provides outputs in the format of fuzzy sets. However, usually what is needed for making decisions/taking actions is a crisp output value. That is why defuzzification is needed to extract a crisp value from the fuzzy sets produced by the inference mechanism.

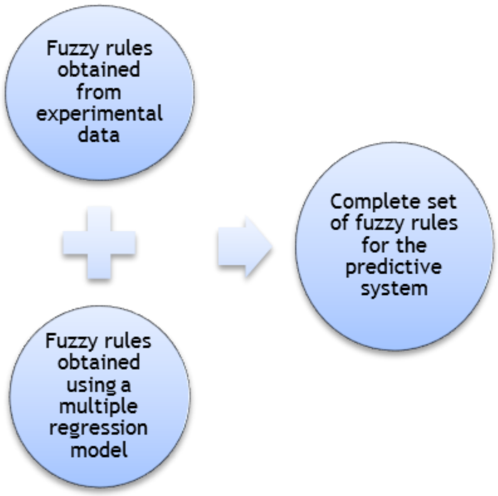

Fig. 4: Sources for generating the fuzzy rules for the predictive system

3.4.4 Defuzzification

According to Passino and Yurkovich [20], defuzzification operates on the implied fuzzy sets produced by the inference mechanism and combines their effects to provide the "most certain" value of the output.

It simply consists of extracting a crisp output value from a fuzzy output set (Kovačić and Bogdan [21]).

According to Lee [22], there is no systematic procedure for choosing a defuzzification strategy. However, the Center of Area (COA) also called the centroid method is the most commonly used defuzzification method. It is this method that we will use for the fuzzy-nets prediction system. It is worth to mention that defuzzification is not considered in the case of Takagi-Sugeno FIS (Takagi and Sugeno [23]).

3.5 The training scheme

The training scheme associated with the fuzzy-nets approach selected to use for surface roughness and average recast layer thickness prediction in WEDM is fuzzy logic membership scheme which requires experimental data to generate the fuzzy rule base of the fuzzy-nets predictive system. Appropriate design of the experiments (e.g., following design of experiments (DOE) approach) is crucial for the success of the approach. That is why a special attention is given to the planning, design, realization and analysis of the experiments.

3.6 The general structure of the predictive fuzzy-nets approach

The technical specifications of the fuzzy-nets predictive system are summarized in Table 2.

Table 2: Technical specifications of the fuzzy-nets predictive system

Aspect of the predictive system	Technical specification
Fuzzy inference system (FIS)	Mamdani FIS
Type of decomposition of inputs and outputs domains into fuzzy regions	Fuzzy partition
Type of membership functions (MFs) for the fuzzy regions of input and output parameters	Triangular MFs with the same width for each parameter
Number of fuzzy regions for input parameters	Same for all input parameters; initially the number of regions is put to 3
Number of rules fired by a set of inputs values	Minimum: 1; maximum: 2^m where m is the number of input parameters relevant to the considered output parameter
Operator (t-norm) used for the membership degrees (MDs) of a fuzzy rule inputs to calculate the degree of the corresponding output	T_{min} ($T_{min}(x,y)=\min\{x,y\}$, $\forall$ x, y $\in$ [0,1])
Operator (t-conorm) for the aggregation of the fuzzy rules	S_{max} ($S_{max}(x, y) = \max\{x, y\}$, $\forall$ x, y $\in$ [0,1])
Defuzzification method	Centroid method
Decision making mechanism	Comparison of the predicted value of the VQC with a desired or reference value (or range of values)

3.7 The predictive procedure

We consider the most general case of fuzzy-nets system where multiple VQCs need to be predicted and for each VQC multiple VPPs need to be adjusted when the predicted value of the VQC is deviating from the desired value.

We assume that the MIMO predictive and adaptive fuzzy-nets system has the following characteristics:

- There are m output parameters: O_j, j = 1, 2, …, m
- Each output parameter O_j, j=1,2, …, m, has $n_j(j)$ input parameters: I_i, i = 1(j), 2(j), …, nj(j)

We have a MIMO predictive system that is decomposed into m MISO predictive systems MISO 1, MISO 2, ..., MISO m. Each MISO j, j = 1, 2, …, m is associated with the output parameter O_j, j = 1, 2, …, m.

