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Fuzzy logic based tool condition monitoring for end-milling

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1. Introduction

In recent years, research on the monitoring of machining operations has been intensively conducted as it significantly contributes to the automation of the manufacturing process and minimizes human factor. Furthermore, automation of the manufacturing process will increase the productivity of any manufacturing system by minimizing the downtime while preserving high quality standards. As a result, interest in Tool Condition Monitoring (TCM) systems has grown considerably and a great deal of multidisciplinary research has been conducted. By investigating the literature related to TCM systems, it was observed that the majority of the research is conducted on turning operations because the tool geometry makes it possible for a more convenient inspection of its cutting condition [1,9]. However, studies on TCM systems considering 3- to 5-axis end-milling have rarely been conducted as it is considered to be complicated due to the complex cutting paths and the varying cutting conditions. Another complication concerning end-milling is related to the compound tool geometry which renders the sensor data obtained from the dynamometer more difficult to process and evaluate. Chen and Li [25] and Li et al. [26] focused on flank wear monitoring of an end-mill based on real-time measurement of the z-axis of the cutting force. Schmitz et al. [27] developed a method for in-process stability evaluation of milling operations by utilizing a microphone signal, and their concepts could also be successfully applied for tool wear monitoring. Vibration signals are widely used in TCM because they are directly affected by the tool's cutting condition. A sharp cutting tool will generate lower levels of vibration and as the cutting condition deteriorates these levels increase. Thus, by analyzing the statistical features of the amplitude of an accelerometer, relatively accurate predictions can be made of the tool's cutting condition [7,11,12,28,29]. Another widely used signal in TCM is Acoustic Emission (AE), which in combination with frequency and time-frequency domain signal processing techniques (such as Fast Fourier Transformation (FFT), Short Time Fourier Transformation (STFT) and Wavelet Transformation (WT)) have provided insight into how sensory patterns evolve as the tool's cutting condition evolves [34–39]. On the other hand, AE signals use extremely high sampling rates (4.8 MHz), which results in high noise, large data size and difficulties in processing and storage. Current consumption of the feed drive and spindle of a CNC machine have been used for cutting forces prediction and tool breakage detection [30–32]. Current measurement seems to be less prone to noise and simple filtering techniques can be applied to sensor data prior to feature extraction.

TCM systems have two main goals: accurate evaluation of the tool's cutting condition and right-on-time tool breakage or tool chipping detection. The occurrence of tool wear during machining is a natural effect of the material removal process and it is very difficult to estimate its level. Tool breakage on the other hand, is the most crucial phenomenon in end-milling as it can cause irreversible damage to the product's surface and it should be prevented. Moreover, tool wear estimation is also the surface quality estimation of the final product; therefore, determining the cutting condition of the tool means that the surface roughness of the final product can be predicted. If tight tolerances are set for the surface quality of the final product, these tolerances can be easily maintained while the tool's cutting condition is continuously monitored. In addition, tool wear estimation is essential as it can determine whether the tool can last until the end of the process. Knowing whether the tool will withstand the entire process makes it easier for the engineers to determine whether the tool or the cutting condition should be changed, so the same tool can finish the operation without interrupting the machining process. In many of the recent efforts to develop a TCM system, multi-sensor signal fusion in combination with Artificial Intelligence methods has been the main focus [2–5,10–15]. Researchers who attempt to develop TCM systems by applying Artificial Neural Networks (ANN) have often failed to consider that ANNs are considered to be inefficient in terms of time series due to issues related to overfitting and local minima [3]. For this reason, a Fuzzy Inference System (FIS) was developed offline which can map online sensor values to their related cutting tool condition. The conditions that were taken into consideration include tool wear, tool breakage and variations in cutting condition [1,2,6,7]. In order to support more accurate tool condition estimation [33], four different sensors were utilized. The purpose of these sensors is to capture the four important signals that are emitted during end-milling operations:

1. Cutting force signal (dynamometer)
2. Current signal from the spindle
3. Spindle vibration signal (accelerometer)
4. Machining sound signal (microphone)

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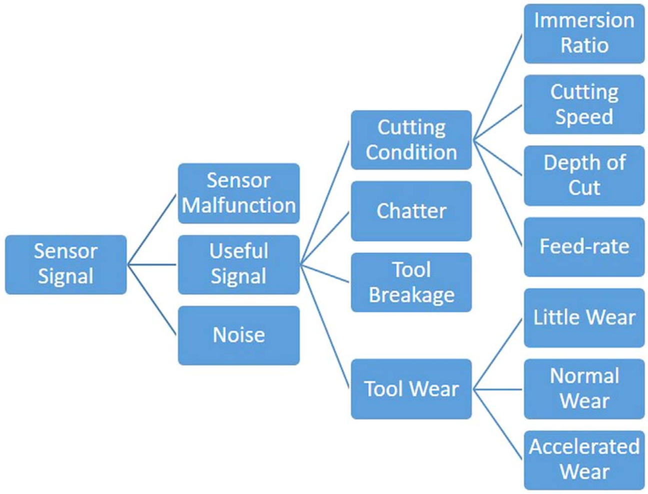

Fig. 1. Steps for signal processing.

In order to obtain useful information from the above mentioned signals, certain steps must be taken. The first step involves selecting the parts of the raw sensor signal that are to be considered as noise or sensor malfunction, or as containing process related information (useful signal). The second step involves determining the parts of the useful signal that could detect chatter and involves providing information related to the tool's cutting condition. Finally, the immersion ratio could be determined and the tool wear could be evaluated. These steps are summarized in Fig. 1.

An important part of this research is the development of a Fuzzy Inference System (FIS). The target was to investigate and implement a TCM system that could perform accurate evaluations about the tool's cutting condition and provide the related level of confidence for each evaluation. Fuzzy Logic systems have been successfully applied to many real-life projects and can be easily implemented on microcontrollers.

2. Experimentation and signal processing

This research focuses on processing and analyzing the various signals that can be obtained during end-milling. The challenge in this task is to be able to process large amounts of data within a limited amount of time in order to ensure the functionality of the online TCM system. Considering this goal, the experiments were based on a simple end-milling operation, in order to pay extra attention to the filtering and merging of the sensor signals.

It is well known that end-milling operations are extremely difficult to monitor because of the large variation of the cutting condition, mainly due to the complexity of the tool-path and the complicated tool geometry. To avoid further complications and in order to focus on determining the process from sharp to blunt of the tool's cutting condition, slot machining with a flat end-mill was considered. The slot machining operation would provide a more stable cutting condition, control over the number of entry and exit points of the tool and minimal chatter.

For the experimental part of the research, a 100 mm length prismatic work-piece was used and slots were repeatedly machined until the tool was severely worn or broken. At the end of every machined slot, pictures of the tool were taken with a microscope camera in order to evaluate the condition of the tool. The tool that was used for the experimentation was a two-fluted High Speed Steel (TiAlN coating) 12 mm diameter flat end-mill. The work-piece was AISI 1045 steel and the depth of cut for each slot was set at 0.3 mm. The cutting speed was set at 150 m/min and the feed-rate was set at 50 mm/min; the spindle speed was thus set at 4000 rpm according to Eq. (1). During machining, no coolant was applied and a summary of the initial cutting condition is shown in Fig. 2.

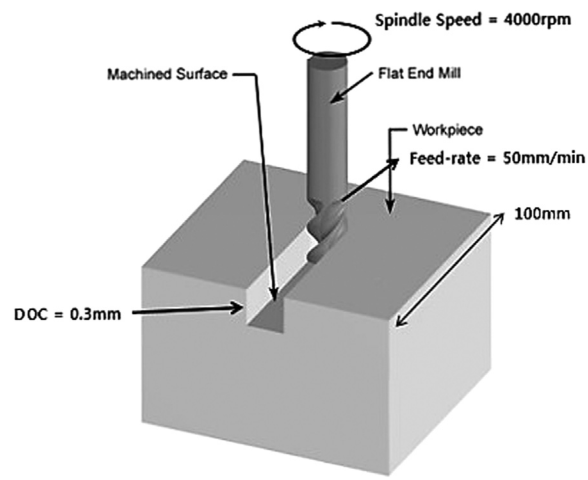

Fig. 2. Machining parameters for the conducted experiments.

$$RPM = \frac{CuttingSpeed}{\pi \times (ToolDiameter)} \tag{1}$$

2.1. Sensor data acquisition

Obtaining the data from four different sensors requires a considerable amount of processing power and memory. For the microphone, the sampling rate was set at 51,200 samples/sec, while for the accelerometer, dynamometer and spindle current sensor, the sampling rate was set at 10,000 samples/sec. This gives a total sampling rate of 81,200 samples/sec. Each sample is stored as a double precision floating point which requires 64 bits; thus, the speed required of the data is 81,200×64=5,196,800 bits/sec. While this speed does not induce any difficulties, considering that the data also needs to be filtered and compared with a certain threshold and that the system must evaluate the tool's condition, many issues could arise, especially in the case of an embedded TCM system. These requirements can be met by either writing a program in a compiled language (such as C or FORTRAN) or implementing the signal processing modules in a Digital Signal Processor (DSP) and the fuzzy controller logic in a microcontroller. The raw sensor data can be obtained through the data acquisition cards provided with the sensors or Analog to Digital Converters (ADC) could be used to implement the same functionality. In order to obtain some useful information related to the cutting condition of the tool, the sensor data must undergo certain processing. According to [8], the general steps of such processing are as follows:

i. Apply Fast Fourier Transformation (FFT) on the raw data and plot the frequency response
ii. From the frequency response, the most significant frequency band needs to be determined
iii. Apply Butterworth filter on the signals in order to obtain a bandwidth related to the most significant frequency
iv. Detect the air-cut from every machined slot
v. Determine the entry and exit point of every machined slot

2.2. Significant frequency band and signal filtering

It is well known that, during data acquisition, noise is a significantly large obstacle to overcome in order to obtain the required results. Obtaining sensor signals inside a machining centre is no exception; on the contrary, more than any other type of operation, machining centres are prone to noise and special attention must therefore be paid to the way the signals are filtered. As mentioned previously, from the signal data, the air-cut needs to be detected and the entry and exit points must then be determined. To achieve this, the sensor signal must be well filtered; otherwise, the important states of the cutting operation cannot be determined because of noise.

