A knowledge based approach for a quality assurance system for laser sintered parts

Thomas MENZEL[1], Jürgen KNOBLACH[1], Manfred GEIGER[1], László CSER[2]
[1]Chair of Manufacturing Technology, University of Erlangen-Nuremberg, Germany
[2]Bay Zoltán Foundation of Applied Research, Miskolc, Hungary
e-mail : T.Menzel@lft.uni-erlangen.de

Abstract

The quality of workpieces is usually influenced by a wide set of process parameters and workpiece properties of the material and the geometry. In the case of prototyping and small-batch production, the exact quantification of optimal process parameters is hampered by the high effort for their acquisition and the small quantity of similar workpieces. Therefore, an inference algorithm using fuzzy set theory is designed to define the complex dependencies between process control parameters and expected workpiece quality. The laser beam sintering of inserts for deep drawing tools acts as an example for detailed explanations.

1 Introduction

The rising use of rapid prototyping in industry can be explained as being the result of every producing company wishing to check and – if necessary – change a construction by means of prototypes, or rather, prototype tools with regard to design, ergonomics, mountability, functionality, etc. (Song, 1996).

A wide range of new options to produce metallic prototypes and tools for prototype parts is provided by the development of laser beam sintering, especially the direct laser beam sintering, where parts are made of metallic powder which is melted together layer by layer. Due to the gained mechanical strength of the sintered parts, selective laser beam sintering can be used for the rapid manufacturing of injection moulds (McAlea, K. and U. Hejmadi, 1996), of electrodes for Electro Discharge Machining or of deep drawing tools (figure 1). The quality of these tools is less than conventional tools, but the required production time is much shorter.

Figure 1: Laser beam sintered tool set (punch and die) for the deep drawing of prototype parts

2 Concept of the quality assurance system

2.1 Principle concept

The quality assurance system (figure 2) for laser sintered parts assists the manufacturer of prototype tools with the help of a knowledge base during all stages of the production process.

For the design of the tools in the CAD system (ProEngineer), the knowledge base provides several predefined features, e. g holes for screws or bolts. For the use as tools, several areas of the laser sintered part need special properties according to the manufacturing process, e. g. the area surrounding screw holes requires a high strength. Additionally, special features can be generated during the design process by the user. They can also be attributed with special geometrical, mechanical and material properties mentioned in section 3.2. The value of these properties is defined by fuzzy attributes, e. g. “low”, “medium” and “high”. The predescribed features and the user-defined areas are separated in the CAD model of the tool. At the end of this process, different CAD models for tool and the features are generated.

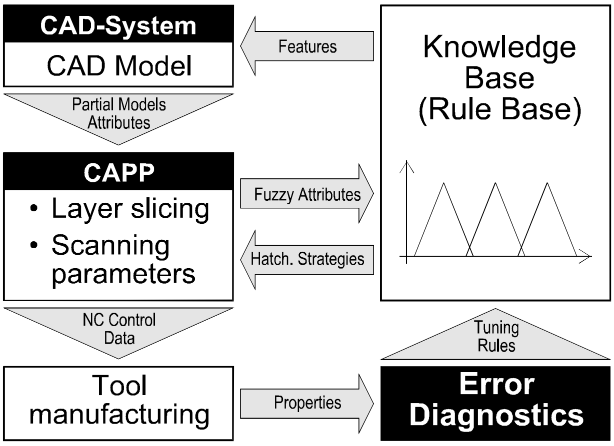

Figure 2: Concept of the quality assurance system

These CAD models and their corresponding properties are handed over to the CAPP system as different partial models connect with attributes. The CAPP system first generates the layers for the laser sintering process by slicing the CAD data. In a second step, the scanning patterns for the movement of the laser beam depending on a set of scanning parameters, called hatching strategy, are determined: The hatching strategy for every partial model is calculated by the fuzzy rule system of the knowledge base according to the defined properties. Finally, the different paths are superimposed to make one workpiece consisting of the several CAD models.

With these data, the tool will be manufactured by using a NC controlled sintering machine. For the generation of the needed NC data, the existing post processor of the process control computer is used. After the production of the tool, the resulting properties should be measured during an error diagnostics. These new results could be used for the fine-tuning of the fuzzy rule set and the knowledge base.

