

Estimation of Residual Stresses Induced by Grinding Using a Fuzzy Logic Approach

Y.M. Ali and L.C. Zhang

Center for Advanced Materials Technology
Department of Mechanical and Mechatronic Engineering
The University of Sydney, NSW 2006, Australia

Abstract

This paper proposes a fuzzy logic approach for the prediction of residual stresses induced by surface grinding. The surface residual stress of a ground component is considered as a function of ten variables including properties of the workpiece material, grinding wheel and the variation of operation parameters. The system extracts, from experimental results, experience and knowledge about the grinding processes and makes better prediction of residual stresses for a given grinding situation. It is shown that the fuzzy logic method provides a flexible framework for modeling the residual stresses induced by the grinding processes, in spite of the existence of experimental errors.

Keywords: grinding, residual stresses, fuzzy logic, membership functions.

Nomenclature

σ_y	yield strength of workpiece material, (MPa)
H	hardness of workpiece material, (HB)
GH	grain hardness, (knoop)
GS	mesh size, (# per inch)
WH	hardness grade of wheel
WS	wheel sharpness, (%)
TS	table speed, (m/s)
SS	spindle speed, (m/s)
LD	log of depth of cut, (μm)
CO	effective cooling rate, (%)
RS	surface residual stress, (MPa)

1. Introduction

Grinding residual stresses in an engineering component can significantly affect its surface integrity and service life by altering its fatigue strength and stress corrosion cracking. For thin elements, residual stresses can also induce massive geometric distortions [1]. Therefore, the ability to predict and control residual stresses induced by grinding is very much in demand. However, grinding is a very complex process that involves the nonlinear interaction of both thermal and mechanical behaviors at microscopic and macroscopic levels [2]. Physical models for grinding processes have limited applications due to the inherent complexity of the processes involved [3,4]. Empirical formulae developed by various research groups depend on the experimental setups of the specific laboratories and the experimental techniques used. Thus, results on residual stresses reported by different laboratories could be different from each other even when nominal conditions were the same [5,6]. In fact, the inconsistency in grinding results stems from the nature of the grinding process itself, which has the following characteristics:

- Grain geometry is irregular and grain distribution is random.
- The mesh number defining grain size is vague.
- Information available about the wheel construction in terms of voids/ grain/ bond volume ratios and the method of baking is often not sufficient [3].
- Methods of wheel dressing and the dressing tools used can affect the residual stress field significantly.
- Methods of measuring residual stresses and their distribution have not been standardized. Corrections for stress redistribution due to layer removal are complex for practical use [7]. The commonly used methods of stress measurement, e.g. beam deflection [8,9], and x-ray or neutron diffraction methods [10-15] are based on different assumptions and have different sources of error [16]. It was estimated that deflection methods can have an error of up to ± 30000 psi (~ 200 MPa) on the surface of the workpiece [8]. A deviation from x-ray diffraction measurements of up to 30% is common [5,18], and even a 250% deviation was reported [6].

Because of the various reasons discussed above, grinding results cannot be formulated simply, either theoretically or experimentally, because of the wide range of uncertainties involved. There is an imperative need for a technique that is flexible enough to absorb the uncertainties in the grinding process and that is capable of learning the experience of skilled operators.

Fuzzy sets can be used to elastically absorb such uncertainties [19]. It is a promising approach to model the complex grinding processes and can make use of the experimental knowledge available. Fuzzy logic has been used successfully in other machining processes [20,21] and in control of the grinding process [22]. This paper proposes a fuzzy logic approach to model residual stresses in various steel alloys as induced by surface grinding.

2. The Approach of Fuzzy Logic Modeling

2.1 Fundamentals

Fuzzy logic is concerned with the continuous transition from truth state to falsity state [19], as opposed to the discrete true/false transition in binary logic. It deals with many sorts of vagueness and uncertainty in data and information about a specific problem. In the meantime, it maintains a formal structure of logical operations as well as a rigorous axiomatic framework like classical binary logic [23]. The possibility theory of fuzzy logic provides a measure of the potential ability of a subset in belonging to another subset [24]. It can be shown that probability theory is a special case of possibility theory [25]. Therefore, fuzzy logic has a wider scope and range of applications than many statistical methods.

Most engineering applications of fuzzy logic belong to "Linguistic Mathematics". It deals with engineering problem where variables cannot be assigned crisp numeric values or can be assigned context-dependent linguistic values [26]. This is exactly applicable to a grinding process. For example, in the context of grinding, grain size cannot be specified by, say, diameter in μm . In practice, words like 'coarse', 'medium', and 'fine' are found very vague but yet very expressive of the main characteristics.