A signal is a function that conveys information about the behaviour or attributes of certain phenomena. Therefore, any quantity that varies in time or in space is potentially an information-carrying signal. According to the theory developed around the Fourier series, it is known that complicated periodic functions can be written as the sum of simple sine or cosine waves. Based on this knowledge, it is possible to decompose the obtained sensor signals to their basic components, so that a decision can later be made about which components contain valuable information and which are merely undesirable noise. The frequency response can be plotted from every sensor signal, the most significant frequency band can be determined and the signal can then be filtered. The most significant frequency should be able to provide the same amount of information as the raw signal, but with a much smaller volume of data.

Knowing that the dynamometer captures the force applied on the work-piece, the most important part of the signal should be considered as that resulting from the contact between each tooth of the tool and the work-piece. In this case, the frequency of each tooth in contact with the work-piece is given by the following equation:

$$f_{dyn} = \frac{RPM \times N_{tooth}}{60sec} \tag{2}$$

In the conducted experiments, the spindle speed was set at 4000 rpm and the tool that was used had two teeth. Considering Eq. (2), the value of 133 Hz would be the most significant frequency for the dynamometer signal. The same logic applies for the current sensor because the spindle consumes higher amounts of electrical power every time each tooth of the tool removes material from the work-piece. This results in higher levels of electrical current flowing through the spindle and, depending on the cutting condition of the tool, these current levels can vary significantly. Thus, by filtering the dynamometer and spindle current sensor signals at 133 Hz, certain variations of their levels of magnitude are observed, which could provide enough information to evaluate the cutting condition of the tool. Concerning the microphone and accelerometer sensor signals, the focus was set on the frequency that had the highest magnitude, and observations were then made on how the magnitude of that signal would evolve as the tool condition would deteriorate. This is based on the fact that the sound and the vibrations with the highest magnitude are those generated by the contact of the tool and the work-piece and everything else should be considered as undesirable noise. In the case of the accelerometer, the frequency with the highest amplitude was found to be 133 Hz, and for the microphone 18.600 Hz. The spectrum of each sensor signal is shown in Fig. 3.

It should be noted that the arguments provided for selecting the significant frequencies might not be well established and unsatisfactory; however, as will be discussed in the following sections, only information on how the frequency magnitudes evolve while the tool's cutting condition deteriorates is necessary. It is known that a signal can transmit information in two ways:

i. Frequency Modulation and
ii. Magnitude Modulation

The sensor signals were filtered out on a specific frequency band; therefore, while frequency modulation does not occur, the required information was extracted from the magnitude modulation of the specific frequency. This means that by observing the variations in the magnitude of the signal, it is possible to deduce the necessary evaluations of the tool's cutting condition. After determining the significant frequencies, the next step involves applying a bandpass filter to the raw sensor data in order to obtain signals with approximately the same amount of information as previously, though with a much smaller volume of data.

2.3. Air-cut removal and feature extraction

In order to make more correct observations and to develop an FIS that can evaluate the cutting condition of the tool, the filtered data needs a further process. First, the data generated during the air-cut must be removed, which is relatively easy since the magnitude of these data is quiet low compared to the magnitude of the data during material removal. Then, special attention must be paid to the entry and exit points of the tool (see Fig. 4), since they provide useful information about the tool's cutting condition, although they should be analyzed separately from the remaining data. During the first contact of the tool and the work-piece, high levels of energy are detected from all the sensors, but this does not imply deterioration of the tool's condition. For this reason, it is suggested that the data at the entry and exit points needs to be analyzed based on different thresholds and in relation to the remaining signal.

After filtering and removing the entry and exit points from the data, they remain bulky and inconvenient to handle. It is thus necessary to apply feature extraction methods in order to significantly reduce the size of the data while maintaining the substantial information related to the tool's cutting condition. In many research works, various feature extraction methods have been applied, some of which can be found in [9–14]. In this paper, only three of these feature extraction methods were applied; it is later proven that no significant difference occurs among them. The methods that were used include Peak-to-peak amplitude, RMS value and the Power of the signal, all of which give good statistical measure of the magnitude of a time varying signal and are especially useful for variables that are periodic with a mean value of zero, such as for accelerometer and microphone signals. The results obtained from feature extraction did not vary significantly among the methods, and for this reason the shown plots will have a different method applied on them. The final result of the processed signals, after the feature extraction, can be seen in Fig. 5.

Thus far, the basis for the development of the TCM system has been described. The steps taken to obtain the signals, filter them and extract certain features should be repeated for every experiment conducted. The number of experiments must be large enough to include a variety of tools with different quality specifications and different cutting lives. Some attention needs to be given to the way the extracted features from each experiment are combined, especially in the case where the tool life in one experiment is much shorter than the tool life in another experiment. A tool that becomes damaged soon provides a smaller amount of data than a tool that operates for a longer period of time. In such a case, it is suggested that the data of each sensor signal is fuzzified, based on the optical inspection of the tool's cutting condition, and to attribute a linguistic value to each sensor. Then, at the end of the experimental phase, all the data that were attributed to the same linguistic value should be unified and processed statistically.

3. Fuzzy inference system and decision making

The main component of a TCM system is a well implemented data acquisition and signal processing system which can obtain and filter the sensor signals with precision. However, the goal of this research is to reach beyond this step. Apart from monitoring of the tool's cutting condition, the system should be able to automatically make decisions and be integrated with the general controlling system of the CNC machine. For the TCM system to be successful, any condition in which the tool would irreversibly damage the work-piece should be avoided; for this reason, it is necessary to determine whether the tool will be blunt or broken before the end of the machining process. If the tool's cutting condition is deteriorated, then one of two decisions can be made: 1) interrupt the machining operation and change the tool or 2)

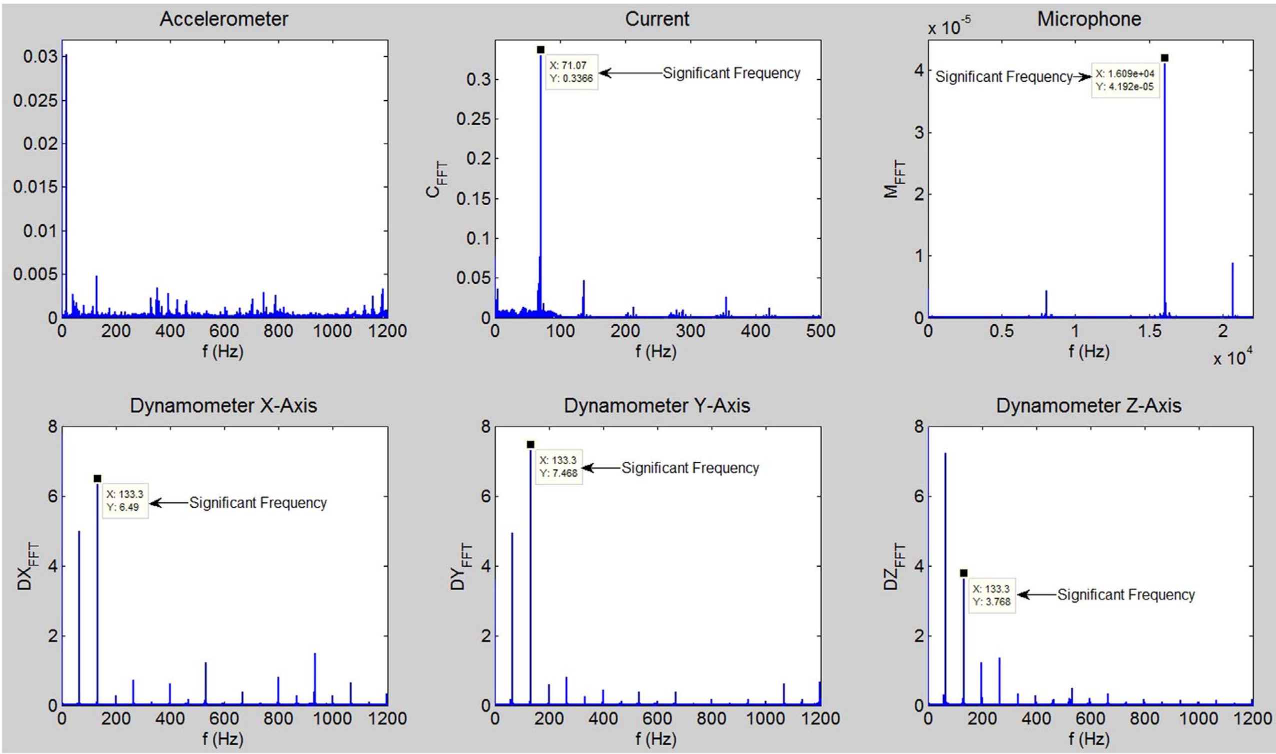

Fig. 3. Frequency spectrum of the sensor signals and their significant frequencies.

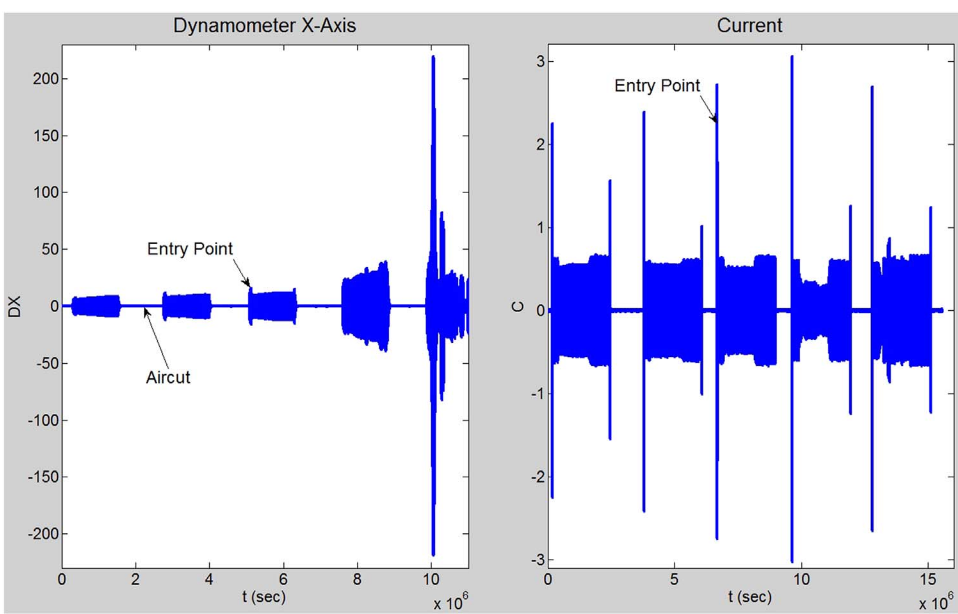

Fig. 4. Entry points and air-cut for the (a) Dynamometer x-axis signal and (b) Current sensor signal.

change the cutting condition (spindle speed, feed-rate). The main factors that determine the life of the tool are the tool and work-piece material, the type of coolant and the cutting speed. Assuming that the coolant, tool material and work-piece material are constant parameters in a machining process, only the cutting speed still needs to be controlled. Therefore, by controlling the spindle speed or feed-rate, it is possible to reduce or extend the life of the cutting tool. In order to estimate and control the life of the cutting tool, fuzzy logic theory was applied, which has been widely implemented in small and large scale projects with considerable success.