2.2 Application on deep drawing tools

The introduced concept is being realised for the rapid production of deep drawing tools (figure 1) for prototype sheet metal parts. Each tool set consists of a punch and a die insert. For applying the quality assurance system on deep drawing tools, specific features are defined and stored in the knowledge base, e. g. different kinds of drawing radii and holes for screws and bolts. These features are connected to a combination of attributes. In deep drawing tools, e. g. the drawing radius must be very smooth, the geometrical deviation must be very low and the hardness must be high in this area of the die. Other predefined features for deep drawing tool sets are the edges of a drawing die, the punch edges, the holes for screws or bolts and the mounting surface.

For selection of optimised process parameter, the influence of the selected hatching strategy on the workpiece properties has to be analysed and a process window has to be defined based on the laser beam sintering process.

3 Laser beam sintering process

3.1 Process description

The mechanism of direct laser beam sintering is based on the melting of the individual particles of a metallic powder by a laser beam. The shape of the workpiece is built up layer by layer using the repetitive steps of lowering the workpiece, adding new powder and melting the powder. For this, the energy is induced by the spot of a laser beam that is moved over the powder in the shape of its current layer. State of the art is the use of a powder consisting of three different components (“M-CU-2201”): nickel, bronze and copper-phosphor compound.

Due to the heating, which is carried out layer by layer with a spot-like source, problems occur with the geometrical, mechanical and material properties (e. g. hardness, tensile strength), thermal stability as well as non-optimal surface quality and accuracy of the part. Usually, the laser sintering process is controlled over its induced line energy by the selection of a suitable hatching strategy, a combination of scan speed v_s and hatching distance h_s: The scan speed of the laser has significant influence on the line energy, which is responsible for the melting of selective parts of the powder and consequently is responsible for resulting hardness, density etc. On the other hand, the hatching distance influences the amount of cooling during the sintering of neighbouring sinter paths of one layer. Therefore, it controls the size and the shape of the heat affected zone, which in turn affects the workpiece properties.

3.2 Properties of laser sintered parts

The parameters of the laser beam sintering process and their effects on the workpiece properties were investigated at the Chair of Manufacturing Technology in many studies (Coremans, 1999). In these studies, the influence of scan speed and hatching distance was compared with the resulting physical properties (density, hardness, Young’s modulus,