The flowchart of the prediction procedure is shown in Fig. 5.

4 The MIMO fuzzy-nets framework

The different cases for the predictive fuzzy-nets approach are shown in Table 3.

Table 3: Different cases of the predictive fuzzy-nets approach

	Single output	Multiple outputs
Single input	SISO predictive system	SIMO predictive system
Multiple inputs	MISO predictive system	MIMO predictive system

It is worth to mention that a system with a single input parameter and a single output parameter is called a SISO (single input-single output) system and a system with a single input parameter and multiple output parameters is a called a SIMO (single input-multiple output) system. Since we focus on predictive systems with multiple inputs, then the SISO and SIMO predictive systems are not considered.

In general, it may be possible that an input parameter is significant for one output parameter but not for another. The simplest case of a MIMO (Multiple input-multiple output) predictive system is when all input parameters are significant for each output parameter.

In the case of a predictive system with multiple outputs having the same n input parameters, the minimum number of fired rules in this case is $\underbrace{1\times 1\times \ldots\times 1}_{n\,times} = 1$ and the maximum number of fired rules is $\underbrace{2\times 2\times \ldots\times 2}_{n\,times} = 2^n$.

The total number of fuzzy rules fired by a data set is between 1 and 2^n. The following cases can be distinguished:

- Each crisp value of an input parameter corresponds to the centre of a fuzzy region. In this case the total number of fired fuzzy rules is 1.
- None of the crisp values of input parameters corresponds to the centre of a fuzzy region. In this case the total number of fired fuzzy rules is 2^n.

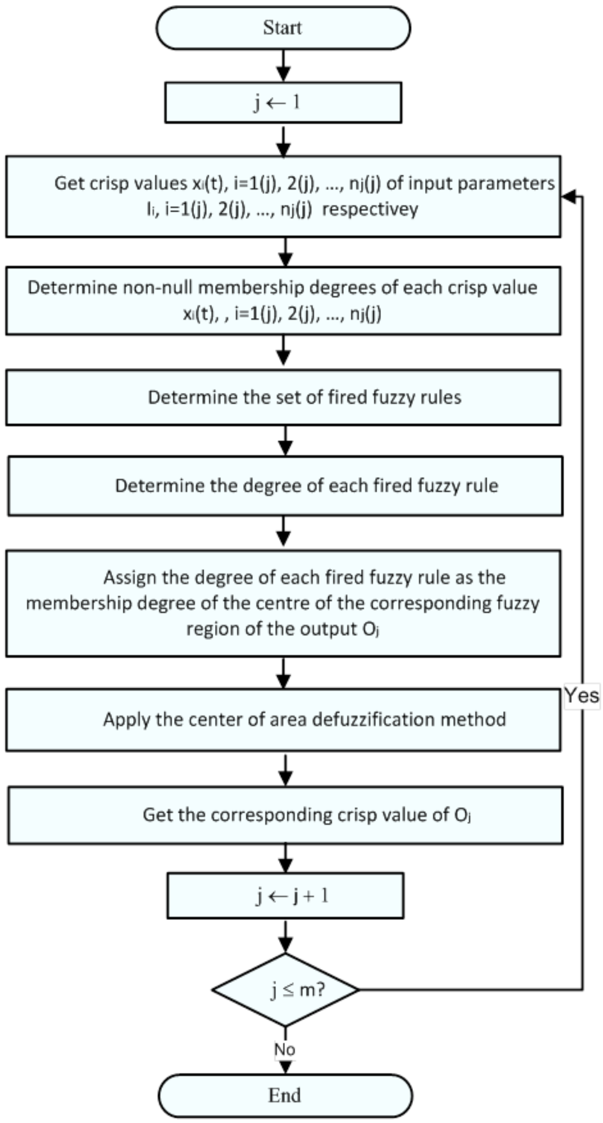

Fig. 5: Flowchart of the predictive procedure

In the other cases, the total number of fired fuzzy rules is strictly superior to 1 and strictly inferior to 2^n.

