astakhov, V. P. (2006). *Tribology of metal cutting*. Oxford: Elsevier.

Attanasio, A., & Umbrello, D. (2009). Abrasive and diffusive tool wear FEM simulation. *International Journal of Material Forming* [Internet], 2, 543–546. doi:10.1007/s12289-009-0475-z

Attanasio, A., Ceretti, E., Fiorentino, A., Cappellini, C., & Giardini, C. (2010). Investigation and FEM-based simulation of tool wear in turning operations with uncoated carbide tools. *Wear, 269*, 344–350.

Attanasio, A., & Umbrello, D. (2009). Abrasive and diffusive tool wear FEM simulation. *International Journal of Material Forming* [Internet], 2, 543–546. doi:10.1007/s12289-009-0475-z

Aurich, J. C. C., & Bil, H. (2006). 3D finite element modelling of segmented chip formation. *CIRP Annals – Manufacturing Technology, 55*, 47–50.

Bonnet, C., Valiorgue, F., Rech, J., & Hamdi, H. (2008). Improvement of the numerical modeling in orthogonal dry cutting of an AISI 316L stainless steel by the introduction of a new friction model. *CIRP Journal of Manufacturing Science and Technology, 1*, 114–118.

Buchkremer, S., Wu, B., Lung, D., Münstermann, S., Klocke, F., & Bleck, W. (2014). FE-simulation of machining processes with a new material model. *Journal of Materials Processing Technology, 214*, 599–611.

Calamaz, M., Coupard, D., & Girot, F. (2008). A new material model for 2D numerical simulation of serrated chip formation when machining titanium alloy Ti–6Al–4V. *International Journal of Machine Tools and Manufacture, 48*, 275–288.

Chagas, G. M. P., Barbosa, P. A., Barbosa, C. A., & Machado, I. F. (2013). Thermal analysis of the chip formation in austenitic stainless steel. *Procedia CIRP, 8*, 293–298.

Davim, J. P., & Maranhão, C. (2009). A study of plastic strain and plastic strain rate in machining of AISI 1045 using FEM analysis. *Materials and Design, 30*, 160–165.

De Oliveira Junior, C., Diniz, A., & Bertazzoli, R. (2014, October). Correlating tool wear, surface roughness and corrosion resistance in the turning process of super duplex stainless steel. *Brazilian Society of Mechanical Sciences and Engineering, 36*, 775–785.

Ducobu, F., Riviére-Lorphèvre, E., & Filippi, E. (2014). Numerical contribution to the comprehension of saw-toothed Ti6Al4V chip formation in orthogonal cutting. *International Journal of Mechanical Sciences, 81*, 77–87. doi:10.1016/j.ijmecsci.2014.02.017

Gilat, A., & Wu, X. (1997). Plastic deformation of 1020 steel over a wide range of strain rates and temperatures. *International Journal of Plasticity, 13*, 611–632.

Guo, Y. B., & Yen, D. W. (2004). A FEM study on mechanisms of discontinuous chip formation in hard machining. *Journal of Materials Processing Technology, 155–156*, 1350–1356.

Guo, Z. L., Saunders, N., Miodownik, A. P., & Schille, J. P. (2007). Quantification of high temperature strength of nickel-based superalloys. *Materials Science Forum, 546–549*, 1319–1326.

Gupta, A., Singh, H., & Aggarwal, A. (2011). Taguchi–fuzzy multi output optimization (MOO) in high speed CNC turning of AISI P-20 tool steel. *Expert Systems with Applications, 38*, 6822–6828.

Haddad, B., & Nouari, M. (2013). Tool wear and heat transfer analyses in dry machining based on multi-steps numerical modelling and experimental validation. *Wear, 302*, 1158–1170.

He, A., Xie, G., Zhang, H., & Wang, X. (2014). A modified Zerilli-Armstrong constitutive model to predict hot deformation behavior of 20CrMo alloy steel. *Materials and Design, 56*, 122–127.

Heisel, U., Storchak, M., & Krivoruchko, D. (2013). Thermal effects in orthogonal cutting. *Production Engineering [Internet], 7*, 203–211. doi:10.1007/s11740-013-0451-9

Hou, Q. Y., & Wang, J. T. (2010). A modified Johnson–Cook constitutive model for Mg-Gd-Y alloy extended to a wide range of temperatures. *Computational Materials Science, 50*, 147–152.

Iraola, J., Rech, J., Valiorgue, F., & Arrazola, P. J. (2012). Characterization of friction coefficient and heat partition coefficient between an austenitic steel AISI304L and a tin -coated carbide cutting tool. *Machining Science and Technology, 16*, 189–204.

Kalpakjian, S., & Schmit, S. R. (2006). *Manufacturing engineering and technology* (5th ed.). Upper Saddle River, NJ: Pearson Education.

Kelestemur, O., Arıcı, E., Yıldız, S., & Gökçer, B. (2014). Performance evaluation of cement mortars containing marble dust and glass fiber exposed to high temperature by using Taguchi method. *Construction and Building Materials, 60*, 17–24.
Klocke, F. (2011). *Manufacturing processes 1: Cutting*. Heidelberg: Springer.