A fuzzy variable is defined by the quadruple [23,26-28]

$$(x, U, T(x), M(x)), \tag{1}$$

The label 'x' is a text in natural language. $U \equiv [UL, UU]$, is the universe of discourse or domain of the variable. A variable can be assigned some linguistic values defined by the term set T. M can be semantic rules or mathematical functions that provide the mapping from U to T and the reverse. A linguistic term, T_i , is defined [26] by the pair

$$(S, P), \tag{2}$$

where $S \equiv [SL, SU]$, $S \subseteq U$, is the supporting subset of T_i , and P is the set of parameters defining the membership function $\mu_{T_i}(x)$ expressing the degree of belonging of the value of x to a specific term T_i . In the present work, membership functions are defined by five parameters $P = \{a, b, c, d, e\}$, Fig.1, where:

$$\mu_T(y) = \begin{cases} 0, & y \notin S \\ \frac{1}{2} \left(\frac{y - SL}{a - SL} \right)^e, & y \in [SL, a] \\ 1 - \frac{1}{2} \left(\frac{b - y}{b - a} \right)^e, & y \in [a, b] \\ 1, & y \in [b, c] \\ 1 - \frac{1}{2} \left(\frac{y - c}{d - c} \right)^e, & y \in [c, d] \\ \frac{1}{2} \left(\frac{SU - y}{SU - d} \right)^e, & y \in [SU, d] \end{cases} \tag{3}$$

Figures 2 to 12 show the membership functions of the grinding variables to be considered in this paper. Each figure demonstrates the domain U for the fuzzy variable x, the supports S for linguistic terms T and the shape of the membership function μ defined by Eq. (3).

If each variable in Table 1 is fuzzified according to Eqs. (1) to (3), the whole table can be transformed into a set of propositions of the form (x is T). In particular, if $y \in U_x$, then y can be expressed as a union of the linguistic terms T, where y belongs to each term to a degree defined by its membership value,

$$y \equiv \bigcup_T (T_i / \mu_{T_i}(x)) \tag{4}$$

Once the crisp values are fuzzified, each experimental result (each record in Table 1) is converted into a set of rules of the form

$$\text{if } \mathbf{A} \text{ then } \mathbf{B}, \tag{5}$$

where **A** and **B** are fuzzy vectors of propositions concerning input and output variables, respectively. The vectors **A** and **B** are also called the antecedent and consequent parts of the fuzzy relation, respectively. The set of rules deduced from this database represents the rule base that is used by the fuzzy logic inference mechanism to infer the outcome of future experiments.

Like most engineering problems, a grinding process model follows a *modus ponens* rule of inference [19,23-28], i.e.,

$$A' \cap (\bigcup_i (A \cap B_i)) \Rightarrow B'. \tag{6}$$

The simplest form of union and intersection operations are the max. and min. operators, respectively [19]. Therefore, inference reduces to the *compositional rule of inference* [26]

$$\mu(B') = \max_i (\min (\mu(A'), \min_i(\mu(A), \mu(B_i)))) \tag{7}$$

Using Eq. (7), one can infer residual stresses for a given grinding condition. The standard procedure for inference in fuzzy logic systems consists of the following four steps:

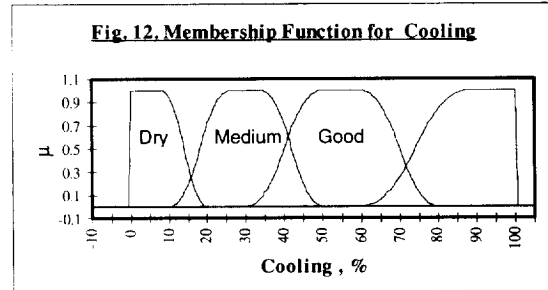
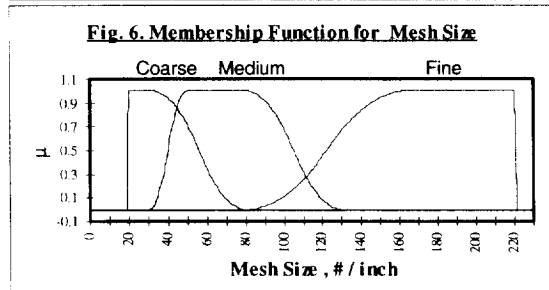
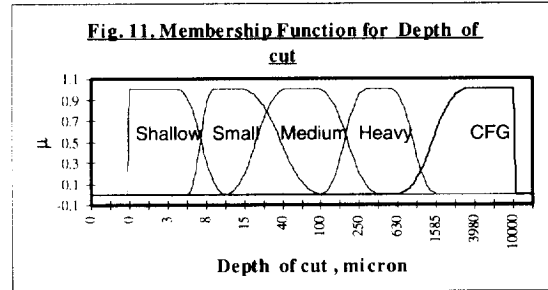
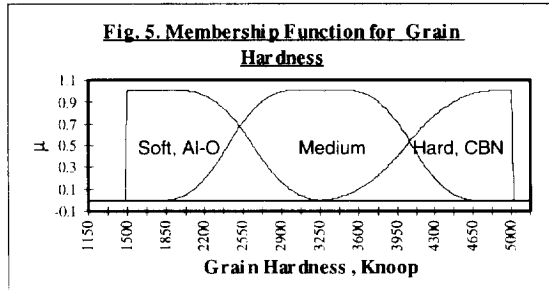
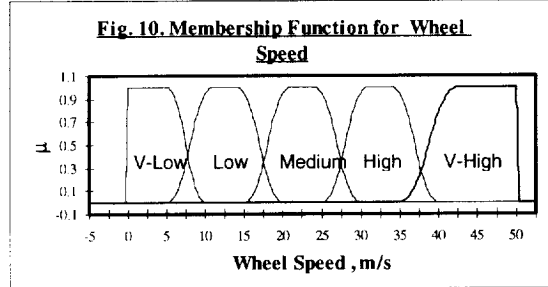
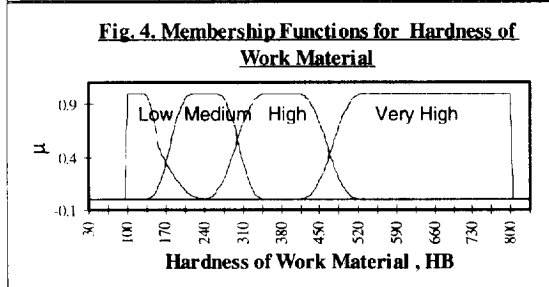
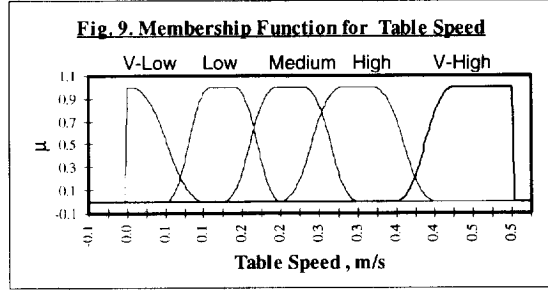
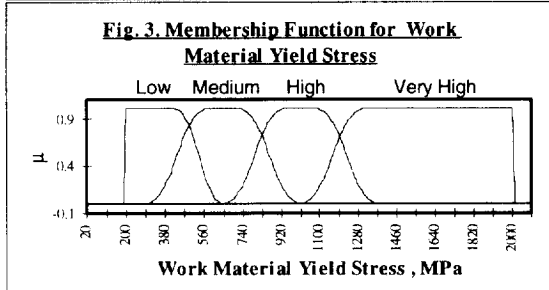
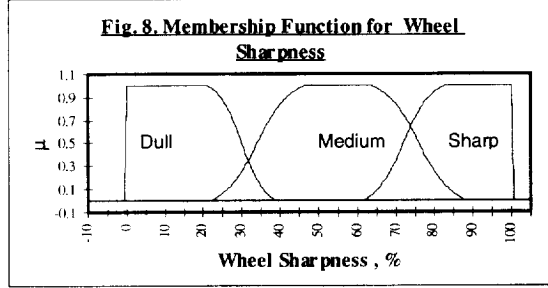
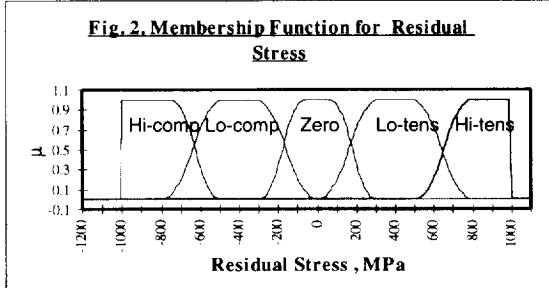
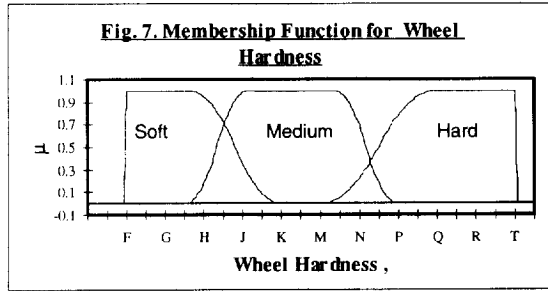
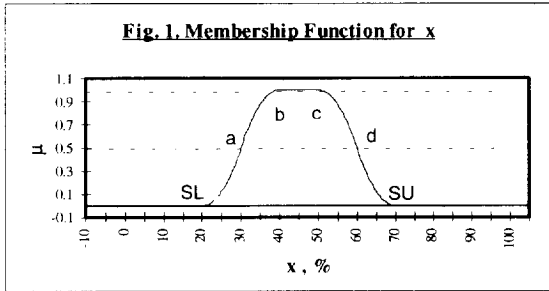
- (1) Fuzzification of the data in Table 1 using Eqs (3) and (4), and construction of vector propositions for input and output data, **A** and **B**, respectively.
- (2) Construction of the rule base. This can be done by building individual rules in the form in Eq. (5), then assembling all rules using a union operation.
- (3) Inference of results. First, input variables are fuzzified to form the antecedent, **A'**. The compositional rule of inference, Eq. (7), is then used to predict the consequent, output, **B'**.
- (4) Defuzzification of the inferred fuzzy set, **B'**. This is done by solving Eqs (3) and (4) backward from T to U for each fuzzy term and taking the weighted average from all terms.