Since the fired fuzzy rules have the same "if-part" and different "then-parts", then the determination of the membership values of input parameters and the identification of fired rules is the same for all output parameters however the defuzzification procedure should be applied separately to each output parameter using the same information regarding the fired rules and the membership degrees of input parameters.

In the case where the output parameters have different sets of input parameters, an important issue to consider is how to organize the rule base and the predictive algorithm in order to benefit as much as possible from the information that is common to the output parameters.

5 The case study

5.1 Case study description

The proposed online prediction and adjustment system will be applied to 'CUT 200 Sp' from GF Machining Solutions.

Some characteristics of CUT 200Sp:

- Type of machining: Submerged
- Workpiece dimensions (W x D x H): 1000 x 550 x 220mm
- Max. workpiece weight: 750kg
- Available wire diameters (Standard): 0.33 - 0.15mm

GF Machining Solutions based in Switzerland is the world's leading provider of machines, automation solutions and services to the tool and mold making industry and to manufacturers of precision components.

The main defects related to surface quality of WEDMed parts include: occurrence of 'lines and marks', surface roughness, and recast layer (also called white layer). In this paper we focus on surface roughness, and recast layer thickness.

GF Machining Solutions is interested in reducing the scrap rate of parts produced by their machines due to surface quality defects and in certifying that surface characteristics (roughness, recast layer) remains within the quality tolerance-band requirements of the customers.

5.2 Motivation and objectives

Based on past experiments different settings with the same surface roughness performance provide significantly different levels of performance for the recast layer thickness. That is why it is important to have technology tables providing indication of not only surface roughness performance but also the maximum recast layer thickness in addition to the possibility for the user to choose other settings for which there will be a need for the prediction of the corresponding surface roughness and recast layer thickness. To achieve this goal, an offline fuzzy-nets prediction and optimization system is proposed.

The overall objective of the offline prediction system is to account for the variation of the surface roughness, recast layer thickness and probability of occurrence of 'lines and marks' according to initial conditions represented by the values of voltage, feed rate and pulse off time.

5.3 Relevant parameters

The VQCs considered for the offline prediction system are surface roughness and average recast layer thickness.

There are two main important sources for the identification of potential parameters that influence the VQCs: (i) the explicit knowledge from the related literature and (ii) the implicit knowledge obtained from the WEDM experts.

The experimental investigation of the impact of the different parameters of WEDM process on the surface roughness revealed that pulse-off time is, by far, the most dominant factor influencing surface roughness followed by feedrate and voltage. In summary, the input and output parameters for this case study are shown in Table 4.

Table 4: Input and output parameters for the case study

Parameter	Type of parameter	Unit
Voltage	Input	[V]
Pulse off time	Input	[mm]
Feed-rate	Input	[mm/min]
Surface roughness	Output	[µm]
Average recast layer thickness	Output	[µm]

Regarding the recast layer thickness the relevant parameters are voltage and feed rate (Morand [24]).

The corresponding fuzzy-nets prediction system is shown in Fig. 6.

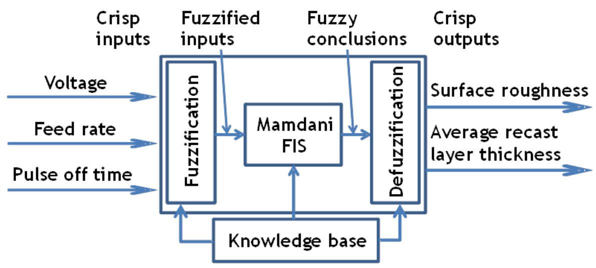

Fig. 6: Fuzzy-nets prediction system for WEDM

5.4 Experimental plan

The main objective of this experimental campaign is to collect training data for the prediction of surface roughness and maximum recast layer thickness based on the initial conditions represented by machining voltage, pulse off time, and feed rate in addition to the type of wire.

For this experiment we consider:

- Material: steel and height: 20 mm
- Type of wire: **hard brass LT25A**

The levels of the input parameters in the experiment are shown in Table 5.