Usually, in engineering applications, notions of crispness are applied, but in the real world, most of the values are analog by nature, so the concepts of fuzzy logic are common. Generally, a fuzzy set is considered as an extension of the crisp set since it also considers partial membership. The most valuable concept in fuzzy logic is that of the "linguistic variable", which is extremely useful for transforming expert's knowledge into a set of values that would be evaluated by the fuzzy logic system. Furthermore, fuzzy concepts are useful for concentrating the data to be processed into fuzzy sets, which can reduce the volume of data by a considerable amount.

A Fuzzy Inference System (FIS) defines a nonlinear mapping of the input data vector into a scalar output, using fuzzy rules. The following components comprise the FIS:

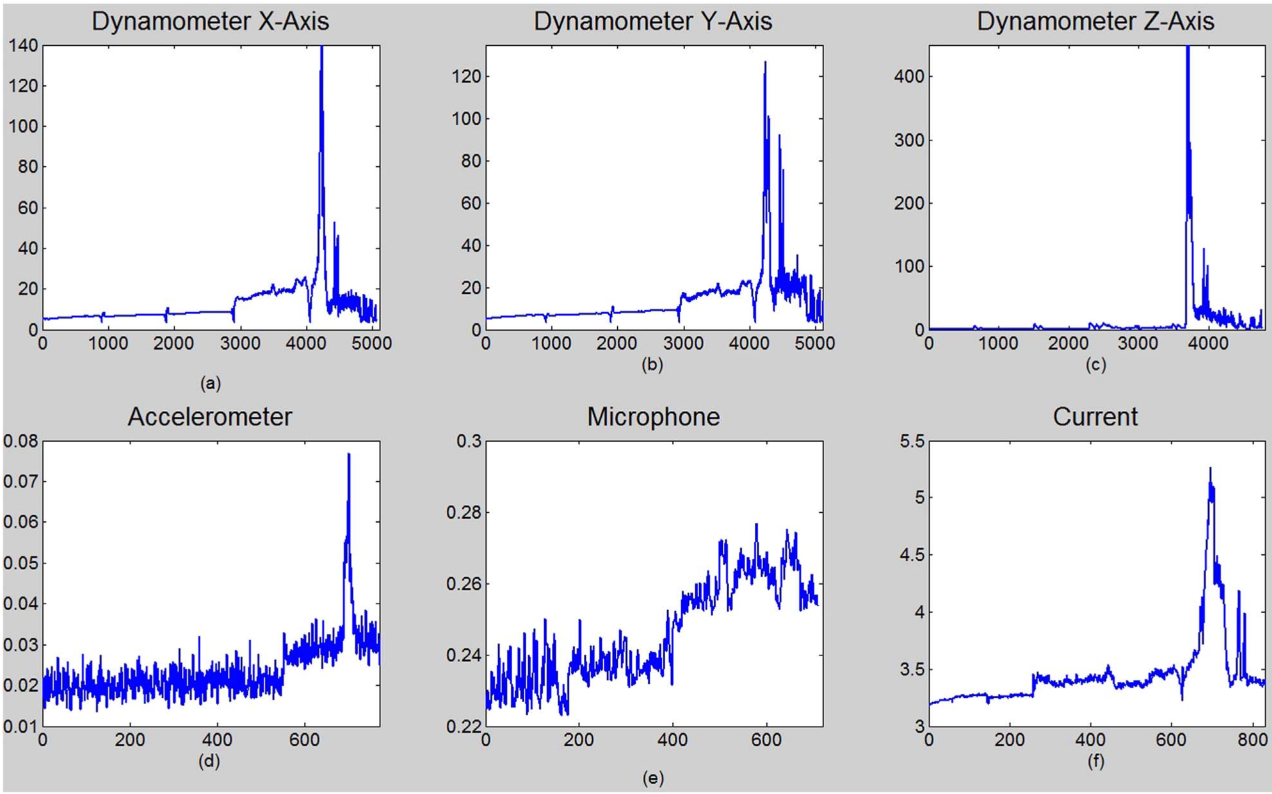

Fig. 5. Result of feature extraction on the (a) Dynamometer x-axis signal, (b) Dynamometer y-axis signal, (c) Dynamometer z-axis signal, (d) Accelerometer signal, (e) Microphone signal and (f) Current sensor signal.

i) Fuzzifier
ii) Inference Engine
iii) Rule Base
iv) Defuzzifier

The purpose of the FIS is to map crisp inputs into crisp outputs. The FIS comprises linguistic rules provided by experts, from personal experience or extracted from numerical data. The Fuzzifier takes input values and determines the degree to which they belong to each of the fuzzy sets (represented by linguistic values) via membership functions. The Inference Engine defines the mapping from input fuzzy sets into output fuzzy sets, based on the rules provided by the Rule Base, and determines the degree to which each rule is satisfied. If one or more rules are activated simultaneously, then the outputs from all the rules are aggregated and the fuzzy sets that represent the output of each rule are combined into a single fuzzy set. The Defuzzifier maps the output fuzzy sets into crisp numbers. Centroid, which is the most popular method used for this process, calculates the centre of gravity of these crisp numbers. The components of the FIS are shown in Fig. 6.

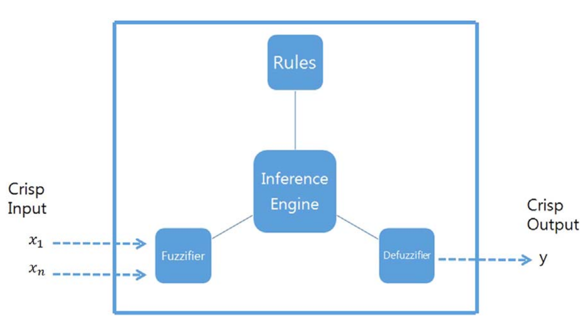

Fig. 6. The Fuzzy Inference System and its components.

3.1. Fuzzification of the sensor data

Considering the sensor signals of the conducted experiments, it is important to first define a way to fuzzify the sensor signals and use them as the input of the FIS. Fig. 7(a) shows the processed signals from the x-axis of the dynamometer, which were combined into one graph. The data from the Dynamometer were divided into four fuzzy sets based on the optical inspection of the tool's cutting condition that was performed during machining. Each fuzzy set has a mean and a standard deviation, which are used for the construction of the Gaussian membership function and, based on the mean, a linguistic value *{Low Data*, Medium Data*, Relatively High Data*, Very High Data} *was attributed to each fuzzy set. Furthermore, the use of polynomial regression is suggested, as a second input to the FIS, in order to perform the first estimation of the tool's cutting condition while obtaining a more robust method for the rule generation, which will be explained in the next section. For this example, a 5th order polynomial was used to fit into the observed data. The absolute value of the error was then calculated, e=|sig(t)-p(t)|*, where sig(t) *is the observed signal value and p(t)* is the predicted value from the polynomial regression. As shown in Fig. 7(b), the absolute error values were divided into three fuzzy sets {Low Error, *Medium Error*, High Error} *based on the mean and standard deviation by which they are characterized. Obviously, some of the data belong to more than one fuzzy set; for this reason, the fuzzy membership functions must be defined in order to determine the degree to which each value belongs to a fuzzy set. At this point, a fuzzy function could also be defined for the description of the sensor data and absolute error, which can be expressed as follows:*

$$S(T) = S_1 \times T_1 + S_2 \times T_2 + S_3 \times T_3 + S_4 \times T_4 = \sum_{i=1}^{4} S_i \times T_i \tag{3}$$

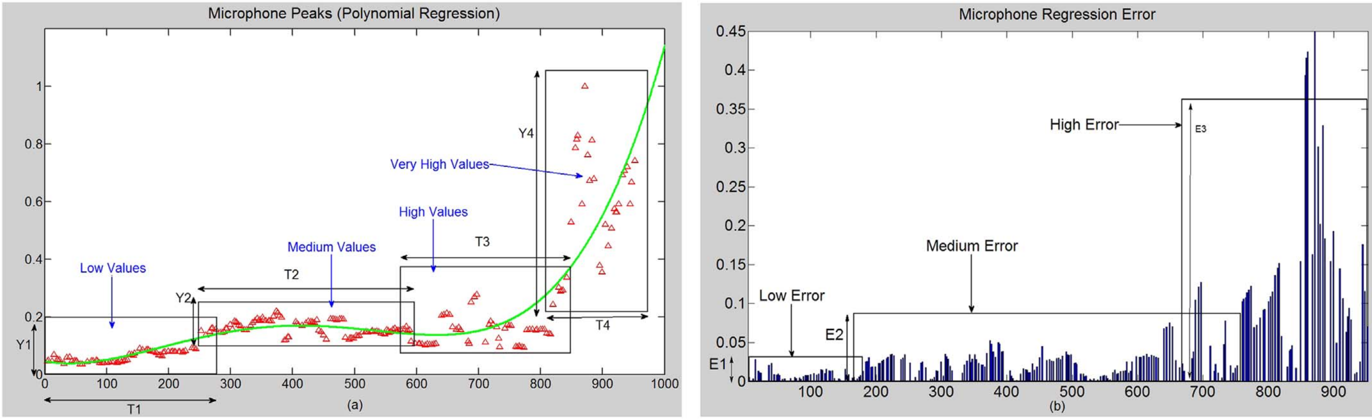

Fig. 7. Example of the fuzzification of the (a) Microphone sensor data and (b) Absolute error values.

$$E(T) = E_1 \times T_1 + E_2 \times T_2 + E_3 \times T_3 = \sum_{i=1}^{4} E_i \times T_i \quad (4)$$

where S_i *represents the fuzzy sets* { S_1, S_2, S_3, S_4 } of the sensor signals, and their limits were defined from the mean +/−3σ. *Also,* E_i *represents the fuzzy sets* { E_1, E_2, E_3 } of the signal's absolute error and their limits were defined in the same manner as for the S_i fuzzy sets.