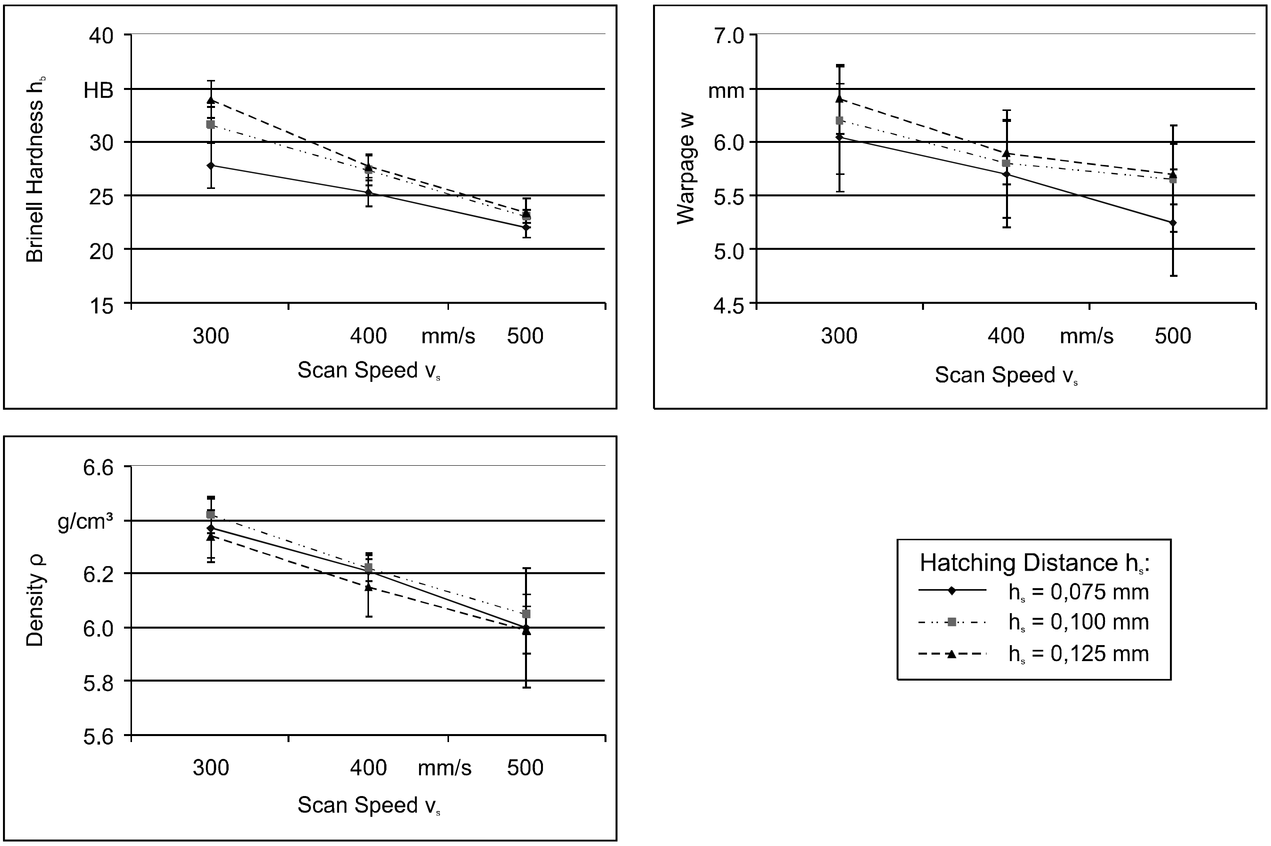

Figure 3: Functional dependencies between hatching strategy and properties
(e. g. Brinell hardness, warpage, density)

tensile and compressive strength), geometrical properties (roughness, size deviation) and residual stresses (warpage). Figure 3 shows by example the influence of the selected hatching strategy on density ρ, Brinell hardness h_b and warpage w:

- Using a slow scan speed (v_s = 300 mm/s) the resulting *density ρ* of a laser sintered part is high. The hatching distance h_s has no significant influence on the density.
- A maximum value for the *Brinell hardness h_b* can be gained for a parameter set with a slow scan speed (v_s = 300 mm/s) and a wide hatching distance (h_s = 0.125 mm).
- The *warpage w* of the laser sintered part is low, if the scan speed is high (v_s = 500 mm/s) and the hatching distance is wide (h_s = 0.125 mm). Figure 3 shows the warpage of an sintered example part with a normal and an optimised hatching strategy with a low line energy.

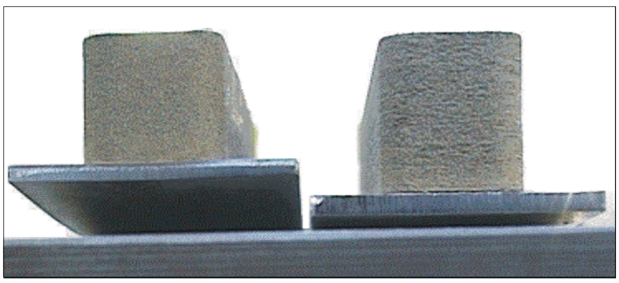

Figure 4: Warpage with normal (left) and optimised hatching strategy (right) (Coremans, 1999)

Although sets of process parameters to optimise only one of the above mentioned properties exist, an achievement of a combination of selected properties is difficult: the parameters are mutually opposed and there is no simple functional coherence between them.

Due to this lack of a functional coherence and the mutually opposed parameter sets, a new approach for the determination of hatching strategies for combined properties is necessary. For this reason, a new solution based on fuzzy set theory is introduced to calculate process parameter sets on base of a complex process window.