Table 5: Levels of input parameters in the experiment

Independent variables	**Levels**		
	Low (1)	**Medium (2)**	**High (3)**
Machining voltage (*V*) [V]	110	150	190
Wire feed speed (*f*) [mm/min]	6	11	16
Pulse off Time (T_{off}) [μs]	1	6	11

5.5 Experimental data

The surface roughness measurement was performed on finished surface by using surface profilometer 'Mahr Perthometer PGK'.

The following steps are followed to measure the recast layer thickness:

- Surface of samples to polish is: **2mm x 7 mm**
  - The samples are mounted using resin which polymerizes at room temperature.
  - There is a need for polishing with 4 grain sizes (**15μm**, **9μm**, **6μm** and **1μm**). 15 and 9 microns are realized with 1200 and 2400 SiC papers respectively and 6 and 1 microns are realized with diamond suspensions.
- Since the samples are in steel, **NITAL** is used for chemical attack of polished samples
- A microscope to measure the recast layer thickness
  - 20 pictures will be taken per surface from the beginning of the machining up to the end
  - On each picture the minimum and the maximum recast layer thickness will be measured

The obtained experimental data is shown in Table 6.

Table 6: Experimental data

Run No.	***V* [V]**	***f* [mm/min]**	**T_{off} [□s]**	**Surface roughness (R_a) [□m]**	**Average recast layer thickness (*RLT*) [□m]**
1	110	6	1	0.46	1.49
2	110	6	6	0.59	1.95
3	110	6	11	0.61	1.73
4	110	11	1	0.5	1.74
5	110	11	11	0.7	2.06
6	110	16	6	0.73	1.08
7	150	6	1	0.62	1.5
8	150	6	6	0.66	1.33
9	150	6	11	0.73	1.69
10	150	11	1	0.64	4.25
11	150	11	6	0.73	1.31
12	150	16	1	0.64	1
13	150	16	6	0.74	1.12
14	150	16	11	0.89	5.07
15	190	6	6	1.12	3.02
16	190	11	1	0.75	6.13
17	190	11	6	1.05	4.02
18	190	11	11	1.06	4.72
19	190	16	6	1.02	4.97
20	190	16	11	0.99	1.03

5.6 Development of the prediction rule base

The input parameters such as voltage, pulse-off time and feed rate are divided into three regions and the output parameters, surface roughness and recast layer thickness are divided into 5 regions as shown in Fig. 7 (triangular membership function for all the parameters). The input parameters are defined with the help of linguistic terms such as high, medium, low and the output parameters are defined with the help of linguistic terms such as high2, high1, medium, low1 and low2. The output of the developed software, the generation of data base for the prediction system, is summarized in Table 7.

The universe of discourse, along with the linguistic variables for each variable is shown in Fig. 7 in the appendix. From the triangular membership function, the degree of membership for each of the input and output process parameters can be determined from its crisp value.

The generated fuzzy rule base is shown in Table 8.

Table 7: Range of values and regions of input and output parameters

Parameter	Min value	Max value	# Regions	Width	Centers
V	110 [V]	190 [V]	3	40	110, 150, 190
f	6 [mm/min]	16 [mm/min]	3	5	6,11, 16
Toff	1 [μs]	11 [μs]	3	5	1, 6, 11
RLT	3.55 [μm]	41.15 [μm]	5	9.4	1,1.86, 2.71, 3.57, 4.42, 5.27, 6.13
R_a	0.46 [μm]	1.12 [μm]	5	0.17	0.46, 0.57, 0.68, 0.79, 0.9, 1.01, 1.12