3.2. Defining membership functions

Every fuzzy set S_i (signal) and E_i (error) must be characterized by a membership function μ_{Si}, μ_{Ei} that takes values in the interval [0,1]. In previous studies on fuzzy logic, various membership functions are used such as Triangular Function, Trapezoidal Function, Gaussian Curves, Polynomial Curves and Sigmoid Functions. For the purpose of this paper, the Gaussian curve was used because of the unknown and random nature of the observed data (they are random within the scope of a set). The values of sig(t) *and e(t)* are the input of the FIS, but membership functions for the output value of the system (the level of tool wear) also need to be defined. As mentioned previously, the level of tool wear was estimated by evaluating the surface roughness of the work-piece (through the 3D reconstruction of its image at the end of the machining process) and by optical inspection of the cutting tool. The observed tool wear was grouped into four fuzzy sets {little wear, medium wear, accelerated wear, breakage}. *For the definition of the membership function of the tool wear values, a triangular function was used because it is not computationally intense and can give quick estimations. Figs. 8–11 show the membership functions for the input and output FIS variables that were generated after statistically processing each of the derived fuzzy sets.*

In the case where a value activates more than one membership function, then their union has to be determined and the resulting value should be taken into consideration. If μ_A, μ_B *are two adjacent membership functions, then their union can be calculated according to one of the following equations:*

$$\mu_{A\cup B}(x) = \max\,[\mu_A(x), \quad \mu_B(x)] \quad (5)$$

$$\mu_{A\cup B}(x) = \quad \mu_A(x) + \quad \mu_B(x) - \quad \mu_A(x)\mu_B(x) \quad (6)$$

3.3. The fuzzy rule base

After defining the membership functions for the input and output fuzzy variables, the fuzzy rule base is constructed; the fuzzy rule base consists of a collection of conditional rules. Concerning the example of the current sensor signal, the following rules were extracted:

i) IF *{signal is low}* AND {error is low} *THEN {tool wear is small}*
ii) IF {signal is medium} *AND {error is low}* THEN {tool wear is medium}
iii) IF {signal is medium} AND {error is medium} *THEN {tool wear is medium}*
iv) IF {signal is high} *AND {error is medium}* THEN {tool wear is accelerated}
v) IF {signal is high} AND {error is high} *THEN {tool wear is accelerated}*
vi) IF {signal is very high} *THEN {tool breakage}*

The above rules can be summarized in a relational matrix (Fig. 12), where the entries would be the fuzzy sets of the signal and absolute error. Some of the cells in the matrix are empty, which means that no rule is associated with them and the sensor data belonging to that category should be neglected. It is important to understand that fuzzy rules map a region of space along the function surface and multiple regions are therefore combined in output space to generate a composite region. Thus, for a given input, more than one rule could be activated and this depends on the number of membership functions. Interpreting a conditional rule is a two-step process [15,16]: (Fig. 13).

i) If the antecedent has multiple parts, fuzzy logic operators are applied and the antecedent is resolved to a single number between 0 and 1, the result of which would be the degree of support for the rule
ii) The implication method is applied using the degree of support for the entire set of rules to shape the output fuzzy set.

The antecedent parts of a fuzzy rule are connected by logical AND operators; two equations can thus be used to estimate the degree of support for the rule:

$$d_i = \min\,[\mu^i{}_A(t), \quad \mu^i{}_B(t)] \quad (7)$$

$$d_i = \mu^i{}_A(t)\bullet\mu^i{}_B(t) \quad (8)$$

Where d_i is the degree of support for the i^{th} rule and $\mu^i{}_A(t)$, $\mu^i{}_B(t)$ are the membership function values of the two parts of the antecedent of the rule.

3.4. Rules aggregation and evaluation

After the estimation of the degree of support, the consequent value of each of the activated rules should be determined to ensure correct mapping between the input and output values is achieved. In Fig. 14, the mapping of the degree of support for the consequent values of the activated rules is shown graphically in order to make it easier to understand the process of the rules aggregation. During aggregation,

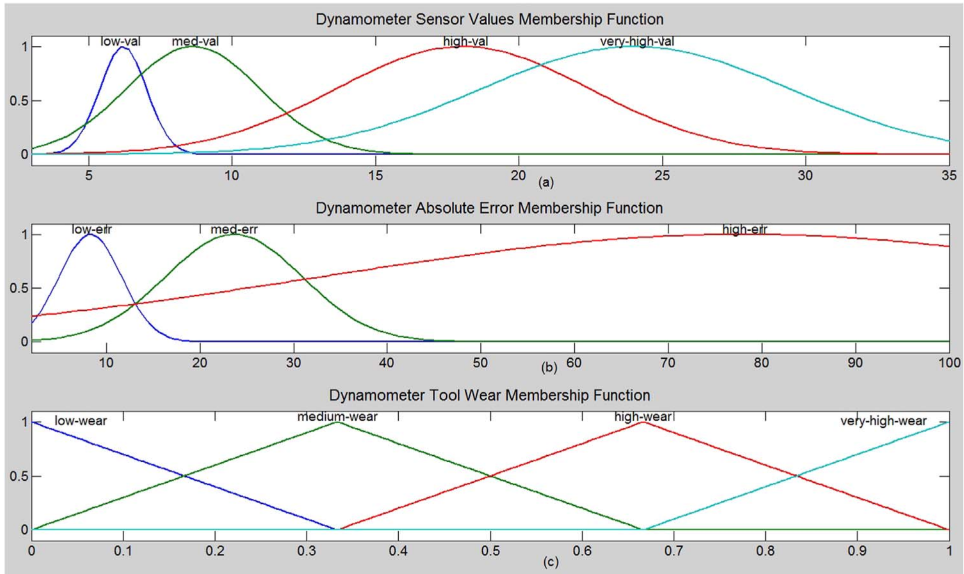

Fig. 8. Membership functions of the Fuzzy Inference System of the dynamometer. (a) Sensor values (input), (b) Absolute error (input), (c) Tool wear evaluation (output).

the fuzzy outputs from all the activated rules are combined into one fuzzy set that will be the input to the defuzzification process. The most commonly used aggregation methods are the maximum and the union of two rules, which are given from Eqs. (5) and (6), respectively.

3.5. Defuzzification

The input of the defuzzification process is a fuzzy set (the aggregated output fuzzy set), and the output should be a single number. Many defuzzification methods have been proposed [15–18], but the most commonly used is the Centroid method. According to [18], the defuzzifier determines the centre of gravity (centroid) of the fuzzy set, and uses that value as the output of the FIS. A simplified equation for the estimation of the centroid is as follows:

$$C = \frac{\sum_{i=1}^{n} w_i \mu_{wi}(t)}{\sum_{i=1}^{n} \mu_{wi}(t)} \tag{9}$$

where w_i is the estimated tool-wear and μ_{wi} *is the value of its membership function, as shown in Fig. 14. After processing all the input variables (sensor signal values and absolute error) through the FIS, the output should be a response surface with the x-axis being the sensor signal values, the y-axis being the absolute error and the z-axis being the estimation of the tool wear. Fig. 14 shows the response surfaces extracted from the utilized sensor signals.*

In summary, the response surface extracted from each sensor can be considered as the logic of the TCM system, based on which evaluation can be made about the tool's cutting condition, and decisions can be taken related to the adjustment of the machining parameters. The response surface of each sensor can be dynamically updated at the end of the cycle of every machining process; this is necessary in order to enable the adaptability of the TCM system to the varying machining conditions.

3.6. Sensor signals integration

In the previous section, the process of generating the response surface of the sensor signals was described. The TCM system will evaluate the tool's cutting condition based on the response surfaces. It is now important to determine whether any of the sensors could

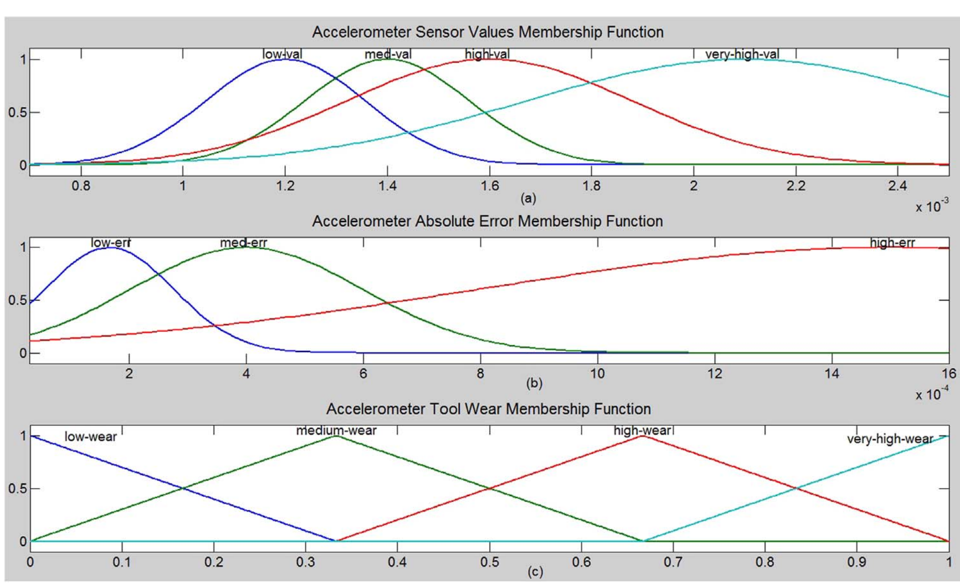

Fig. 9. Membership functions of the Fuzzy Inference System of the accelerometer. (a) Sensor values (input), (b) Absolute error (input), (c) Tool wear evaluation (output).