4 Knowledge base design

The main module of the quality assurance system is the fuzzy rule system of the knowledge base. The knowledge base aims at reproducing the knowledge acquired by workpiece samples as illustrated in figure 5 (Cser, 1999). For a given set of quality features, the optimal process parameters keeping in mind the hatching distance and the scanning speed should be inferred. For this purpose, a procedure of defining formal fuzzy set equations representing the process knowledge is investigated (*knowledge acquisition*, figure 5). These equations are used to design the rule base. Finally, the evaluation of the rule base must be performed in order to infer optimised hatching strategies (*knowledge reproduction* in figure 5). Further, an tuning approach is needed which takes the quality of knowledge reproduction into account.

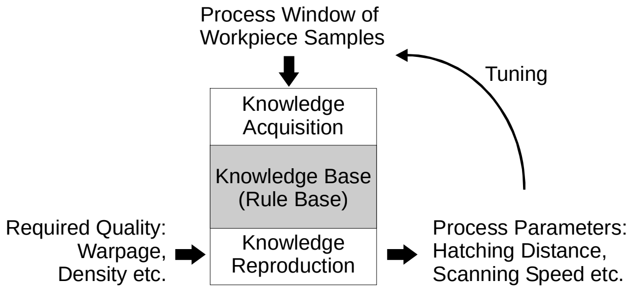

Figure 5: The knowledge based acquisition and the reproduction process parameters.

4.1 The representation of the acquired process knowledge

The quality properties of sintered part samples are the basic data used for the knowledge base design. In order to generate a base of the acquired process knowledge, the functional relation between hatching distance, scan speed and the quality properties has been described by equations formally. As shown in the figure 3, they are linear approximated. The tolerance incorporated in terms of the standard deviation should be emphasised. Due to this tolerance, the definition of quantities and their functions uses the fuzzy set theory.

Taking into account the partial linearity, each part of the functions satisfies a linear equation, e.g. $h_b = g\, v_s + i$ for the Brinell hardness h_b, where g defines the gradient and i the value for $v_s = 0$ (intersection point with h_b-axis). Furthermore, the deviation of process from this behaviour is included in the standard deviation. Therefore, the functions have been described by fuzzy sets. This can be done with the identification of lower and upper ranges as well as the most likely value (highest degree of possibility, *mean value*). This approach results in a fuzzy set defined formally by a *LR fuzzy number* (Zimmerman, 1991; Zimmerman, 1983). The steady *membership function* $\mu(x)$ of a fuzzy number determines an uncrisp (non-real) numeric value by the real triple (m, α, β) where m, α, β are the *mean value*, the left and the right support (figure 6, 7). The shape of the fuzzy set can be influenced by choosing a function L(u), R(u) for the left and the right hand side, respectively, such as

$$\mu(x) = \begin{cases} L\left(\dfrac{m-x}{\alpha}\right); & \text{for} \quad x \le m \\ R\left(\dfrac{x-m}{\beta}\right); & \text{for} \quad x > m \end{cases} \qquad (1)$$

$$\text{and } L(u) = R(u) = max(0, 1-u)$$

which leads to a partial linear membership function μ (Zimmerman, 1991; Dubois 1987). A membership degree $\mu(x) = 1$ means a high degree of possibility. In contrast, a membership degree $\mu(x) = 0$ indicates that the related values are impossible.

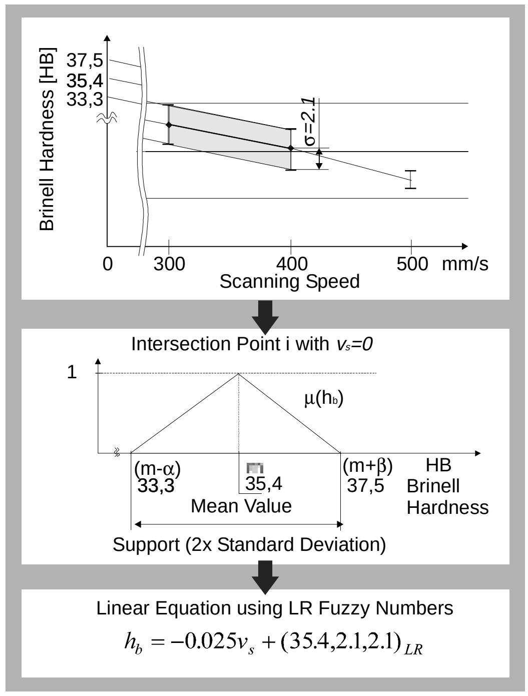

Fig. 6: Formalisation of the functional context of scanning speed v_S and Brinell hardness h_b (h_s *= 0.075 mm*)