Table 8: Generated fuzzy rule base

No. of rule	
1	IF voltage IS low AND feed rate IS low AND pulse-off time IS low THEN recast layer thickness is low2 AND surface roughness is low3
2	IF voltage IS low AND feed rate IS low AND pulse-off time IS medium THEN recast layer thickness is low2 AND surface roughness is low2
3	IF voltage IS low AND feed rate IS low AND pulse-off time IS high THEN recast layer thickness is low2 AND surface roughness is low2
4	IF voltage IS low AND feed rate IS medium AND pulse-off time IS low THEN recast layer thickness is low2 AND surface roughness is low3
5	IF voltage IS low AND feed rate IS medium AND pulse-off time IS high THEN recast layer thickness is low2 AND surface roughness is low1
6	IF voltage IS low AND feed rate IS medium AND pulse-off time IS medium THEN recast layer thickness is low2 AND surface roughness is low1
7	IF voltage IS low AND feed rate IS high AND pulse-off time IS low THEN recast layer thickness is low3 AND surface roughness is low2
8	IF voltage IS low AND feed rate IS high AND pulse-off time IS medium THEN recast layer thickness is low3 AND surface roughness is low1
9	IF voltage IS low AND feed rate IS high AND pulse-off time IS high THEN recast layer thickness is low1 AND surface roughness is medium
10	IF voltage IS medium AND feed rate IS low AND pulse-off time IS low THEN recast layer thickness is low2 AND surface roughness is low2
11	IF voltage IS medium AND feed rate IS low AND pulse-off time IS medium THEN recast layer thickness is low3 AND surface roughness is low1
12	IF voltage IS medium AND feed rate IS low AND pulse-off time IS high THEN recast layer thickness is low2 AND surface roughness is low1
13	IF voltage IS medium AND feed rate IS medium AND pulse-off time IS low THEN recast layer thickness is high1 AND surface roughness is low1
14	IF voltage IS medium AND feed rate IS medium AND pulse-off time IS medium THEN recast layer thickness is low3 AND surface roughness is low1
15	IF voltage IS medium AND feed rate IS high AND pulse-off time IS low THEN recast layer thickness is low3 AND surface roughness is low1
16	IF voltage IS medium AND feed rate IS high AND pulse-off time IS medium THEN recast layer thickness is low3 AND surface roughness is medium
17	IF voltage IS medium AND feed rate IS high AND pulse-off time IS high THEN recast layer thickness is high2 AND surface roughness is high1
18	IF voltage IS medium AND feed rate IS medium AND pulse-off time IS high THEN recast layer thickness is low1 AND surface roughness is medium
19	IF voltage IS high AND feed rate IS low AND pulse-off time IS low THEN recast layer thickness is high2 AND surface roughness is high1
20	IF voltage IS high AND feed rate IS low AND pulse-off time IS medium THEN recast layer thickness is low1 AND surface roughness is high3
21	IF voltage IS high AND feed rate IS low AND pulse-off time IS high THEN recast layer thickness is low2 AND surface roughness is high3
22	IF voltage IS high AND feed rate IS medium AND pulse-off time IS low THEN recast layer thickness is high3 AND surface roughness is high2
23	IF voltage IS high AND feed rate IS medium AND pulse-off time IS medium THEN recast layer thickness is high1 AND surface roughness is high2
24	IF voltage IS high AND feed rate IS medium AND pulse-off time IS high THEN recast layer thickness is high1 AND surface roughness is high2
25	IF voltage IS high AND feed rate IS high AND pulse-off time IS low THEN recast layer thickness is high1 AND surface roughness is medium
26	IF voltage IS high AND feed rate IS high AND pulse-off time IS medium THEN recast layer thickness is high2 AND surface roughness is high2
27	IF voltage IS high AND feed rate IS high AND pulse-off time IS high THEN recast layer thickness is low3 AND surface roughness is high2

5.7 Illustration of the use of the fuzzy-nets prediction model

The example to illustrate the inference model considers the input data set in Table 9.

Table 9: Data set for fuzzy inference model

***V* [V]**	***f* [mm/min]**	T_{off} **[□s]**
130	11	6

According to Fig. 7.a, voltage has a non-null membership degree in two regions: low (L) and medium (MD) as shown in Fig. 8.