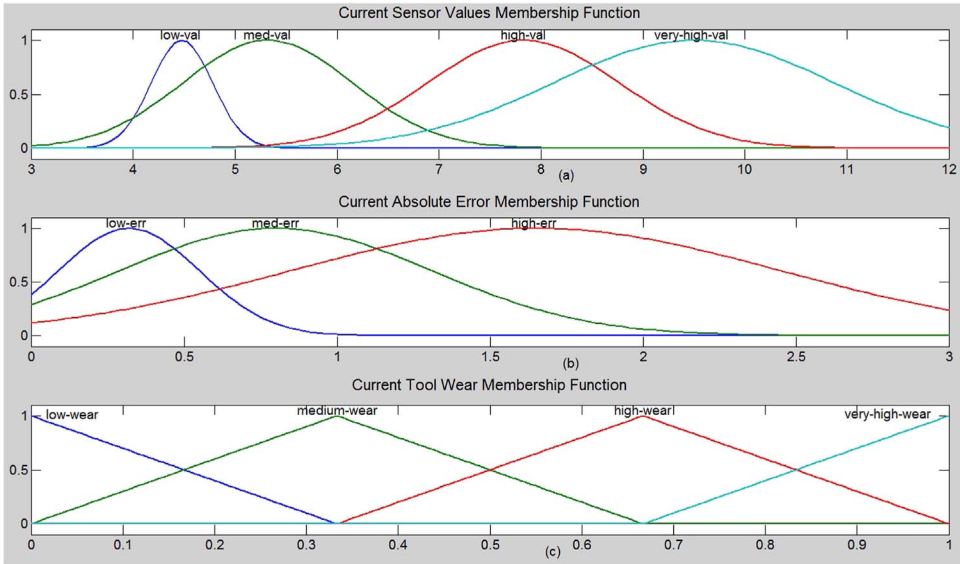

Fig. 10. Membership functions of the Fuzzy Inference System of the current sensor. (a) Sensor values (input), (b) Absolute error (input), (c) Tool wear evaluation (output).

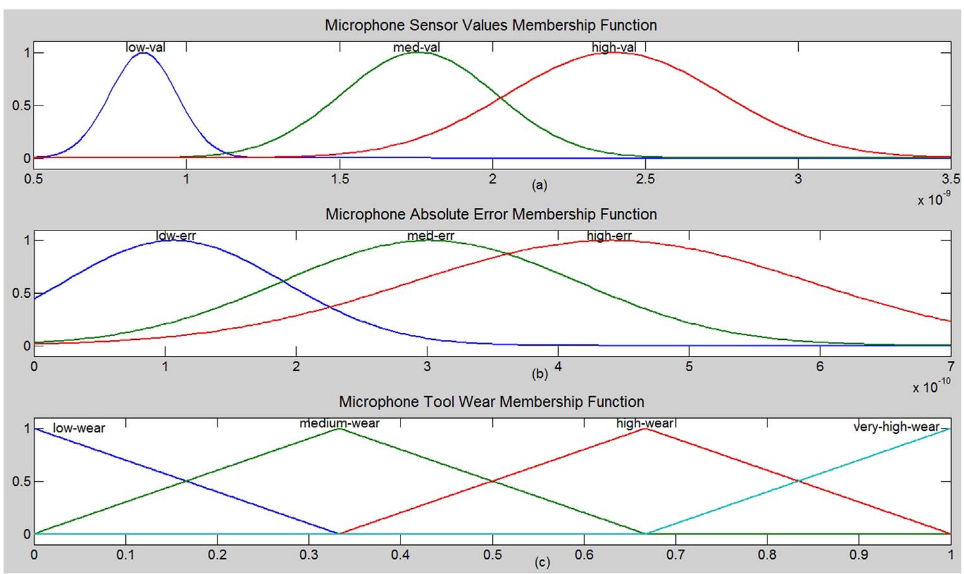

Fig. 11. Membership functions of the Fuzzy Inference System of the microphone. (a) Sensor values (input), (b) Absolute error (input), (c) Tool wear evaluation (output).

Fig. 12. Generated matrix from the Rule Base of the Fuzzy Inference System of the current sensor signal.

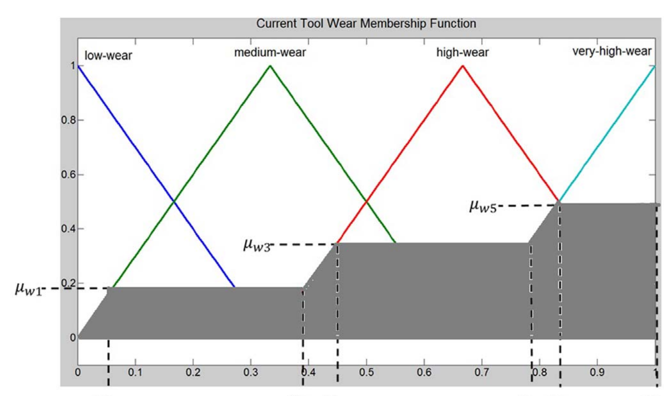

Fig. 13. Aggregation of the outputs of the activated rules and centroid evaluation.

provide more reliable estimations and to what extent these estimations should be taken into consideration. Fig. 14 shows that some sensors are more responsive to variations in the tool's cutting condition and some sensors are more prone to error because of the high level of dispersion that characterizes their signal. Therefore, certain objective criteria should be defined for the sensors' evaluation, which could also be utilized for the estimation of the weight that should be attributed to

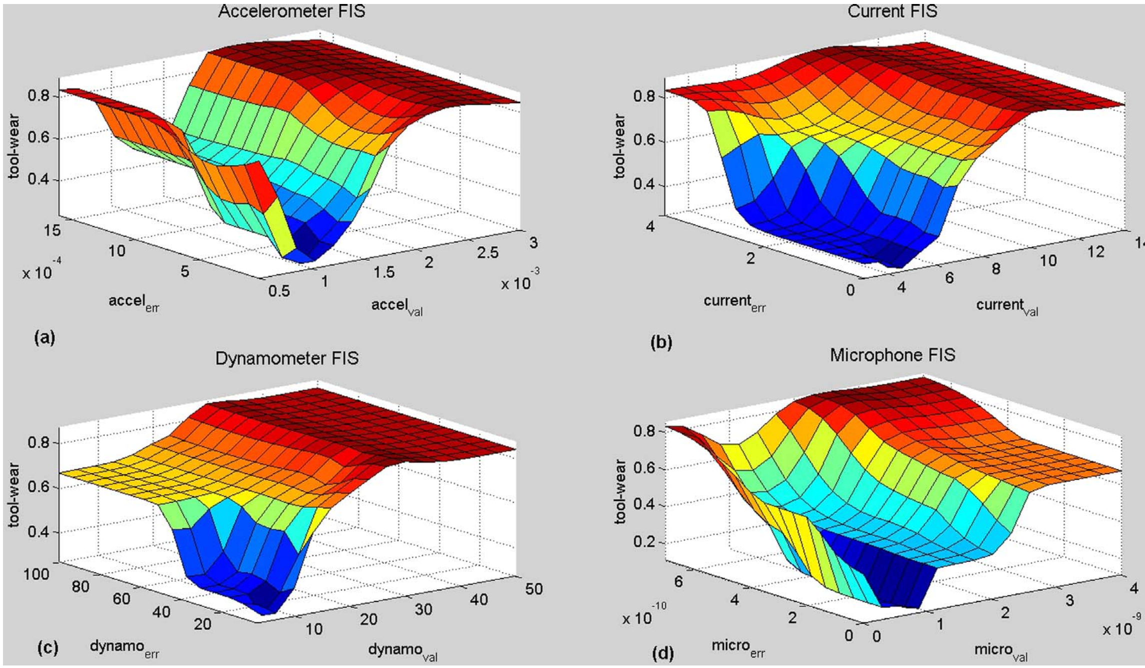

Fig. 14. Response surface for the (a) Accelerometer, (b) Current sensor, (c) Dynamometer and (d) Microphone.