The Brinell hardness regarding the range $v \in$ [300 mm/s, 400 mm/s] and $h_s = 0.075$ mm acts as an example which aims at devising fuzzy set equation. This equation represents the functional relation between scan speed and Brinell hardness. The deviation of workpiece samples from this behaviour is also taken into account. The gradient g is supposed to be determined exactly g = -0.025 HB s / mm. In contrast, the intersection point with the axis of the Brinell hardness i at $v_s = 0$ mm/s needs to incorporate these workpiece samples which dos not satisfy the exact behaviour. It should take the standard deviation $\sigma = 2.1$ HB into account. Therefore, the intersection point i is described by a fuzzy set keeping in mind its mean value m and its left and right support (α, β). Consequently, the intersection point i is set to i=(35.41, σ, σ)$_{LR}$ HB = (35.41, 2.1, 2.1)$_{LR}$ HB. Considering i and the gradient g, the equation is defined by $h_b = -0.025*v_s+(35.4,2.1,2.1)_{LR}$ (without physical units). This fuzzy set function encloses the possible range.

Another application of fuzzy set theory occurs with the representation of the output quantities (hatching distance and scan speed). Their fuzzy sets are designed to envelope the valid ranges for each linear part of the function. They are associated with an linguistic term (e.g. *slow*, *medium* or *fast*, figure 7) but their formal description uses also the LR representation of fuzzy numbers.

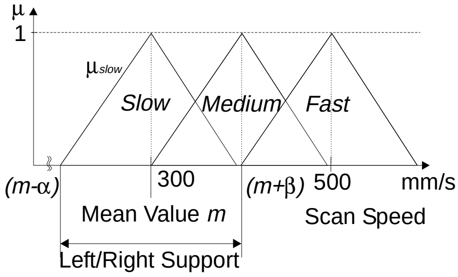

Fig. 7: Linguistic terms and LR-Fuzzy-Numbers for fuzzy set quantities.

4.2 Generation of the rule base using fuzzy set theory

This section focuses on defining a rule base of optimal process parameters assuming the existence of the functional dependencies which are given by equations. It is designed to derive the output quantities of knowledge reproduction in terms of hatching distance and scanning speed. It takes into account the required quality properties of workpiece (input quantities), such as Brinell hardness, warpage, etc.

In general, a rule base consists of a set of rule statements. In turn, each rule contains a *premise* and a *consequence* (see figure 7). The contribution of consequence to the final result depends on the truth or the degree of truth of this premise which belongs to it.

In the case of fuzzy rule systems, the premises and the consequence are quantified in terms of fuzzy sets. This can be done using linguistic variables, such as v_s = slow (Zimmermann:91). Usually, the design of the rule systems needs fuzzy sets for all involved quantities. Their definition causes a high effort in knowledge design. In contrast, the approach described aims at defining the scan speed and hatching distance by fuzzy sets. However, the knowledge is incorporated in terms of fuzzy set equation sets instead of its complete approximation by linguistic terms.

General Design:

IF (premise) THEN consequence

Applied Structure:

IF
$v_s = slow$ AND
$h_b = small$ AND
$\rho = -0.002 v_s + (6.85, 0.11, 0.11)_{LR}$ AND
$h_b = -0.025 v_s + (35.413, 2.1, 2.1)_{LR}$ AND
$w = -0.003 v_s + (7.06, 0.302, 0.302)_{LR}$
THEN
$v_s = slow$
$h_b = small$

IF
$v_s = slow$ AND
$h_b = medium$ AND
$\rho = -0.002 v_s + (7.02, 0.067, 0.067)_{LR}$ AND
$h_b = -0.042 v_s + (44.313, 1.7, 1.7)_{LR}$ AND
$w = -0.004 v_s + (7.4, 0.31, 0.31)_{LR}$
THEN
$v_s = slow$
$h_b = medium$

Fig. 8: The general and the applied structure of the rule base (without physical units).