Therefore the membership degree of the voltage in both regions is calculated as follows:

$$\begin{cases} \mu_L(Voltage) = 1 - \dfrac{130-110}{150-110} = \dfrac{20}{40} = 0.5 \\ \mu_{MD}(Voltage) = 1 - \dfrac{150-130}{150-110} = \dfrac{20}{40} = 0.5 \end{cases}$$

Feed rate has non null membership function degree in one region MD as shown in Fig. 9. The membership degree is one ($\mu_{MD}(FeedRate) = 1$) as the value of feed rate falls on the center of the region MD.

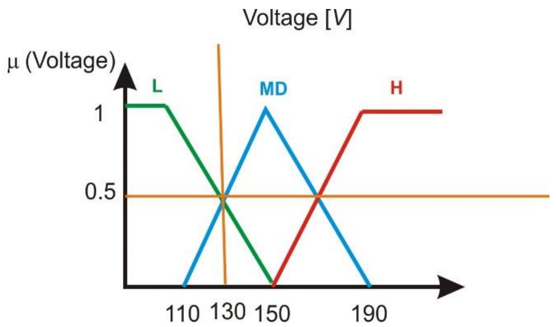

Fig. 8: Voltage membership degree determination

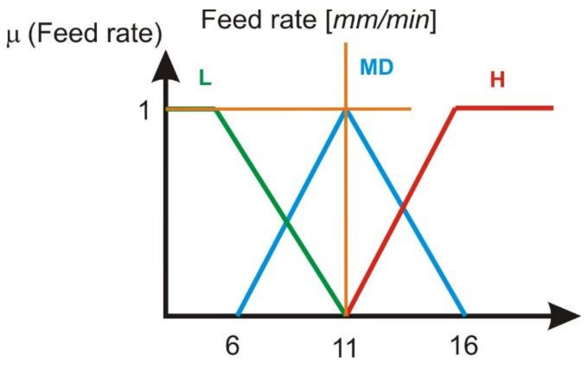

Fig. 9: Feed rate membership degree determination

Pulse-off time has non null membership function degree in one region MD as shown in Fig. 10. Also in this case the membership degree is one ($\mu_{MD}(Pulse-off\ \ Time)=1$) due to the value of pulse-off time which is equal to the center value of the membership function MD.

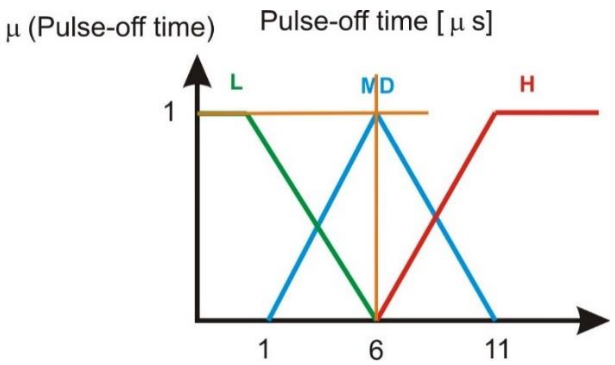

Fig. 10: Pulse off time membership degree determination

The two fired fuzzy rules are the rules number 6 and 14 listed in Table 8: (i) IF voltage is low AND feed rate is medium AND pulse-off time is medium THEN recast layer thickness is low1 AND surface roughness is low1, and (ii) IF voltage is medium AND feed rate is medium AND pulse-off time is medium THEN recast layer thickness is low1 AND surface roughness is medium.

The membership degrees of surface roughness and recast layer thickness with respect to these two fuzzy rules if 0.5.

In both of the fired fuzzy rules, the fuzzy region of recast layer thickness is low1. Therefore the center value of region low1 for recast layer thickness is 12.95 [µm]. The crisp values of recast layer thickness is calculated as follows:

$$y_{RLT}=\frac{0.5\times12.95+0.5\times12.95}{0.5+0.5}=\frac{12.95}{1}=12.95$$

The fuzzy regions of surface roughness in the first and second fired fuzzy rule are respectively low1 and medium, and the corresponding center values of these regions are respectively 0.63 [µm] and 0.79 [µm]. The crisp values of recast layer thickness is calculated as follows:

$$y_{Ra}=\frac{0.5\times0.63+0.5\times0.79}{0.5+0.5}=\frac{0.71}{1}=0.71.$$

6 Conclusion

We presented for the first time a general Multiple-Input Multiple-Output (MIMO) fuzzy net architecture and approach; we demonstrated the application of the new MIMO framework for part quality prediction in WEDM and input process parameters planning. We have identified the process parameters influencing the part surface roughness (pulse off time, feed rate and voltage,) and those influencing the recast layer thickness (voltage and feed rate).