The theories and applications of fuzzy logic can be found in Refs. [23,25,27-29].

2.2 Residual Stress Modeling

For a given experimental setup and environment, residual stresses induced by grinding depend on four groups of process variables:

- (1) **Workpiece material:** The characterization of workpiece material is very hard. The set of variables that constitute a complete definition of a material is vague. For the simplest case of homogeneous isotropic materials, some key variables involved are the elastic parameters, yield strength (which is not a crisp



value [30]), strain-hardening exponent and tensile strength or hardness. Thermal expansion coefficient, heat capacity, thermal conductivity melting point temperature, viscosity, surface tension, phase transformation temperature(s), fracture toughness, fatigue strength, as well as micro-mechanical properties such as grain size and texture are also needed. Chemical properties can be important for specific types of coolants and wheels. Moreover, many of these variables can be temperature, strain, and strain rate dependent.

However, for the present work, all workpiece materials used in Table 1 are iron based. They include, near-pure-iron, low carbon, medium carbon, chromium, and high strength alloy steels of various types. Under these conditions, it is reasonable to assume that all of these material properties are "more or less the same". This is an acceptable statement in fuzzy logic. Therefore, the difference between workpiece materials is in their alloying elements composition. This composition affects mainly the yield strength and hardness of the material. Therefore, *yield strength and hardness* are used in characterization of various steel workpieces.

(2) Grinding Wheel: The only standard information about a grinding wheel is its nameplate marking. For steels, the most commonly used grains are Aluminum Oxides and CBN, of various grades. Grain type can be defined reasonably by its hardness. All experimental data of Table 1 were with vitrified bond wheels. Therefore, the effect of bond material is excluded from this study. Moreover, many manufacturers tend to supply 'controlled structure' wheels and structure is not specified. Therefore, a grinding wheel can be reasonably specified by its *grain hardness, grain size, and wheel hardness*. These three variables are used in the present study. Moreover, there is a need for an idea about *wheel sharpness* to include dressing effects.

(3) Coolant: The concept of coolant is also vague. Water can be viewed as coolant better than oil that is a better lubricant. On the other hand, a lubricant reduces heat generated by friction. Hence, characterization of a coolant can be very complex and depends on the properties of its constituents. Moreover, flow rate of coolant and its direction of application are not specified in most published work. To avoid this complication, cooling effect is defined as the amount of heat not reaching the workpiece, due to application of the coolant. This can be a direct cooling effect by heat transfer or an implicit cooling by reducing friction. For example, air has a 5% cooling effect while some oil-based coolants can have 90% cooling effect. It is important to note that these figures are qualitative in nature and reflect one's perception of the overall effectiveness of the coolant application method. This is also another example where fuzzy sets are more successful in representing imprecise variables, as will be discussed later.

(4) Grinding operating parameters: Table speed, spindle speed, and depth of cut are the most predominant variables in a grinding process and are very important in controlling the residual stresses induced. Although these can be the most accurate values, they also have their ambiguities. For example, spindle speed can be lower than the nominal machine speed. Wear and or dressing of the wheel may also results in a

continuous reduction in tangential wheel speed. Therefore, these variables do not have sharp specific values.