For each pair of scan speed and hatching distance, a set of equations is generated. These equations represent the functional relation between process parameters and quality properties as described in section 4.1. However, their equality cannot be clearly decided as true or false because of the fuzzy sets involved. A membership degree μ_E for each equation will be calculated to represent a degree of equality. In turn, the degree of equality decides how much the associated process parameters of the rule consequence should be considered for process control.

This approach is applied in this research work. It includes the arithmetic functions within the knowledge base directly. To sum up, it should be underscored that the applied design of the fuzzy rule system leads to the following advantages:

- Fuzzy rules are designed without formalising the whole range of all quantities by fuzzy sets,
- no loss of knowledge about functional context between input and output quantities,
- tolerances and vagueness in functional context are taken into account.

5 The evaluation of the knowledge base

The evaluation of the fuzzy rule system (inference algorithm) aims at inferring optimised process parameter, taking into account required quality properties of Brinell hardness, density and warpage and their dependencies as defined by equations and rules within the knowledge base. The following steps must be carried out:

- Each set of equations associated with linguistic terms of the scan speed and the hatching distance has been assessed. A degree of equality (membership degree μ_E) for each equation set has been calculated. Furthermore, a degree of equality μ_P for each set of equations has been inferred in order to describe the truth of the premise.
- The degree of truth μ_P of the equation set (premise) is assigned to each pair of process parameter keeping in mind hatching distance and scan speed (linguistic terms). Afterwards, a real value has been calculated for process design.

5.1 The evaluation of the equation sets

The definition of the equations by fuzzy numbers requires that their evaluation be performed by fuzzy numbers and fuzzy number based arithmetic operations as well. First, both side of each equation are evaluated using basic arithmetic operations (e.g. multiplication, addition etc.). For this purpose the *extension principle*, which extends the conventional numerical operations for fuzzy quantities, could be applied. It is defined for two argument numbers in terms of membership functions $\mu_a(x)$ and $\mu_b(x)$ (Bothe, 1995; Zimmerman, 1991) as follows:

$$\mu_{a\otimes b}(z) = \sup_{z=x\times y} min\{\mu_a(x), \mu_b(y)\} \qquad (3)$$

In the case of LR fuzzy numbers, there exists a set of predefined operators, such as (Dubois, 1987; Zimmerman, 1991):

$$\begin{aligned}(m,\alpha,\beta)_{lr} \oplus (n,\gamma,\delta)_{lr} &= (m+n, \alpha+\gamma, \beta+\delta)_{lr} \\ (m,\alpha,\beta)_{lr} \odot (n,\gamma,\delta)_{lr} &= (mn, m\gamma+n\alpha, m\delta+n\beta)_{lr}\end{aligned} \qquad (4)$$

for the addition and the multiplication, respectively. In order to obtain triangular fuzzy numbers with a linear membership function, the result obtained by the extension principle has to be slightly modified (Zimmerman, 1991).

Taking the results for the left and right hand side of the equation, the degree of equality (or inequality) is derived for each equation separately. First, the fuzzy number for both sides *x, y* are subtracted by z = x - y. Two cases have been distinguished for the obtained fuzzy set *z* (figure 9):

- The fuzzy set *z* is situated on the left or right hand side completely of μ-axis. Then the relation can be decided clearly to be true or false.
- The membership function μ_z intersects the μ-axis. Then, the position of intersection has been investigated. The degree of equality is determined by the membership degree $\mu_z(0)$. To derive the degree of inequality needs to consider the distribution of the surface areas on the negative or positive side. For example, the surface area $A_{<0}$ in relation to the compete fuzzy set area A_{ges} is treated as the degree of the inequality x < y (figure 9).