The proposed fuzzy logic based approach for part quality prediction and process planning in WEDM was demonstrated through its application to a WEDM machine (CUT 200 sp) from GF Machining Solutions where the considered part quality characteristics are recast layer thickness and surface roughness. This resulted in a paradigm change in WEDM process planning where not only the desired surface roughness can be targeted but also the average recast layer thickness. This is very important for practical applications since it is well known that the WEDM is often not recommended in safety critical applications due to the uncontrollable generation of recast layer thickness which could be detrimental to the respective component fatigue strength.

In the future work we will investigate the combination of the MIMO fuzzy-nets prediction approach with an optimization method to determine the set of initial conditions which provides the best performance with respect to recast layer thickness and surface roughness simultaneously.

7 Acknowledgements

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8 Appendix

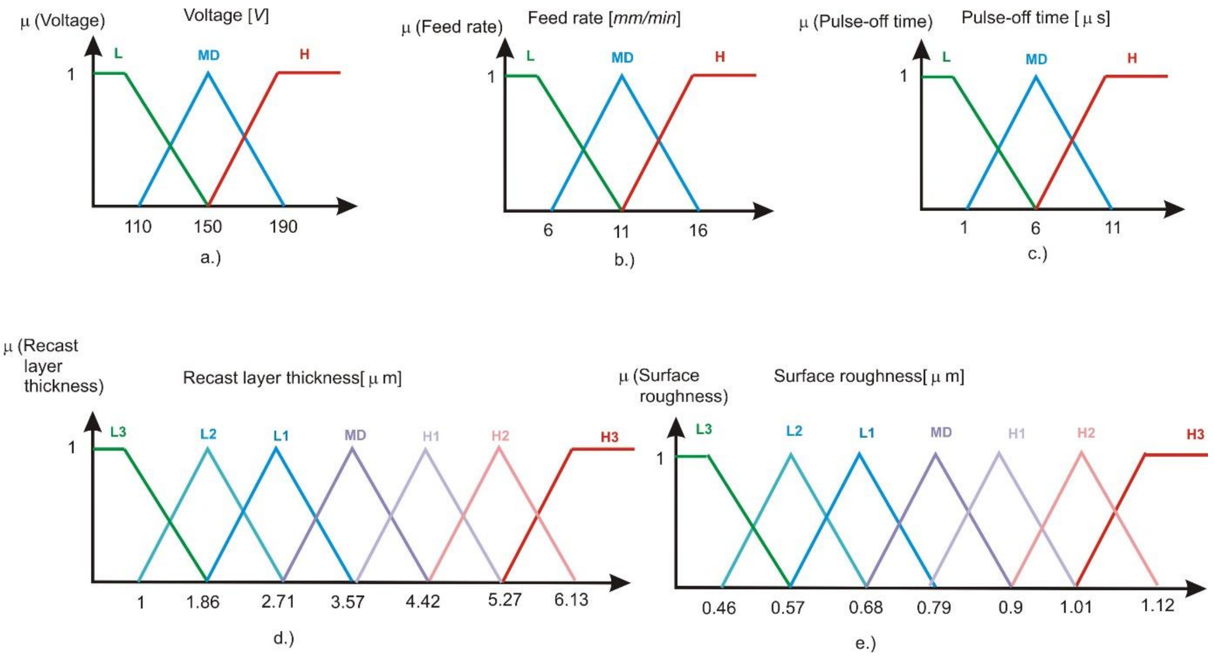

Fig. 7: Fuzzy regions and related membership functions of a.) Voltage [V] b.) Feed rate [mm/min] c.) Pulse-off time [µs] d.) Average recast layer thickness [µm] e.) Surface roughness [mµ]