Considering the above discussion, we can make the following definitions that follow directly from the formulation given by Eqs. (1) to (7) and Figs.1 to 12.

x = "Residual Stress"

U = [-1000, 1000] MPa

T = {High compression, Low compression, Zero, Low Tension, High tension}

The definitions of M, S, and P are shown in Fig.2. For example, a residual stress value of -200 MPa can be fuzzified as *Low_compression/0.72, Almost_Zero/0.35*. Similarly, fuzzy formulations for other variables can be constructed, Figs (3) to (12). A typical example of a fuzzy rule according to the first line in Table 1 is:

If	<i>(workpiece yield strength</i>	<i>is</i>	Low/Medium)
	and	<i>(workpiece hardness</i>	<i>is</i> Low/Medium)
	and	<i>(Grain hardness</i>	<i>is</i> Soft, Al-Oxide)
	and	<i>(Grain size</i>	<i>is</i> Coarse/Medium)
	and	<i>(Wheel hardness</i>	<i>is</i> Soft/Medium)
	and	<i>(Wheel sharpness</i>	<i>is</i> Medium/Sharp)
	and	<i>(Table speed</i>	<i>is</i> Very Low)
	and	<i>(Wheel speed</i>	<i>is</i> High)
	and	<i>(Depth of cut</i>	<i>is</i> Shallow)
	and	<i>(Coolant</i>	<i>is</i> Dry, i.e. air)
then	<i>(Residual stress</i>	<i>is</i>	Zero/Low tension)

3. Results and Discussion

As shown by Kruszynski et al. [5], experimental results from one laboratory can be formulated with a confidence interval of 20-30%. Results from different laboratories diverge even a lot more. Using the present fuzzy model, an average error of 0.02-3.6% was achieved for results from one laboratory. This result is better than empirical formulae and below the range of reported experimental error. Accuracy can be improved further by more computational effort.

For example, residual stress measurements were obtained for creep-feed grinding of a high chromium bearing steel [15]. These tests are listed in lines 62 to 67 in Table 1. A rational fit of the data is to use the empirical formula

$$\sigma = K \left(\frac{V_w \cdot d}{V_s} \right)^n, \quad (8)$$

where V_w is table speed, V_s is spindle speed, d is depth of cut, and K and n are constants. As can be seen from Table 2, this formula has an average absolute error of about 12% as opposed to only about 0.04% by the fuzzy logic model. This accuracy is even lower than possible experimental error in the experiments. However, it has to be clear that this result is not typical. Performance of the model can vary from one experimental group to another depending on experimental accuracy of the techniques used by this particular group. The technique used in [15], for example, is very consistent and is considered reliable. This may not always be the case, especially for those obtained by the beam deflection method. However, it is always true that the fuzzy

logic model is able to make predictions with an average error lower than its empirical formula counterpart.

The better predictions of the fuzzy model are because of the following reasons:

- The model includes ten independent variables. The hundred data points in Table 1 are not enough to perform a good regression analysis and cannot be fitted to a ten-dimensional equation. In fuzzy logic, the number of parameters P for all terms and all variables is very large. Therefore, fuzzy logic implicitly fits the data to a higher order nonlinear equation, and therefore, achieves greater evaluation accuracy.

- The input of wheel hardness as 'H', 'K', etc. cannot be processed numerically. Therefore, an empirical formula is restricted to one wheel type. However, fuzzy logic can process this type of linguistic input and therefore, can handle a wider variety of input.

- Although cooling and wheel sharpness are input as numerical values, they are actually qualitative in nature. Fuzzy logic is insensitive to small variations in variables and therefore can absorb these qualitative uncertainties.

- Inputs like VU (meaning vague/unknown), or V2029 (vague but 20% high to 90% very-high) cannot be handled numerically. This kind of input represents a common situation where a certain variable is not reported. For example, if the workpiece material is not defined precisely, but is given as "typical high carbon high chromium bearing alloy", one can still make use of these results by giving a yield strength input as V2029. Fuzzy logic is the only technique that can make use of such vague inputs.

4. Conclusions

The present work demonstrates the ability of fuzzy logic to model one of the most complex aspects of grinding, residual stress. The level of prediction accuracy obtained is below the uncertainty in experimental results. This is because fuzzy logic is able to extract partial knowledge from apparently ambiguous and conflicting experimental results. However, there is an urgent need for the development of standard procedures for experimental studies of grinding, so that more precise experimental conditions can be recorded. In addition, there should be an established method for measuring residual stresses with complete specifications of error estimation and correction procedures. Such a standardization of experimental procedures will improve the fuzzy logic rule base to a much greater extent.

Acknowledgment: This work was supported by an ARC Large Grant.

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