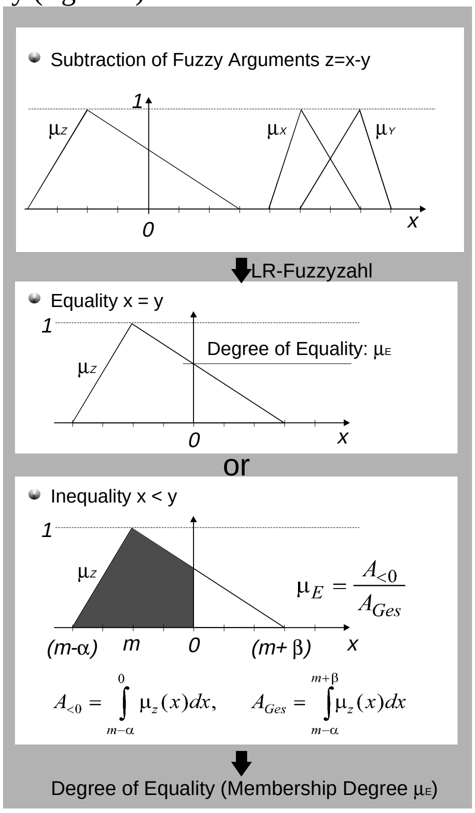

Fig. 9: The evaluation of equality

Finally, the membership degrees single equations μ_E are aggregated by the minimum operator in order to calculate the degree of truth of an equation set μ_P.

However, the application of arithmetic fuzzy operators or the introduced equality/inequality-relations must take into account that it may result in unexpected values. These may occur if an *improper function* appears which is caused by the algebraic terms (Dubois, 1987). These terms contain a variable, or a function of this variable, more than once. The arithmetic fuzzy operators are trying to extend the range as much as possible without taking into account any dependencies between their argument values. As a consequence, the following requirements have to be taken into account alternatively by model design:

- Terms containing a variable more than once should be avoided,
- the use of isotronic functions (Dubois, 1987),
- the numeric evaluation by the extension principle incorporating additional conditions (Dubois, 1987).

These approaches can often be considered by modifications of the structure of equations. The equation sets incorporated in the introduced knowledge base contain each variable one time. Therefore, no improper function appears that needs to be removed in the example.

5.2 Defuzzification method

Two facts have been taken into account in order to compute real values for process control. The consequences are fuzzy numbers in terms of linguistic variables. Secondly, more than one consequence might have a membership degree greater then zero because of the fuzzy set equations. Therefore, a defuzzification has been applied. It results in real values for the process control. It might be performed using Max-prod-method or the centre of gravity (Zimmerman, 1991). Figure 10 shows the defuzzification using the centre of gravity in the case of scan speed. Similar, the hatching distance is derived.

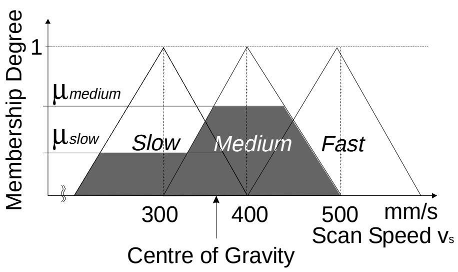

Figure 10: An example of defuzzification of the scan speed by the centre of gravity.

6 Verification and tuning approaches for laser beam sintering

The verification of the rule base and the inference algorithm is approached as follows: On the one hand, it should be investigated whether the inferred hatching strategies match the process windows as illustrated in figure 3 and formalised within the rule base. This procedure aims at proving that the generated process parameters do not contradict the functional relations. On the other hand, the application of laser beam sintering might confirm some examples.

The first approach requires the specification of extensive sets (ρ, h_b, w) of quality properties which contain the required density ρ, the warpage w and the Brinell hardness h_b. For each of these sets, the hatching strategies are derived.