Klocke, F., Lung, D., & Buchkremer, S. (2013). Inverse identification of the constitutive equation of inconel 718 and AISI 1045 from FE machining simulations. In *Procedia CIRP* (Vol. 8, pp. 212–217), Turin, Italy.

Koné, F., Czarnota, C., Haddag, B., & Nouari, M. (2011). Finite element modelling of the thermo-mechanical behavior of coatings under extreme contact loading in dry machining. *Surface and Coatings Technology*, 205, 3559–3566.

Koné, F., Czarnota, C., Haddag, B., & Nouari, M. (2013). Modeling of velocity-dependent chip flow angle and experimental analysis when machining 304L austenitic stainless steel with groove coated-carbide tools. *Journal of Materials Processing Technology*, 213, 1166–1178.

Koyee, R. D., Heisel, U., Eisseler, R., & Schmauder, S. (2014, October). Modeling and optimization of turning duplex stainless steels. *Journal of Manufacturing Processes*, 16, 451–467.

Koyee, R. D., Schmauder, S., & Eisseler, R. (2013). Machining of stainless steels: A comparative study. In A. Maffei & A. Archenti (Eds.), *3rd International Conference on Advanced Manufacturing Engineering and Technologies* (pp. 53–62). Stockholm, Sweden.

Krolczyk, G., Legutko, S., & Gajek, M. (2013). Predicting the surface roughness in the dry machining of duplex stainless steel (DSS). *Metalurgija*, 52, 259–262.

Li, H. Y., Li, Y. H., Wang, X. F., Liu, J. J., & Wu, Y. (2013). A comparative study on modified Johnson Cook, modified Zerilli-Armstrong and Arrhenius-type constitutive models to predict the hot deformation behavior in 28CrMnMoV steel. *Materials and Design*, 49, 493–501.

Liu, R., Melkote, S., Pucha, R., Morehouse, J., Man, X., & Marusich, T. (2013). An enhanced constitutive material model for machining of Ti-6Al-4V alloy. *Journal of Materials Processing Technology*, 213, 2238–2246. doi:10.1016/j.jmatprotec.2013.06.015

Lorentzon, J., & Järvästråt, N. (2008). Modelling tool wear in cemented-carbide machining alloy 718. *International Journal of Machine Tools and Manufacture*, 48, 1072–1080.

Lorentzon, J., Järvästråt, N., & Josefson, B. L. (2009). Modelling chip formation of alloy 718. *Journal of Materials Processing Technology*, 209, 4645–4653.

Maranhão, C., & Paulo, D. J. (2010). Finite element modelling of machining of AISI 316 steel: Numerical simulation and experimental validation. *Simulation Modelling Practice and Theory*, 18, 139–156.

Nasr, M., Ng, E.-G., & Elbestawi, M. (2007). Effects of workpiece thermal properties on machining-induced residual stresses – Thermal softening and conductivity. *Proceedings of the Institution of Mechanical Engineers. Part B: Journal of Engineering Manufacture*, 221, 1387–1400. doi:10.1243/09544054JEM856

Nieslony, P., Grzesik, W., Chudy, R., & Habrat, W. (2014). Meshing strategies in FEM simulation of the machining process. *Archives of Civil and Mechanical Engineering*. Retrieved from http://dx.doi.org/10.1016/j.acme.2014.03.009

Nomani, J., Pramanik, A., Hilditch, T., & Littlefair, G. (2013). Machinability study of first generation duplex (2205), second generation duplex (2507) and austenite stainless steel during drilling process. *Wear*, 304, 20–28.

Odeshi, A. G., Al-ameeri, S., & Bassim, M. N. (2005). Effect of high strain rate on plastic deformation of a low alloy steel subjected to ballistic impact. *Journal of Materials Processing Technology*, 162–163, 385–391.

Olovsvjo, S., Hammersberg, P., Avdovic, P., Ståhl, J.-E., & Nyborg, L. (2012). Methodology for evaluating effects of material characteristics on machinability – Theory and statistics-based modelling applied on Alloy 718. *The International Journal of Advanced Manufacturing Technology*, 59, 55–66.

Outeiro, J. C., Umbrello, D., & M’Saoubi, R. (2006). Experimental and numerical modelling of the residual stresses induced in orthogonal cutting of AISI 316L steel. *International Journal of Machine Tools and Manufacture*, 46, 1786–1794.

Paro, J., Hänninen, H., & Kauppinen, V. (2001). Tool wear and machinability of HIPed P/M and conventional cast duplex stainless steels. *Wear*, 249, 279–284.

Pu, Z., Umbrello, D., Dillon, O. W., Lu, T., Puleo, D. A., & Jawahir, I. S. (2014). Finite element modeling of microstructural changes in dry and cryogenic machining of AZ31B magnesium alloy. *Journal of Manufacturing Processes*, 16, 335–343.