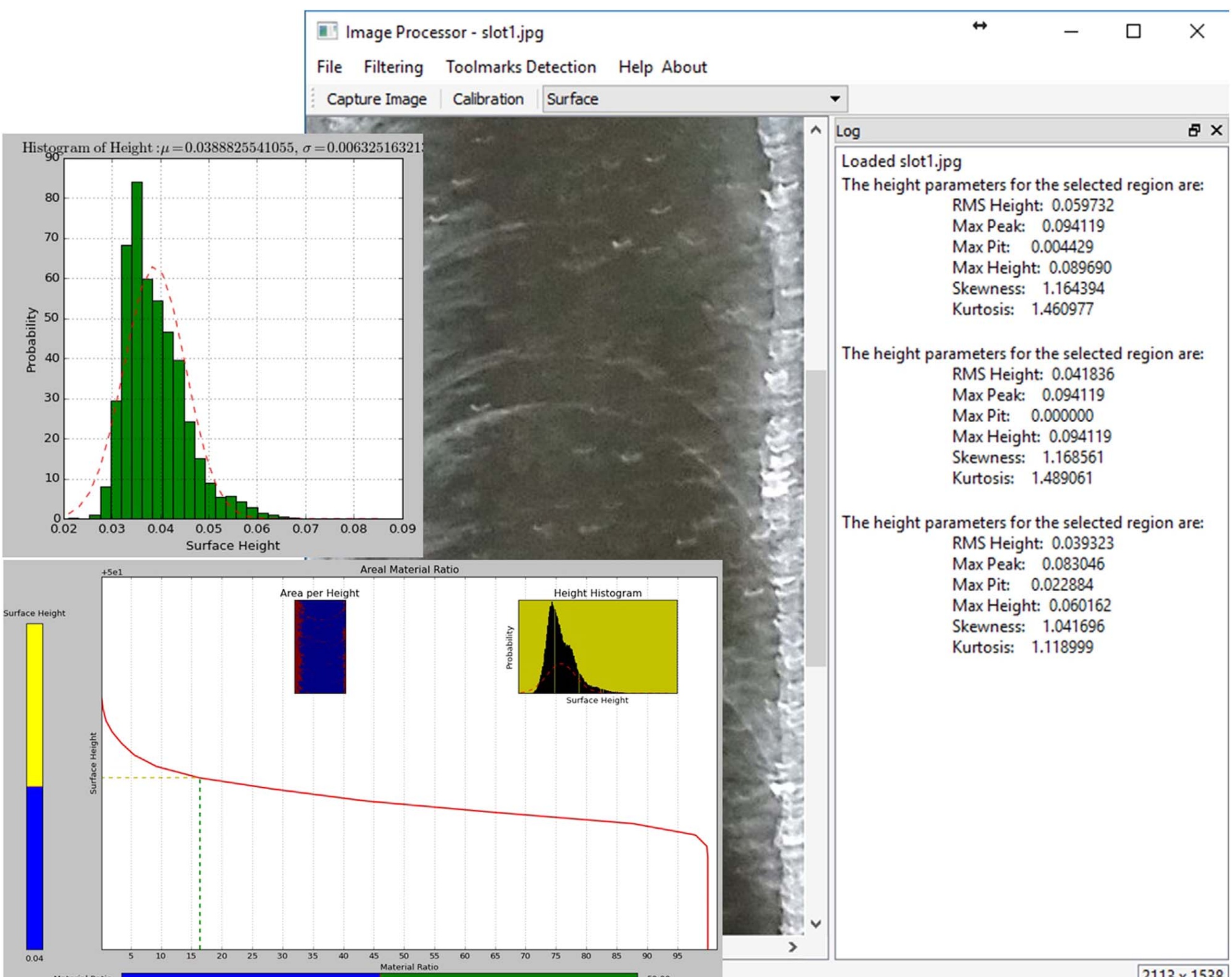

Fig. 15. Developed software for the evaluation of surface roughness of the machined workpiece.

Table 1
Criteria for sensor evaluation.

Sensor Feature	Description	Evaluation
Responsiveness	The ability of the sensor to easily distinguish between two consecutive states of the tool's cutting condition. It is evaluated by the mean of the Hamming distances of consequent fuzzy sets.	$R = \frac{\sum_{i=1}^{n-1} \mid S_{i+1} - S_i \mid}{n-1}$ (11) S_i: the fuzzy set i of the sensor signal n*: the number of fuzzy sets*
Error Ratio	Shows the degree to which the sensor signal is prone to error. It is evaluated by the mean of error to signal value ratio.	$ER = \frac{\sum_{t=1}^{N} \frac{e(t)}{sig(t)}}{N}$ (12) *e(t)*: absolute error of sensor signal sig(t)*: sensor signal values*
Overlapping of Membership Functions	It measures the level of overlapping amongst the fuzzy sets. The higher the overlapping, the lower the confidence about the tool wear evaluation.	$O = \frac{\sum_{i,\ j}^{n} [S_i \times T_i] \cap [S_j \times T_j]}{\sum_{k=1}^{n} S_k \times T_k}, \quad i \neq j$ (13)
MF Mean Distance	Indicates the average distance between two consecutive membership functions. The larger its value, the smaller the overlapping of the fuzzy sets.	$MFMD = \sum_{i=1}^{n-1} \frac{\lvert \overline{S_{i+1}} - \overline{S_i} \rvert}{n-1}$ (14)
Sampling Rate	Indicates the sensitivity of the sensor and its ability to obtain data in a wider frequency range.	

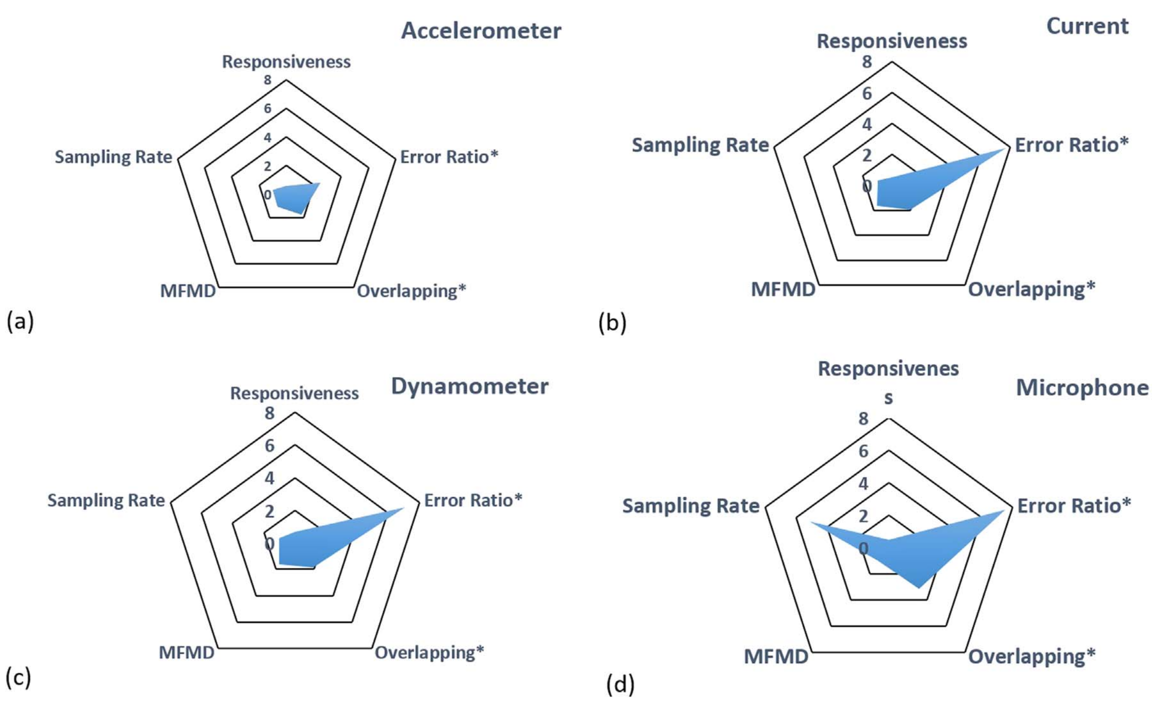

Fig. 16. Radar plots of the sensor features, (a) Accelerometer, (b) Current sensor, (c) Dynamometer, (d) Microphone.

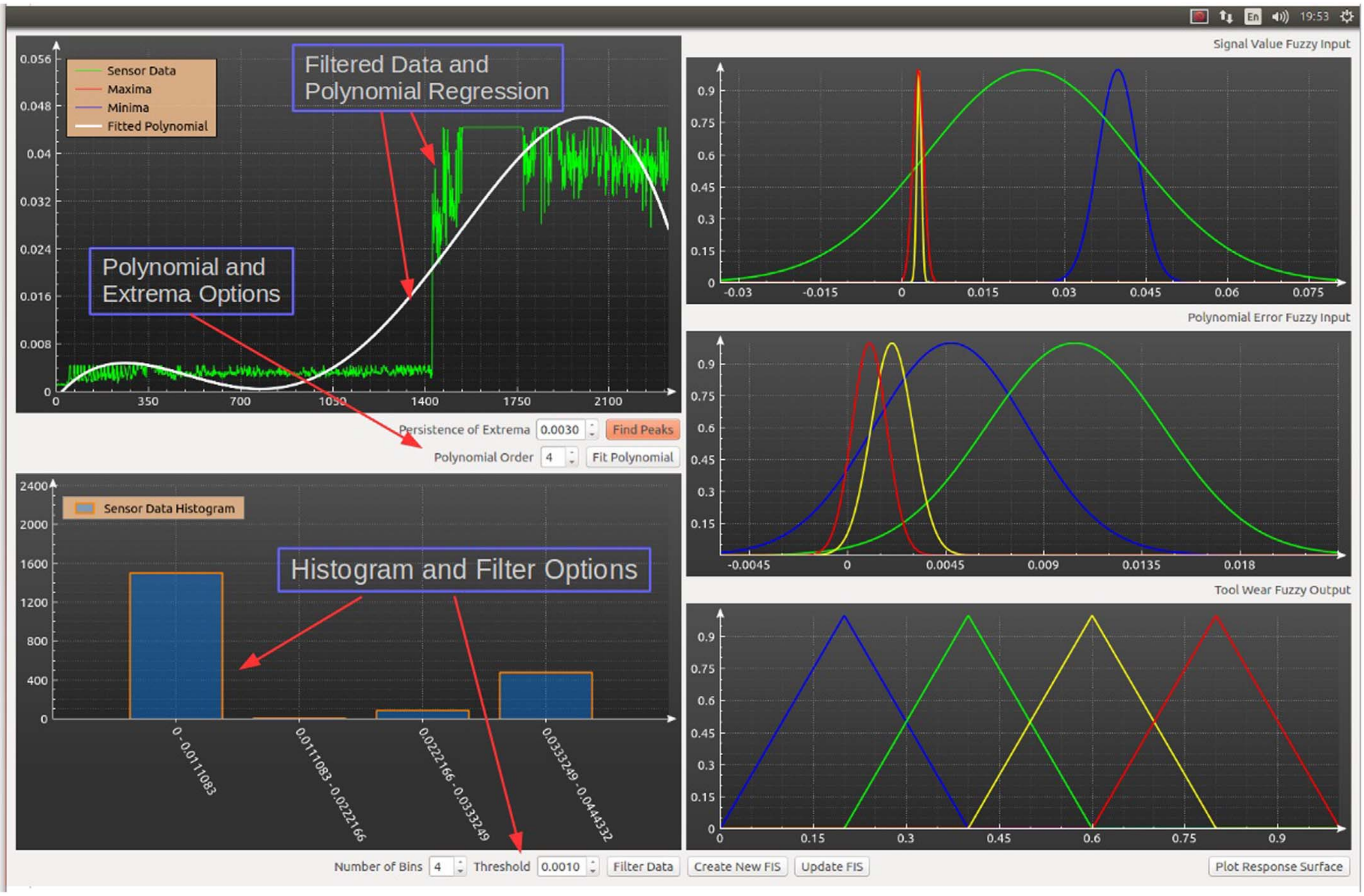

Fig. 17. Offline signal processing and FIS creation/update functionality of the developed software.

them. A detailed description of the criteria used for the evaluation of the sensors is given in the next section.