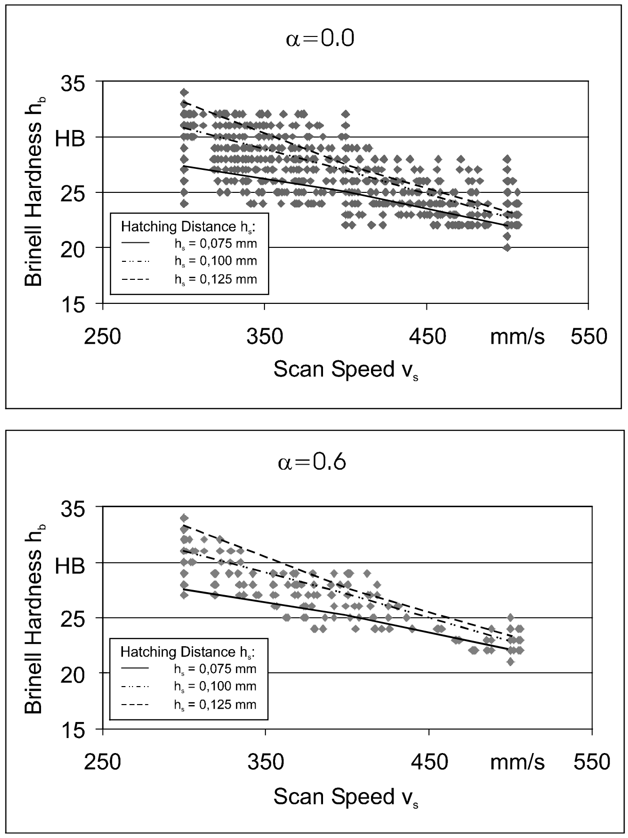

Figure 11: The approximation of the acquired process window for different α-cuts.

Figure 11 shows the comparison of original equations with the scan speed which is inferred by the knowledge base due to 15^3 arbitrary distributed sets (ρ, h_b, w). It can be observed that the values of scan speed approximate the diagrams as shown in figure 3. However, the upper diagram includes a couple of points which do not satisfy the original equations. They are caused by the quantification of hatching distance and scan speed by fuzzy sets, e.g. $v_s = (500,100,100)_{LR}$ mm/s. The wide support of this membership function might cause small membership degrees μ_E of such equation sets which are not close to v_s = 500 mm/s. If no further equation set is satisfied by higher membership degrees, the consequences influence the result strongly. This supposition can be confirmed as follows: Only the fuzzy sets of the consequences which have a membership degree $\mu_P > \alpha$ (α-cut) are taken into account next. The results are shown in the lower part of figure 11. It contains the scan speed which is inferred by at least one rule consequence with membership degree $\mu_p > \alpha = 0.6$. The example in figure 12 illustrates that only the fuzzy set *medium* affect the inferred result, despite of the non-zero membership degree of *slow*.

Clearly, the original functional dependencies between scan speed and Brinell hardness are approximated more exactly. The required membership degree causes a loss of derived values for the scan speed. This happens if no rule statement matches the membership degree for the given set of input quantities. The loss of values means in fact that the rule base represents no exact knowledge of a process window due to the required quality properties.

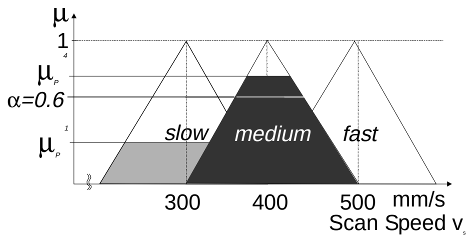

Figure 12: The α-cuts in order to exclude rule consequence with small membership degrees from final result.

Considering the dependency of exactness from α, it is obvious that the highest membership degree of rule statements is a measure of the reliability of the inferred results. Indeed, a low degree indicates less knowledge about the process regarding the required quality properties. Moreover, the knowledge base should be tuned by this process window and the resulting quality properties (figure 5). This requires a diagnosis of quality properties after producing the workpiece and the generation of corresponding fuzzy set equations and their implementation in the knowledge base. In contrast, a high satisfaction of equation sets means that the process parameter are close to the acquired knowledge represented in the rule base.

7 Summary

A new approach for a quality assurance system in the field of rapid prototyping was introduced in this article. The concept of this software system is being realised for the manufacture of prototype tools for the deep drawing of sheet metal parts with laser beam sintering.

In this system, knowledge base supports the designer during the whole CAD/CAM process: On the one hand, pre-defined features and their corresponding properties are provided for the design of the tool sets. On the other hand, optimised process parameters for the laser beam sintering of the tool set are automatically calculated by a fuzzy rule system.

The determination of the process parameters is hindered by their lack of functional coherence, their mutually opposed parameter sets for different properties in the manufactured part, and the vaguely known relation between the process parameters. For this, a knowledge based fuzzy rule system was developed to calculate optimised process parameters for required workpiece properties. Fuzzy equations are employed to represent the complex process window in the rule base. With the production of more workpieces in the future, a fine-tuning of the rule base would be possible.

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