Pujana, J., Arrazola, P. J., M’Saoubi, R., & Chandrasekaran, H. (2007). Analysis of the inverse identification of constitutive equations applied in orthogonal cutting process. *International Journal of Machine Tools and Manufacture*, 47, 2153–2161.
Puls, H., Klocke, F., & Lung, D. (2012). A new experimental methodology to analyse the friction behaviour at the tool-chip interface in metal cutting. *Production Engineering, 6*, 349–354.

Quiza, R., & Davim, J. P. (2011). Computational methods and optimization. In J. P. Davim (Ed.), *Mach hard mater* (pp. 191–208). London: Springer-Verlag.

Rao, R. V. (2013). *Decision making in manufacturing environment using graph theory and fuzzy multiple attribute decision making methods*. London: Springer.

Rhee, J., Arrazola, P. J., Claudin, C., Courbon, C., Pusavec, F., & Kopac, J. (2013). Characterisation of friction and heat partition coefficients at the tool-work material interface in cutting. *CIRP Annals – Manufacturing Technology, 62*, 79–82.

Rhim, S. H., & Oh, S. I. I. (2006). Prediction of serrated chip formation in metal cutting process with new flow stress model for AISI 1045 steel. *Journal of Materials Processing Technology, 171*, 417–422.

Riedmiller, M., & Braun, H. (1993). A direct adaptive method for faster back propagation learning: The RPROP algorithm. In *Proceedings of IEEE International Conference on Neural Networks* (pp. 586–591). San Francisco, CA.

Rosochowska, M., Balendra, R., & Chodnikiewicz, K. (2003). Measurements of thermal contact conductance. *Journal of Materials Processing Technology, 135*, 204–210.

Samantaray, D., Mandal, S., & Bhaduri, A. K. (2009). A comparative study on Johnson–Cook, modified Zerilli–Armstrong and Arrhenius-type constitutive models to predict elevated temperature flow behaviour in modified 9Cr–1Mo steel. *Computational Materials Science, 47*, 568–576.

Saunders, N., Guo, Z., Li, X., Miodownik, A. P., & Schille, J. P. (2004). Modelling the material properties and behaviour of Ni-based superalloys. *Superalloys, 2004*, 849–858.

SFTC. (2010). DEFORM v10.2.1 User’s manual. Columbus, OH, USA.

Shrot, A., & Bäker, M. (2012). Determination of Johnson–Cook parameters from machining simulations. *Computational Materials Science, 52*, 298–304.

Simha, M., & Özel, T. (2010). Modified material constitutive models for serrated chip formation simulations and experimental validation in machining of titanium alloy Ti–6Al–4V. *International Journal of Machine Tools and Manufacture, 50*, 943–960. doi:10.1016/j.ijmachtools.2010.08.004

Smolenicki, D., Boos, J., Kuster, F., Roelofs, H., & Wyen, C. F. (2014). In-process measurement of friction coefficient in orthogonal cutting. *CIRP Annals – Manufacturing Technology, 63*, 97–100.

Song, W., Ning, J., Mao, X., & Tang, H. (2013). A modified Johnson–Cook model for titanium matrix composites reinforced with titanium carbide particles at elevated temperatures. *Materials Science and Engineering: A, 576*, 280–289.

Ulutan, D., & Özel, T. (2013). Determination of tool friction in presence of flank wear and stress distribution based validation using finite element simulations in machining of titanium and nickel based alloys. *Journal of Materials Processing Technology, 213*, 2217–2237.

Umbrello, D., M’Saoudi, R., & Outeiro, J. C. (2007). The influence of Johnson–Cook material constants on finite element simulation of machining of AISI 316L steel. *International Journal of Machine Tools and Manufacture, 47*, 462–470.

Vaziri, M. R., Salimi, M., & Mashayekhi, M. (2011). Evaluation of chip formation simulation models for material separation in the presence of damage models. *Simulation Modelling Practice and Theory, 19*, 718–733.

Wang, X., Huang, C., Zou, B., Liu, H., Zhu, H., & Wang, J. (2013). Dynamic behavior and a modified Johnson–Cook constitutive model of Inconel 718 at high strain rate and elevated temperature. *Materials Science and Engineering: A, 580*, 385–390. doi:10.1016/j.msea.2013.05.062

Xue, Q., Liao, X. Z., Zhu, Y. T., & Gray, G. T. (2005). Formation mechanisms of nanostructures in stainless steel during high-strain-rate severe plastic deformation. *Materials Science and Engineering: A, 410–411*, 252–256.

Yang, X., & Liu, C. R. (2002). A new stress-based model of friction behavior in machining and its significant impact on residual stresses computed by finite element method. *International Journal of Mechanical Sciences, 44*, 703–723.

Yang, X. S. (2010). *Nature-inspired metaheuristic algorithms*. London: Luniver Press.

Zorev, N. (1963). Inter-relationship between shear processes occurring along tool face and on shear plane in metal cutting. *ASME International Research in Production Engineering, 42–49.*