The final evaluation of the tool's cutting condition should include the results obtained from all the sensors, to which a weight should be attributed. The results are then summed up. Eq. (10) shows the estimation of the Tool Condition Evaluation (TCE) from all the sensors combined.

$$TCE = w_a tce_a + w_c tce_c + w_d tce_d + w_m tce_m \tag{10}$$

where tce_a, tce_c, tce_d, tce_m are the tool condition evaluations obtained from the response surface of each sensor (output of FIS), w_a, w_c, w_d, w_m are the weights attributed to each *tce* and $w_a + w_c + w_d + w_m = 1$. In order to estimate the weights, the features for the sensor evaluation should first be normalized and the mean value for each sensor should then be obtained. Based on the experiments conducted, the weights attributed to the sensors are: $w_a=0.181, w_c=0.253, w_d=0.261, w_m=0.306$. As will be shown in the next section, the microphone signal should be attributed a higher weight than the remaining sensors, while the dynamometer and current sensor should be attributed similar weight values and, because of its high Error Ratio, the accelerometer should be given less consideration.

By evaluating the sensors and attributing objective weights to their signals, the system would be rendered more resistant to various sensor malfunctions that might occur [3,11]. Furthermore, the negative characteristics of the sensors will diminish and their signals will become less prone to error. Also, by merging multiple sensor signals, a wider view of the tool's cutting condition can be obtained by combining the abilities of each sensor.

4. Results and discussion

4.1. Tool wear measurement

Developing an online TCM system was somewhat complicated. The main obstacles were caused by the milling process itself, which is very complicated with many parameters to consider. For the generation of FIS, many experiments need to be performed in order to obtain a solid relationship between the amplitude levels of the sensory signals and the evolution of the tool wear. These experiments provide information on the statistical features of the obtained signals, which were used for the generation of the fuzzy sets and for the construction of the membership functions. An issue that arose during the experimental phase was ensuring the correct evaluation of the tool wear in order to generate the required rule base for the construction of the FIS.

In previous studies, it was frequently reported that during the experimental phase, the tool wear evaluation is made by optical inspection of the cutting edge using a microscope [19–24]. While this method might be considered more direct and more efficient, it has certain disadvantages, especially when an evaluation needs to be made of end-milling tools. In contrast to the turning tools, the geometry of which is very convenient for optical inspection, end-milling tools have a complex geometry and multiple cutting edges. The compound geometry renders it difficult for the microscope to focus on a wide area without shadows and the multiple edges make the process time consuming for proper evaluation. In addition, the main issue with optical inspection is the need to interrupt the machining process during the experimental phase in order to observe and record the evolution of the tool wear. Thus, the cutting tool is given the time to cool down and as a result the expected tool life is extended and this is something that

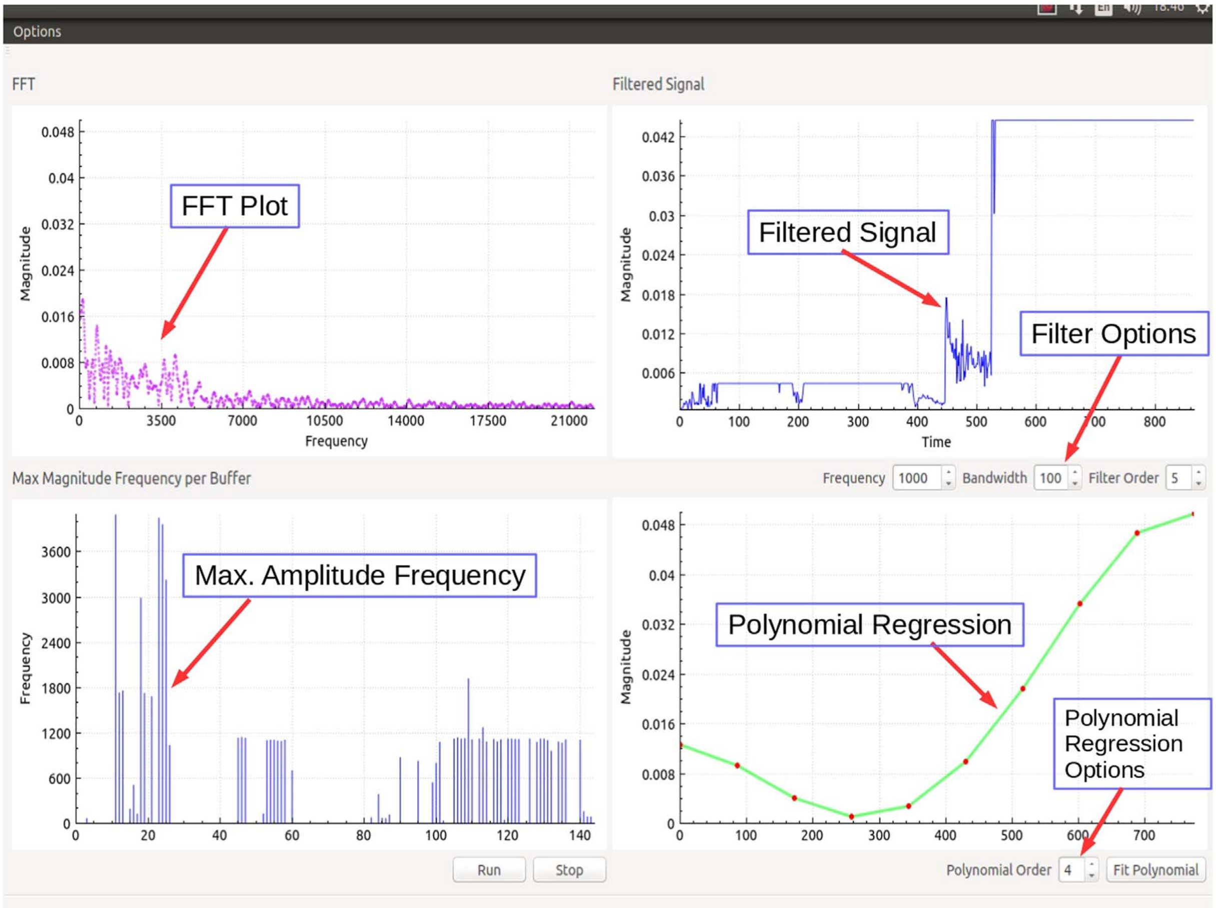

Fig. 18. Online acquisition and processing of the sensor signals.

does not reflect the reality. It was observed that when the machining process was interrupted for optical inspection of the tool wear, the tool life would then increase by 30% compared to when the machining process is carried out without any interruption. The tool wear evaluation was therefore performed by estimating the surface roughness of the work-piece.

During the experiments, the machining process continues uninterrupted until the tool becomes severely damaged. Images of the work-piece are then captured using a microscope camera. Because the FIS requires only a "fuzzy" evaluation of the tool wear such as {"low", *"medium"*, "high"*, "very high"*}, only the inspection of the work-piece surface integrity is needed to provide adequate information to make the appropriate conclusions. For the purpose of evaluating the surface roughness of the work-piece, software with image processing capabilities was developed that has the following functionality:

a) Image acquisition and filtering
b) Foreground extraction and segmentation
c) Surface roughness 3D reconstruction and calibration
d) Height parameters evaluation (ISO 25178)
e) Spacing parameters evaluation (ISO 25178)

Fig. 15 shows the developed software and the obtained results from the evaluation of the height parameters of the surface roughness for various sampled regions of the obtained image. In this paper, although the value of the RMS height was chosen to determine the level of tool wear, any of the height parameters can provide the required information.

4.2. Sensor evaluation

According to the experimental results, the microphone signal proved to be very successful in detecting the change from medium-wear *to high-wear* in the tool's cutting condition, which is very important because it enables the system to react by changing the tool or by adjusting the cutting speed to prevent breakage. The excellent results using the microphone are due to the high sensitivity and high sampling rates of the sensor, which make it possible to analyze a wider frequency range. For these reasons, the evaluations obtained from the microphone's response surface should have a higher weight. Although the sampling rate and sensitivity of the dynamometer are less than those of the microphone, the dynamometer can provide a three-dimensional view of the tool's cutting condition because it detects signals from the three axes of the machining process. The peaks detected by the dynamometer at the entry points of the tool in the work-piece could provide extra information on the tool's cutting condition, and this is more evident when observing the z-axis signal (see Fig. 5(c)). Furthermore, the x-axis and y-axis signals of the dynamometer follow the same trend and their correlation value is very high; they could thus be used to check the validity of their tool wear evaluations. A negative aspect of the dynamometer is revealed when observing its response surface, where the evaluation of the tool wear changes very abruptly from low *tool wear to high* tool wear. This means that if only the dynamometer signal is used for online TCM, the system will most likely not be able to react in time to prevent any sudden tool breakage. This also applies to the current sensor signal. This is because both the current sensor and the dynamometer signals follow the same trend, their fuzzy sets have similar statistical distribu-

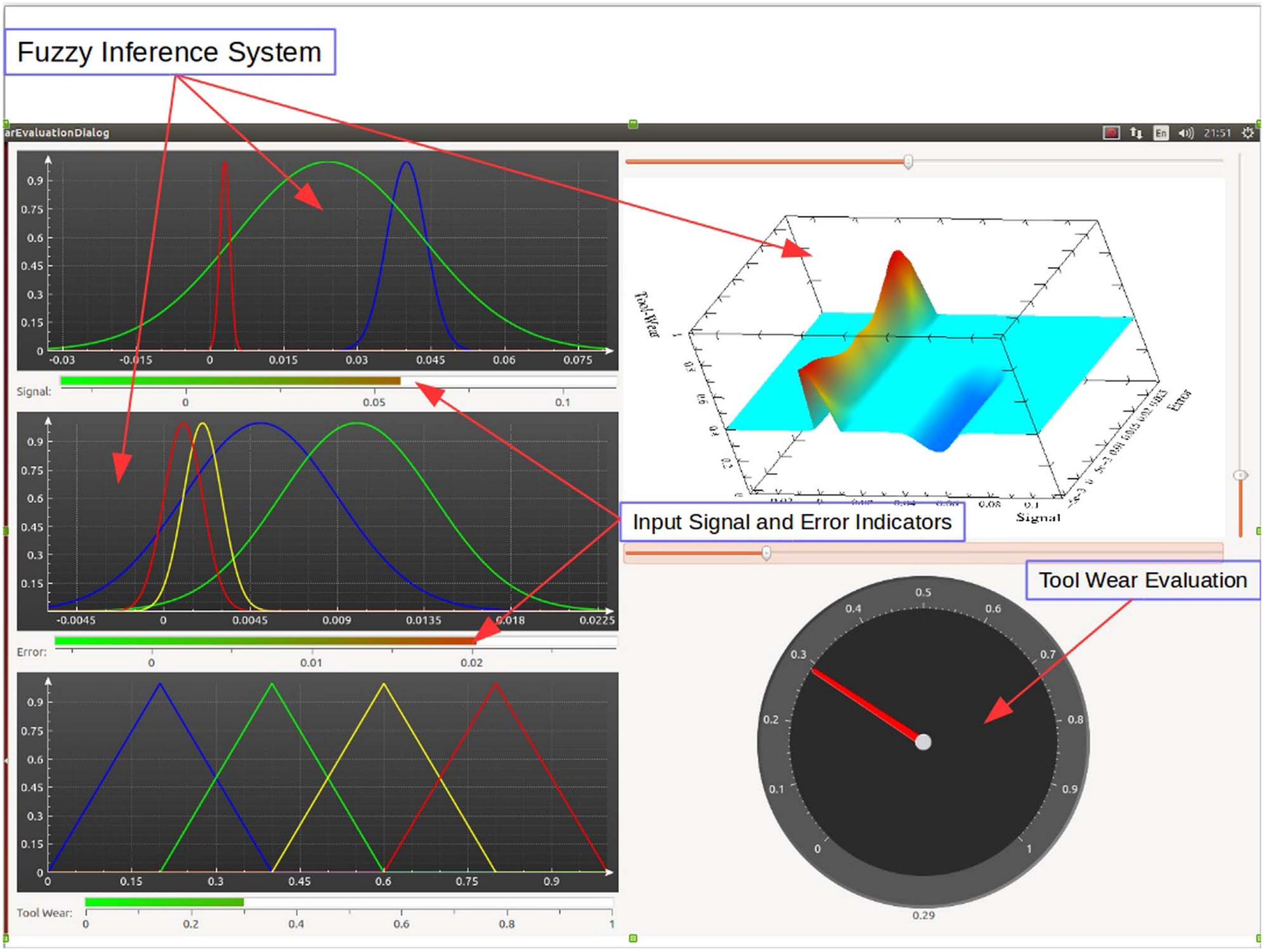

Fig. 19. Online tool wear evaluation based on given FIS.

tions and their response surfaces are similar. Related to the accelerometer, it can be concluded that the signal is too noisy and that the absolute error is quiet high. High values of absolute error can cause many problems and can render the tool wear evaluations unreliable. As can be observed from the response surface of the accelerometer signal, the evaluations for high *tool wear can be given even when the sensor values are low*.

The general observations made about the sensors were based on certain features that were used for their evaluation. Table 1 shows a brief description of these features and their process of evaluation, while Fig. 16 shows their radar plots. It is important to note that in the radar plot, the Error Ratio and Overlapping of the Membership Functions were inversed in order to reveal their negative impact on the sensors' evaluation.

The quantization of the performance of the sensors enabled the integration of all the signals into one online TCM system. Based on the sensors evaluation, a weight can be attributed to each of the tool wear estimations that are generated by the FIS. The result is a system that monitors the machining process from different positions, thus rendering it more robust and less prone to error.

4.3. TCM system

The observations and the knowledge accumulated in this research enabled the development of an online TCM system which was implemented by using C++ programming language and Qt framework. The software has signal processing capabilities for the filtering of the sensor signals and it automatically extracts statistical features in order to generate the required membership functions for the FIS. The software has two main functionalities: (a) data acquisition/filtering and FIS generation for a specific sensor during the experimental phase and (b) online tool wear evaluation functionality based on the given sensor signals and the FIS generated during the experimental phase. Figs. 17–19 show the developed software with its basic functionality.

5. Conclusions and further research

The flowchart shown in Fig. 20 summarizes all the basic constituents of the suggested TCM system which were extensively examined in this paper. To summarize the work accomplished thus far, the following conclusions can be made:

1) Monitoring the cutting condition of the tool in end-milling is very complicated and prone to error task.
2) Filtering and processing the data can be extremely time-consuming because of the relatively high sampling rates and the very high levels of noise that are generated during machining operations.
3) The frequency bandwidth of the applied filter should be carefully considered because the signal to noise ratio is very high in machining operations.
4) Many experiments are required to correctly define the fuzzy sets of the obtained sensor data. Based on these fuzzy sets, the sensor data can be attributed a membership function by considering their statistical features.
5) The sensors need to be evaluated based on certain objective criteria and the weight of their signal should then be defined to integrate them in the TCM system.
6) The microphone signal gave better and more reliable results

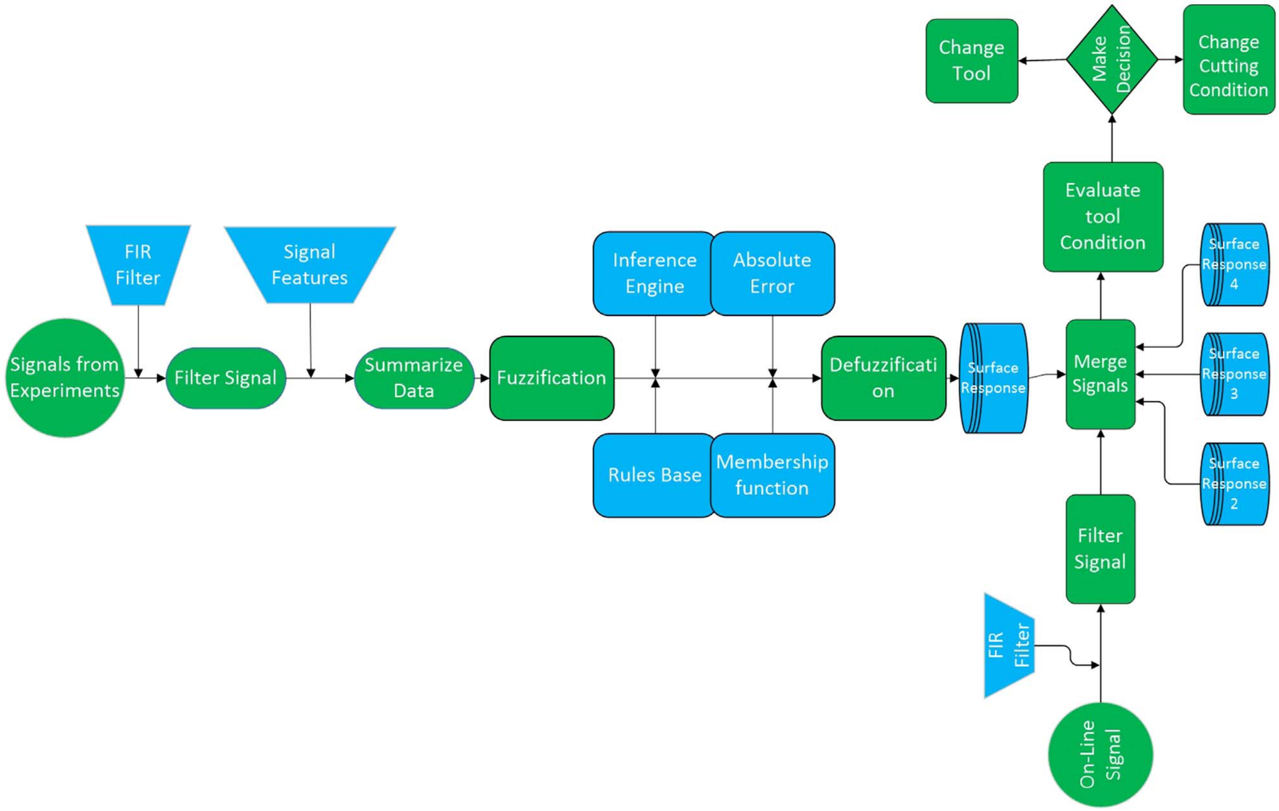

Fig. 20. Flowchart of the suggested Tool Condition Monitoring System.

because of its low Error Ratio, low Overlapping Effect and high Sampling Rates.

7) The dynamometer signals are very important as they can provide a three-dimensional view of the machining process (x, y and z-axis). Also, the dynamometer could detect the part of the tool that is most deteriorated since the flank is related to the z-axis and the rake is related to the x- and y-axis of the sensor. The peaks that appear in the dynamometer sensor data during the tool's entry point into the work-piece could be used to evaluate the tool's cutting condition as they seem to increase as the tool's cutting condition deteriorates.
8) The results for the current sensor were the same as those for the dynamometer and, because of their high correlation, each sensor can be used to validate the other sensor's result.
9) Filtering of the accelerometer signal was very difficult and it was prone to error.

Considering the above conclusions, the conducted research can be improved in nine different directions, which could lead to the development of a TCM system applicable for a production-line. This research was based on a very simplified tool-path with a simple flat end-milling tool on a three-axis CNC machine. Thus, it is important to further experiment with more complex tool-paths on three- and five-axis CNC machines, with tools of different sizes and geometries.

In this paper, it was demonstrated that by controlling the cutting speed of the machining process it is possible to extend the tool's life, and this is essential to avoid interruption of the machining process by sudden tool breakage or tool change operation. Thus, in order to control the tool life, it is very important to ensure a more precise relation between the cutting speed and the tool life. Moreover, since the online signal processing of the TCM system is a computationally intense process, the hardware implementation of the signal processing operations is suggested. For the embedded implementation of the system, digital signal processors should be used for computationally intense operations, and microcontrollers should be used for the data acquisition and implementation of the fuzzy inference system. Further progress in the sectors mentioned above would lead to the development of a practical and human independent TCM system that could be successfully implemented even in large scale automated manufacturing plants.

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